Personalisation of a multimethod digital health behaviour change intervention (DHBCI) for midlife women in the UK.

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https://doi.org/10.34737/ww762

Personalisation of a multimethod digital health behaviour change intervention (DHBCI) for midlife women in the UK

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A thesis submitted in partial fulfilment of the requirements of the University of Westminster for the degree of Doctor of Philosophy

May 24, 2024

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Abstract

Background:

Healthy lifestyle behaviours, including healthy diet and regular physical activity, are important behavioural determinants of the quality of life in midlife women. Midlife for women is also a key life stage that is associated with increased health risks of developing long-term health conditions, including heart disease, dementia, and osteoporosis. With over half of the global population being women and over a third of the entire UK female population currently experiencing menopause, promoting greater options for women to manage their healthy lifestyle behaviours is a public health priority. Moreover, the accessibility, convenience, and wide reach of digital health media, including mobile applications and wearable devices, makes it possible to deliver digital health behaviour change interventions (DHBCIs) to midlife women that are personalised, timely, and at scale. However, theory-and-evidence-based intervention designs are needed to improve our understanding of how to explain, influence, and predict health behaviours. Although there is a lot of interest to develop accessible and scalable DHBCIs that empower people to self-manage modifiable risk factors, there are currently no DHBCIs that provide personalised long-term lifestyle health management to midlife women in the UK.

Aim:

The aim of this PhD thesis was to design and optimise theory and evidence-based personalised DHBCI to enhance lifestyle health behaviours among midlife women in the UK.

Methods:

The thesis consists of four empirical studies and a co-production approach with a design phase followed by an optimisation phase of a DHBCI. The multimethod design consists of three design workstreams including: 1) a systematic review of behaviour change techniques (BCTs) used in DHIs for midlife women, 2) a mixed-method study to understand UK-residing midlife women's lived experiences with lifestyle health behaviours using focus groups, and 3) a co-production approach to co-design key components of the DHBCI. Underpinned by the Behaviour Change Wheel (BCW) framework, the design is theory and evidence-based, with a group-level personalisation facilitated by a Person-based approach (PBA) in the design phase. Subsequently, the multimethod intervention design was tested in a 4) a single-arm feasibility and acceptability study (intervention) utilising multiple data collection modalities (e.g., ecological momentary assessment (EMA) app, fitness tracker, survey), and optimised in 5) a study exploring machine learning (ML) algorithms to identify predictors and groups of BCTs to the target behaviours using the intervention dataset, and to identify strategies for dynamic, continuous and individualised DHBCI for women in midlife, in the UK.

Results:

Many DHBCIs lack theoretical grounding and identification of their key intervention components (e.g., BCTs, mechanism of action, intervention content) and are therefore too generic to be effective and are difficult to replicate. Personalisation of interventions requires input from the target population strengthened by co-production to ensure the intervention meets the needs of the target population. Applying the BCW framework to identify intervention components in the combined multi-study design is feasible and provides a systematic and replicable design. Testing the design in the intervention reached feasibility with a high level of participant engagement with no dropouts, and high level of acceptability. Finally, using supervised ML feature selection models to identify sets of intervention components (with intervention features linked to groups of BCTs) with the greatest impact on predicting target behaviours (using the intervention dataset) was feasible. Prediction accuracy of the ML model and predictive power was found acceptable in social science research.

Conclusion:

Identifying behavioural determinants personalised for the target population and providing coaching support is essential to achieve high level of engagement and retention in DHIs. Considering multiple complementary design inputs provides the necessary foundation for DHBCIs designs that are multi-faceted with wide-ranging considerations. Additionally, co-designing DHBCIs with the public facilitates greater relevance of the content and acceptability of the intervention. The intervention's multiple data collection modalities allow for capturing a wide range of behavioural data that can be further exploited by ML algorithms to identify predictors that are the most relevant in behaviour change. Utilising ML has the potential to improve personalisation, engagement, and effectiveness of adaptive and continuous DHBCIs on a long-term basis. Therefore, a multi-behavioural, multi-design, multimethod, and multimodal intervention aimed to improve healthy eating and regular physical activity in UK-residing midlife women is feasible and acceptable.

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List of Presentations and Publications

Publication: Study 1

Sediva H, Cartwright T, Robertson C, Deb S. (2022). Behavior Change Techniques in Digital Health Interventions for Midlife Women: Systematic Review. *JMIR Mhealth Uhealth 2022;10(11):e37234 https://mhealth.jmir.org/2022/11/e37234*, 10 (11), e37234. Available from https://doi.org/10.2196/37234

Protocol registrations: Study 1 and Study 3

Sediva H, Deb S, Cartwright T, Robertson C. (2021). A Systematic Review of Behaviour Change Techniques in Digital Health for Midlife Women. PROSPERO. CRD42021259246 Available from: https://www.crd.york.ac.uk/prospero/display_record.php?ID=CRD42021259246

Sediva H, Thomas L, Cartwright T, Deb S. (2023). A study exploring the impact of a digital health programme on improving dietary and physical activity habits in midlife women. ISRCTN 15365883 Available from: https://doi.org/10.1186/ISRCTN15365883

Code and data: Study 4

Sediva H. (2024). PhD Thesis Data and Code for Chapter 8. Available from: https://doi.org/10.5281/zenodo.13254518

Presentations: A list of oral and poster presentations arising from this thesis (**Table 1**)

Table 1: A list of oral and poster presentations arising from this thesis

Study presented	Year	Conference	Award received
1	2021	University of Westminster: Nutrition conference	
1	2021	University of Westminster: Life Sciences doctoral research event	
1	2022	Society of Behavioural Medicine (SBM), USA	'Outstanding Student Abstract', Theories and Techniques of Behaviour Change Interventions (TTBCI) SIG 'Best Systematic Review Abstract', Evidence-based Behavioural Medicine SIG
1	2022	International Behavioural Trials Network (IBTN), Canada	'Outstanding Poster Presentation', CMDO Award of Merit

		In collaboration with Cardiometabolic Health, Diabetes and Obesity Research Network (CMDO)	
1	2022	UK SBM	
1	2022	University of Westminster: 3-minute thesis (3MT) competition	
1	2022	The European Health Psychology Society (EHPS)	
2 and co-production	2023	UK SBM	
1	2023	University of Westminster: Social Sciences doctoral research event	
3 and 4	2024	IBTN, Canada	
4	2024	EHPS	

Other awards:

Co-production: Funding award

Sediva H, Cartwright T, Robertson C, Deb S. (2022, March). Participatory Research Award. Using co-production and behaviour change theory to design a digital health intervention for midlife women in the UK. *Participatory Research and Policy Support Funds 2022.* University of Westminster, UK.

Study 2: Funding award towards cost of collaboration

Sediva, H, Arigo D. (2022, May). Health and Behavioural International Collaborative (HBIC) Award. Designing a digital health behaviour change intervention with UK-residing midlife women using focus groups: A mixed-method study. *Society of Behavioural Medicine (SBM) USA: Collaboration with an international mentor on a project*. Rowan University. Glassboro, USA.

Acknowledgments

First of all, I would like to thank my supervisory team: Professor Louise Thomas who stepped in as my Director of Studies in the most challenging phase of my thesis when I was preparing to launch my intervention study. Dr Sanjoy Deb with whom this thesis came to life and who supported me as a Director of Studies in the first two years of my PhD. He was my sounding board in crafting the thesis proposal several months prior to commencing my studies and who encouraged me to explore research topics that were deeply meaningful to me, making my PhD journey more enjoyable. Dr Tina Cartwright, who guided me through the qualitative work of the thesis, and Dr Claire Robertson for her support in recruitment. There were also many others, including Dr Dipankar Sengupta and the entire Centre for Optimal Health team who showed interest in my work and stepped in to provide their expertise.

I express my sincere gratitude to everyone who participated in the various research studies of my PhD. The women who shared their lived experiences on menopause and lifestyle, which in some cases they shared with anyone for the first time. To the group of women, specifically Sally, Shideh, Clare, Bridget, and Ana, who worked tirelessly with me to design the intervention and spent their weekends testing and providing feedback to ensure it was as complete, relevant, and enjoyable for the intervention participants, as possible. The intervention content creators: Dr Laura Wyness and Dr Meera Kumar, and recruitment support from GPs, Dr Sohere Roked, Dr Sumi Soori, and Dr Michele Engel. Last but not least, to my family and my loved ones. A PhD is more than research, it is a personal journey that requires personal sacrifices that affected everyone close to me. Thank you to Laurelie, Jens, Mike, Robert, Simon, and Klaudia who supported me in every way they could.

Author’s Declaration

I declare that all the material contained in this thesis is my own work and has not been submitted to any other university.

Hana Sediva, May 24, 2024

Funding

Although this research was self-funded, funding was obtained for the following two components: 1) a one-year license for the Ilumivu EMA software used in intervention. 2) purchase of 60 Garmin Vivosmart4 devices, also used by the participants in the intervention (see Study 3, Chapter 7). Both, the software and devices were funded by the University of Westminster, Centre for Nutraceuticals and obtained by Dr Sanjoy Deb (initial DoS). Funding the PPI group was possible though a Participatory Research Award, funded by the University of Westminster, and applied for by the supervisory team, led by Dr Sanjoy Deb. There were no commercial partnerships formed to support the research.

Contributors

The intervention content provided to the participants digitally during the intervention was developed in collaboration with Dr Laura Wyness, a nutritionist specialising in menopause and a co-author of 'Eating Well for Menopause' award-winning book. All medical content was developed by an NHS General Practitioner (GP) Dr Meera Kumar, and exercise content by my supervisor and exercise physiologist, Dr Sanjoy Deb. Additionally, inter-rater reliability in Study 2 was completed by Dr Danielle Arigo, a mentor awarded to me for the Health and Behaviour International Collaborative (HBCI) Award in 2022, by the Society of Behavioural Medicine (SBM), USA. The purpose of the grant was to facilitate a mentorship collaboration with an international research group under the guidance of the mentee's selected international mentor. I chose Dr Arigo as my mentor for this collaboration given her expertise in digital health interventions with focus on improving physical activity specifically targeting midlife women.

List of Abbreviations

AD	Alzheimer Disease
ACTIVATE	Activity and Technology
Adj R^2	Adjusted R-squared
AI	Artificial intelligence
AIC	Akaike's information criterion
ANOVA	Analysis of Variance
APEASE	Acceptability, Practicability, Effectiveness, Affordability, Side-effects, and Equity
App	Application (software)
BCC	Behaviour Change Category
BCIO	Behaviour Change Intervention Ontologies
BCT	Behaviour Change Technique
BCTO	Behaviour Change Technique Ontology
BCTTv1	BCT Taxonomy Version 1
BCW	Behaviour Change Wheel
BHE	Barriers to Healthy Eating
BIC	Bayesian Information Criterion
BMD	Bone Mineral Density
BMI	Body Mass Index
BMS	British Menopause Society
CALO-RE	Coventry, Aberdeen, and London-Revised
CBT	Cognitive Behaviour Therapy
CM	Correlation Matrix
COM-B	'Capability' 'Opportunity' 'Motivation' - 'Behaviour'
CVD	Cardiovascular Disease
DBCI	Digital Behaviour Change Intervention
DEXA	Dual-energy X-ray Absorptiometry
DHBCI	Digital Health Behaviour Change Intervention
DHI	Digital Health Intervention
DMHIs	Digital Mental Health Interventions
EMA	Ecological Momentary Assessment
FS	Feature Selection
GB	Gradient Boosting Regressor
GP	General Practitioner
HBCP	Human Behaviour Change Project
HCP	Healthcare Professional
HE	Healthy Eating
HRQoL	Health Related Quality of Life
IFSMT	Individual and family self-management theory
ILM	Intensive Longitudinal Measures
ITHBC	The Integrated Theory of Health Behavior Change
JITAI	Just-in-Time Adaptive Interventions
LRT	Likelihood-Ratio Test
MAE	Mean Absolute Error
MANOVA	Multivariate Analysis of Variance

MeDi	Mediterranean Diet
MI	Multiple Imputation
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MLM	Multilevel Models
MoA	Mode of Delivery
mPED	Mobile Phone–Based Physical Activity Education
MRC	Medical Research Council
MRT	Micro-randomised Trials
MT	Menopausal Transition
MVPA	Moderate-to-Vigorous Intensity Physical Activity
NHS	National Health Services
NICE	National Institute for Health and Care Excellence
N-of-1	Multiple Crossover Trial (N=1)
NRMSE	Normalised RMSE
OP	Osteoporosis
PA	Physical Activity
PN	Precision Nutrition
PPI	Public/Patient Involvement
PREDICT	Personalised Responses to Dietary Composition Trial
PREFER	Paving the Road to Everlasting Food and Exercise Regimes
R^2	R-squared
RCOG	Royal College of Obstetricians & Gynaecologists
RCT	Randomized Controlled Trial
RF	Random Forest
RFE	Recursive Feature Elimination
RMSE	Root Mean Squared Error
r_s	Spearman Correlation Coefficient
RSE	Residual Standard Error
SCM	Stages of Change Model
SCT	Social Cognitive Theory
SDT	Self-determination Theory
SELF	Self-Efficacy Lifestyle Focus
SET	Self-efficacy Theory
SMART	Self-Monitoring and Recording using Technology
STBS	Striving to be Strong
STRAW	The Stages of Reproductive Ageing Workshop
SWAN	Study of Women's Health Across the Nation
T2DM	Type 2 Diabetes Mellitus
TA	Thematic Analysis
TaTT	Theory and Techniques Tool
TCS	Theory Coding Scheme
TDF	Theoretical Domains Framework
UK	United Kingdom
US; USA	United States of America
VSM	Vasomotor Symptoms
WWP	Women's Wellness Program

1. Introduction

1.1 Background

"The relative lack of attention to midlife health ignores the evidence that critical changes are occurring during this life-stage that warrant changes in lifestyle, behaviour, social engagement and health care practices. As suggested by the old saying -- At 40, your eyesight starts to go; at 50 everything else starts to go -- the midlife is a period of substantial physiologic change that requires adaptive change to optimise health and functioning." (Harlow and Derby, 2015).

Currently, there are thirteen million women experiencing menopause in the UK alone (NHS, 2022b), 985 million globally (UN, 2022), and it is expected there will be 1.2 billion menopausal women globally by 2030 (Hill, 1996). Although women in the UK on average live longer than men, women spend a greater proportion of their lives in ill health compared with men (Office for National Statistics, 2021). Nonetheless, more effort is needed to address the lack of research into women's health conditions (e.g., menopause, fertility, menstrual health, mental health and wellbeing, healthy ageing) to improve evidence base and data gap (Department of Health, 2022). Thus, there is a need to prioritise the quality and longevity of life for women in the UK, in line with the goals of the Women's Health Strategy for England (Department of Health, 2022).

Moreover, midlife represents a window of opportunity to promote health and support women to make healthier lifestyle choices (Simpson, Doherty and Timlin, 2023), in accordance with the National Institute for Clinical Excellence guidelines for menopause management (NICE, 2022b). Interventions to improve modifiable health behaviours, including maintenance of physical activity, healthy diet, and healthy body weight are recommended to moderate health risks in midlife (Harlow and Derby, 2015). However, identifying appropriate strategies to improve health behaviours specifically for the population of midlife women are less clear. Therefore, population-based research addressing interventions that promote a healthy transition during midlife and with menopause are needed (Harlow and Derby, 2015). According to the UK Government report (Department for Work and Pensions, 2023), over 4.4 million women between the ages of 45 and 55 are employed in the UK (Office for National Statistics, 2024), representing the fastest growing segment of workforce. Nevertheless, evidence shows that better treatment options are needed to support women in midlife. For example, a qualitative study with peri-/menopausal women, general practitioners (GPs), and gynaecologists in the UK (Barber and Charles, 2023) revealed women felt that their menopausal symptoms were dismissed by healthcare professionals (HCPs), HCPs not recognising some of the less common symptoms, or not offering options for treatments whether hormonal and non-hormonal (Barber and Charles, 2023). Providing a health-promoting intervention specifically for midlife women in the UK is therefore timely, particularly within the context of healthy eating and regular physical activity behaviours. Delivering such intervention digitally can further support greater scalability and reach more women, while providing content that is addressing unique needs of midlife women and empowering women to take charge of their own health and wellbeing. Although women make up one of the largest groups of consumers of digital self-tracking technologies, there is an unmet need for research and digital health tools appropriate for women experiencing menopause (Karim et al., 2024). Consequently, this research comes at an opportune time to address this gap in literature and identify intervention strategies that can support healthy lifestyle behaviours personalised to the population of midlife women, in the UK.

1.2 Outline of the Thesis

"This is the age of personalisation. Personalised practices permeate everyday life in the UK – we are invited to participate in personalised medical, health and care services, to benefit from personalised customer experiences, to find our way with personalised maps, acquire a personalised education, keep up to date with personalised news, get a bargain with personalised prices and so on." (Lury and Day, 2019).

The aim of this thesis is to design a personalised DHBCI targeting a population of midlife women (aged 40 – 65 years), in the UK. In total, four empirical studies and a co-production approach are presented in this thesis that is divided into two phases of design and optimisation (**Figure 1**). The three-workstream design phase aims to identify intervention components tailored to the target population, and includes a systematic review (Study 1), a mixed method focus group study (Study 2), and co-production. The design is tested and optimised in the optimisation phase of the thesis and includes a feasibility and acceptability study ("intervention") (Study 3), and an optimisation of the intervention components using machine learning (Study 4). Although the initial objective did not change throughout the thesis, the machine learning (Study 4) was included in the later phase of the project to strengthen the interpretation of the DHBCI findings. Therefore, the findings of the thesis include not only testing feasibility of the personalised DHBCI design, but it also includes identification of the most influential intervention components in predicting health behaviour change. To obtain a more representative sample and reduce burden on participants, all activities involving participants were conducted online (using Microsoft Teams) including participant recruitment, training, and group discussions (for Studies 2 and 3, and co-production). Together, the findings from the conducted studies can be used to inform personalised designs, optimisations, and evaluations of future DHBCIs targeting midlife women.

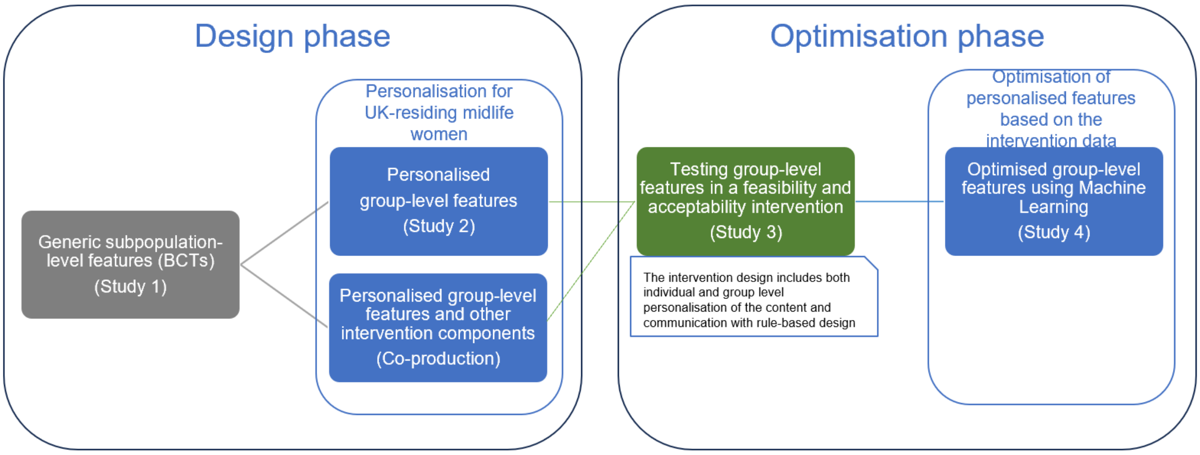


Figure 1: Overview of studies within the thesis

A systematic review (Study 1) was carried out to synthesise evidence on behavioural components of digital health interventions (DHIs) for midlife women, to inform the intervention design of this thesis and future directions in this research area. The findings of the systematic review demonstrated that DHI designs may not be reproduceable and generalisable across different contexts due to high level of heterogeneity in the designs of the interventions and selections of specific behaviour change techniques (BCTs). The included studies had 1) weak theoretical grounding, 2) limited description of their components, and 3) low level of treatment fidelity. The review demonstrated that there is a need for better tools and intervention designs guidelines to facilitate better utilisation of behaviour change theories in behavioural interventions. The review findings informed the feasibility DHBCI design (Study 3) by providing the most frequently used set of 33 BCTs (e.g., goal setting, self-monitoring, feedback on behaviour, social support) targeting global population of midlife women (not UK-residing). This review was published in *JMIR mHealth and uHealth* journal and is presented in Chapter five.

The subsequent mixed method focus group study (Study 2) and co-production provided the next level of granularity in identifying group-level DHBCI components, personalised to the target population of midlife women, in the UK. This study involved focus group discussions supplemented by a survey to understand how women in midlife experience healthy eating and regular physical activity. Through thematic analysis, barriers and facilitators to healthy lifestyle behaviours were extracted, providing an insight into how UK-residing midlife women feel about menopause and how it influences their healthy lifestyle behaviours. The analysis revealed multi-factorial influences on health behaviours. For example, the COVID-19 pandemic had an impact on lifestyle habits, which in some cases persisted after the lockdowns. Social connection, whether through group exercise classes or eating out with friends was one of the key themes, and it was therefore included in the intervention by encouraging the participants to join group classes and by regular coaching interaction between the researcher and the participants (Study 3). Further analysis showed that joining group exercise classes in the past was significantly associated with increased physical activity in the exploratory study (Study 4). Alcohol consumption increased and persisted after the lockdown and therefore, this target behaviour was also included in the feasibility study. The participants also highlighted sleep problems as one of the key menopausal symptoms that also led to their experience of elevated fatigue and consequently reduced physical activity and increased unhealthy eating. Sleep was therefore included to a limited extent in the intervention design through educational content and daily sleep data collection. Sleep duration showed in a significant negative association with diet quality in the intervention (Study 4). The BCW framework provided the overreaching synthesis for describing these lived experiences. Key themes were deductively mapped to 39 BCTs, providing a novel approach to identifying intervention components that are based on lived experiences of midlife women. Finally, increased use of technology (e.g., to track daily physical activity, join online exercise classes, order meals online) was a key theme in the focus groups that was reflected the high acceptability of the intervention by the intervention participants (Study 3). Feasibility of conducting an inter-rater validity of BCT mappings by a second reviewer was established in both studies one and two. The study is presented in Chapter six.

The co-production approach involved co-designing key intervention components with a public/patient involvement (PPI) group representing the target population of UK-residing midlife women. Through a series of three workshops, the group identified and prioritised: i) 26 target behaviours for physical activity and healthy eating, ii) topics for educational content, and iii) ways to interact with the DHI users, to improve healthy eating and physical activity. The group also tested and provided feedback on all intervention elements (e.g., all surveys, intervention prototype flow and wording) prior to the intervention launch. Following the BCW guide for developing interventions and defining key components of the intervention through co-production was feasible. The feedback from the PPI group indicated their acceptability of the co-design process. The DHBCI (Study 3) consolidated the three-study design inputs by merging the identified BCTs, resulting in a multimethod design with the final set of 34 BCTs. A subset of ten target behaviours was identified as a realistic scope for the intervention to minimise overwhelming the participants with too many behavioural prompts. The final design was operationalised through 'if-then' process flows to assist in developing and setting up intervention technologies capturing multi-modal data (i.e., an Ecological Momentary Assessment (EMA) mobile application, Garmin fitness tracker, baseline survey). Emphasis was placed on recruiting a diverse group of intervention participants across the UK to observe within and between-person variability in the target behaviours of participants with different sociodemographic backgrounds. All study procedures, including recruitment, retention, and data collection were feasible. This novel co-produced, theory and evidence based DHBCI resulted in high acceptability from the participants, which indicates that the multimethod design approach was successful. Furthermore, with improvements in all ten target behaviours, the intervention design has the potential to be effective for the target population, on average. However, multilevel modelling analysis of the longitudinal intervention dataset shows greater within-/between-person variability and fluctuations in the outcomes over time, indicating the need for further personalisation of the intervention components. Study 3 is presented in Chapter seven.

The final exploratory analysis (Study 4) was initially not planned to be included in the thesis. However, although the intervention tested a set of BCTs, not all BCTs were assumed to have contributed to behaviour change equally. It remains a challenge to isolate effective BCTs from a group of both effective and ineffective BCTs that are included in intervention designs (Michie, West, et al., 2018a) as well as to identify effective BCTs in real-time, "on the fly", to achieve adaptive intervention adjustments and personalisation (Nandola and Rivera, 2013; Moller et al., 2017). This study was therefore included for two reasons: 1) to interpret the intervention findings (Study 3) by using predictive analytics (i.e., machine learning (ML)) to identify group-level predictors linked to groups of BCTs that had the greatest impact on predicting target behaviours in the intervention and 2) to identify these predictors for future optimisation phase studies, in which further personalisation can be explored by adjusting the selection of predictors at an individual-level. The novel use of supervised ML feature selection algorithm was feasible in identifying group-level predictors linked to BCTs in all ten target behaviours. The goodness-of-fit (R-squared) of the ML algorithm was acceptable in other behavioural science research. This study provides a step forward in building a dynamic and continuous model, linked to theoretical behavioural components, that predicts healthy eating and physical activity outcomes. Future studies can potentially incorporate existing research in classification systems by assigning individuals to predefined groups (e.g., rule-based clusters) based on profiling parameters and adjusting the degree of generalisation vs personalisation as required. Latest technological advancements in Causal ML exploring cause-end-effect relationships of different intervention personalisation and their effect on the intervention outcome (through simulations of intervention arms) has the potential to provide further granularity of personalised intervention strategies and complement more costly and lengthy RCTs (Feuerriegel et al., 2024). Including an element of intervention support though coaching (e.g., human, virtual, or hybrid) has the potential to further optimise personalisation and intervention re-calibration at an individual level. This study highlights the increasing need to develop adaptive and continuous (long-term) interventions that support personalised health-promoting behaviours in midlife women. The study is presented in Chapter eight.

1.3 Personal Reflections

"A researcher's background and position will affect what they choose to investigate, the angle of investigation, the methods judged most adequate for this purpose, the findings considered most appropriate, and the framing and communication of conclusions." (Malterud, 2001).

Reflexivity, the process of engaging in self-reflection about who I am as a researcher and how my subjective biases guide and inform the research process is considered not only in the qualitative methods in Study 2 (**Section 6.2.4.5**) and co-production (**Section 7.2.5.1.4**) but also throughout the process of thesis conceptualisation and data collection and analysis. For me, it is evident how my previous experiences influenced my choice of the research topic and population and my decision-making throughout this research. With almost twenty years of experience in technology working for leading technology organisations, combined with an undergraduate degree in computer systems and an MBA in technology management, my dominant stance is in the positivist epistemology. Being a realist, my epistemological perspective is driven primarily by predictability, consistency, and repeatability of experiments. I enjoy working with data, which is evident in the dominant quantitative research approach in this thesis. Although these qualities are advantageous in developing digital health solutions, they also lack the perspective of the individual. It was during this research that I developed deeper appreciation for the epistemology of subjectivism by engaging with over 70 women who took part in my research. I developed a deeper appreciation for developing my pragmatic stance to research that combines both quantitative and qualitative approaches, thus bringing a more holistic perspective to this thesis.

Furthermore, working primarily with men in the technology sector made me aware of the gender gap that is perhaps more pronounced in technology than in any other sector. I have always been interested in health and wellbeing and became a yoga teacher and a nutritionist through my MSc in Sports and Exercise Nutrition. As I entered midlife, I became more aware of the challenges midlife women experience with the lack of information on how to best support their health and wellbeing, as well as the lack of therapies specifically designed for women experiencing menopause. Traditionally, menopause has been a taboo topic, associated with middle aged and older women and often the target of jokes and considered irrelevant. The choice of the topic was therefore very clear to me from the start of crafting my PhD proposal. Combining aspects of technology, nutrition, physical activity, behaviour change, and with the focus on midlife women has been personally very meaningful to me. Although I had no experience in working with many women prior to this research, I have developed stronger collaborative relationships with women during this PhD. I learnt that while all women experience menopause, the specific experiences are unique to each woman. This research helped me to appreciate how much it means to women to share their experiences and have their voices heard. I became aware of my own biases towards what I believed were the best strategies to support healthy lifestyle for midlife women, based on my own experiences. It was also for this reason that I engaged collaborators in the development of the intervention's educational content, to ensure other views and perspectives were incorporated in this research.

My lasting take-away from conducting this research is that interventions that promote healthy behaviours are needed now, more than ever. I hope this research may inspire technology companies to bring to market effective health-promoting digital health solutions and that future research will continue to advance our understanding in personalising digital health interventions for women in midlife.

2. Midlife for Women, Lifestyle Factors and Health-Promoting Interventions: Literature Review

2.1 Overview of Chapter

This chapter will introduce the midlife stage for women, in terms of long-term health risks and menopausal symptoms associated with midlife. Epidemiology of menopause will be discussed with references to its prevalence and demographics. Pathophysiology of menopausal symptoms and current mainstream treatment options are included. The treatment options will emphasise modifiable lifestyle factors, including diet and physical activity, in line with the focus of this thesis. Health interventions, including DHBCIs are discussed to demonstrate their efficacy in improving diet and physical activity in midlife women. Three main themes that are at the forefront of health/behavioural research in efforts to improve long-term effectiveness of DHBCIs are presented, including 1) personalisation of interventions, 2) designing adaptive and continuous interventions for long-term support, and 3) adherence to interventions to ensure people fully benefit from DHBCIs.

2.2 Menopause Epidemiology and Pathophysiology of Symptoms

Menopause is a biological stage that all cis-gender women experience between ages 45 and 55, on average (WHO, 2022). The mean age of natural menopause (i.e., not involving early or induced menopause (Stuenkel et al., 2015)) is 51 years in the UK (O'Neill and Eden, 2014) with the menopausal transition (MT) usually starting at about 47 years (Roberts and Hickey, 2016). Menopause that occurs earlier than the normative age range includes premature ovarian insufficiency (younger than 40 years), early menopause (between 40 and 45 years) and induced menopause (oophorectomy with or without hysterectomy, bilateral salpingo-oophorectomy, the removal of ovaries and fallopian tubes, or ovarian ablation through radiation) (Stuenkel et al., 2015). A longitudinal study of almost two decades based on the data from the National Health and Nutrition Examination Survey (NHANES and NHANES II) with postmenopausal woman (N=14,161) revealed that later natural menopause age was related to a longer lifespan, while early natural menopause presented with an increased risk of all-cause mortality (Xing and Kirby, 2024). The age at natural menopause appears to be associated with certain environmental and hormonal factors (e.g., nulliparity or low parity, early menarche, irregular menstrual cycle before age 25, high socioeconomic status) (Stanford et al., 1987), but also with lifestyle factors (e.g., smoking, or being underweight) (O'Neill and Eden, 2014). Therefore, the age of menopause holds intrinsic clinical and public health interest as the age at which natural menopause occurs may be a marker of ageing and health (Snowdon et al., 1989; Wise, Krajnak and Kashon, 1996; Cooper and Sandler, 1998).

Furthermore, as reproductive ageing associated with loss of follicular activity in the ovaries occurs within a wide age range (42-58 years), chronological age is an unreliable indicator for the stage of reproductive ageing (Batrinos, 2013). Therefore, the Stages of Reproductive Ageing Workshop (STRAW) criteria has been proposed for classification of reproductive ageing and it is the gold standard for characterising reproductive ageing through menopause (Harlow et al., 2012). The revised STRAW+10 staging system divide the adult female life into three broad phases (e.g., reproductive, menopausal transition, and postmenopause) and seven stages of reproductive ageing, with five before and two following the final menstrual period (Harlow et al., 2012). The late reproductive stage of premenopause is the beginning of the termination of the reproductive stage with irregular menses (Batrinos, 2013). Menopausal transition (MT; also known as the climacteric (Blümel et al., 2014)) marks the phase of physiologic changes as women approach reproductive senescence (Harlow et al., 2012). Evidence supports the clinical importance of the MT for many women as a period of temporal changes in health and quality of life (including vasomotor symptoms (VSM), depression, sleep disturbance) and longer-term changes in several health outcomes (e.g., bone health, metabolic changes) (Bromberger et al., 2005; Freeman et al., 2007; Avis et al., 2009). Clinically, it is more precise to define the menopause as the specific event of the cessation of menses, and the climacteric as the gradual change of ovarian function that starts before the menopause and continues thereafter for a while (Blümel et al., 2014). The diagnosis of natural menopause is therefore clinical, and it is marked by twelve months of permanent cessation of menses (i.e., amenorrhea), for which no other pathological or physiological cause can be established (O'Neill and Eden, 2014). Postmenopause is marked by more than twelve consecutive months of amenorrhea (Harlow et al., 2012; NICE, 2022). In research, the STRAW+10 stating system provides helpful guidance for assessing reproductive ageing and helps to improve comparability of studies and in the clinical context, it facilitates clinical decision making (Harlow et al., 2012).

2.3 Health Risks in Midlife

Midlife for women is associated with increased risk of developing noncommunicable diseases, including cardiovascular disease (CVD) and type 2 diabetes mellitus (T2DM) (Ko and Kim, 2020), as well as neurodegenerative diseases (e.g., Alzheimer disease) (Brinton et al., 2015; Mosconi et al., 2018a). Postmenopausal women are also at increased risk of low bone-mineral density (BMD), fractures, and osteoporosis (OP) (Johansson, Mellström and Milsom, 1993; Compston et al., 2017). Furthermore, OP is also associated with physical inactivity, with the highest prevalence in women and in elderly individuals (Dallanezi et al., 2016). A cross-sectional clinical study with postmenopausal women revealed that the rate of sedentary lifestyle was higher in postmenopausal women who had OP than in those women with either osteopenia or normal bone mineral density (BMD) (Dallanezi et al., 2016). Therefore, there may be an opportunity to intervene with physical activity interventions to reduce sedentary behaviours in midlife women.

Dementia was the third leading cause of death in high-income countries in 2016 (WHO, 2020) and it has become the leading cause of death in women in the UK (Prince et al., 2021). Alzheimer disease (AD) is the most common type of dementia (Mosconi et al., 2007), and epidemiologic studies have consistently shown for years that women comprise two-thirds of people living with AD, regardless of age and ethnicity (Farrer et al., 1997). Female sex is one of the major risk factors for developing late-onset AD (Farrer et al., 1997), with the preclinical AD phase coinciding with endocrine transition in perimenopause (Mosconi et al., 2017). Although AD has been perceived as the disease of old age, recent research shows that it may in fact be the disease of midlife (Farrer et al., 1997; Gaugler et al., 2016), with the preclinical AD phase coinciding with endocrine transition in perimenopause (Mosconi et al., 2017). Therefore, an optimal window of opportunity for therapeutic interventions, including dietary (Mosconi and McHugh, 2015; Berti et al., 2018) and stress reduction interventions (Mosconi et al., 2024), to prevent or delay progression of AD in women is early in the endocrine ageing process during midlife (Mosconi et al., 2018b, 2024). Due to limited efficacy of pharmacological treatments, there is an increasing interest in implementing brain-protective lifestyle changes during the preclinical phase of AD (Mosconi and McHugh, 2015). However, interventions need to account for biochemical individuality and personalised medicine will be most useful to assess specific individual modifiable lifestyle factors (Mosconi and McHugh, 2015).

Moreover, during MT, an emergence of various lipid metabolic disorders, exacerbated by hormonal changes (e.g., decreased levels of oestrogens and increased levels of circulating androgens), may lead to the development of metabolic syndrome and increased risk of developing CVD and T2DM (Ko and Kim, 2020). A five-year follow up in the longitudinal Study of Women's Health Across the Nation (SWAN) study with midlife women (N=6,296) reported that relative androgen excess (i.e., a higher baseline testosterone/oestradiol (E2) ratio) can predict incidence of metabolic syndrome, including dysregulated lipid metabolism and obesity (Torréns et al., 2009). Therefore, metabolic changes that are typically associated with overweight and obesity (Bergman and Ader, 2000; Eckel, Grundy and Zimmet, 2005; O'Donovan et al., 2024) have also been observed during MT, including weight gain (Greendale et al., 2019), ectopic fat deposition (Kavanagh et al., 2013), insulin resistance and impaired glucose tolerance (El Khoudary et al., 2019). Furthermore, studies show that postmenopausal women experience significant rise in low-density lipoprotein, triglyceride, cholesterol, and blood pressure (after adjusting for covariates of age and BMI) (Dasgupta et al., 2012), which have been associations with increased visceral fat and CVD risk in menopausal women (Fenton, 2021).

In summary, there are several factors that contribute to metabolic changes (including weight gain) in a synergistical manner and that appear to play a role in menopause. These factors include 1) hormonal changes (e.g., hypoestrogenism, increases in bioavailability of androgens), 2) genetic factors (e.g., ethnicity, epigenetic alterations), 3) exogenous factors (e.g., poor nutrition and physical inactivity, medication use and disease status) (Grammatikopoulou, Nigdelis and Goulis, 2022). Finally, while lifestyle health interventions have been shown to improve metabolic health (in overweight and obesity), the large inter-individual variation in response to these interventions complicates both the assessment and provision of effective intervention options (O'Donovan et al., 2024). Therefore, individual factors (e.g., ethnicity, current health status, socioeconomic status) need to be considered in health-promoting interventions targeting midlife women, to maximise their effectiveness for each individual.

2.4 Menopausal Symptoms and Treatments

According to the joint report by the British Menopause Society (BMS) and the Royal College of Obstetricians & Gynaecologists (RCOG), menopausal symptoms have been under-reported and under-treated for years (Joint RCOG, 2021), with a recent survey of 4,014 UK women confirming these findings (Barber and Charles, 2023). The majority of women (77%) reported experiencing one or more menopausal symptoms they describe as very difficult and 10% of women have left their jobs because of these symptoms (The Fawcett Society, 2022). The symptoms of menopause can be distressing, particularly at the time when women have important roles in society, within family and at the workplace (Monteleone et al., 2018). These symptoms affect many biological systems and include central nervous system-related disorders, metabolic, weight, cardiovascular and musculoskeletal changes, urogenital and skin atrophy, and sexual dysfunction (Monteleone et al., 2018). Although findings from longitudinal studies have shown that ethnic, geographical, and individual factors affect symptoms prevalence and severity (Monteleone et al., 2018), some of the more common symptoms women report include poor concentration, tiredness, poor memory, feeling low or depressed and lowered confidence (Hardy, Hunter and Griffiths, 2018). Menopause symptoms also include hot flushes and sweats, tiredness and sleep disturbance, joint and muscle ache, heart palpitations, mood swings, anxiety and depression, forgetfulness, lack of concentration, heavy bleeding, headaches, increased urinary frequency or urgency and vaginal atrophy (Carr, 2003; Dennerstein et al., 2007; Hale and Burger, 2009; O'Neill and Eden, 2014; Muharam et al., 2017; Mulhall, Andel and Anstey, 2017), although this is not an exhaustive list of symptoms (BMS, 2022).

Research suggests that certain menopausal symptoms might serve as markers for future health, for example, severe VSM with sleep disorders might increase cardiovascular risk, whereas severe VSM with depression might affect cognitive function (Monteleone et al., 2018). VSM, including hot flushes and night sweats, affect up to 80% of women during MT (Archer et al., 2011). Research shows that hormone replacement therapy (HRT) is the most effective treatment for VSM and other symptoms of the climacteric (Stuenkel et al., 2015). It is also recommended by NHS (NHS, 2022b) and healthcare professionals are recommended to screen women for cardiovascular and breast cancer risks before initiating HRT and individualise therapy based on clinical factors and patient preferences (Stuenkel et al., 2015). Cognitive behaviour therapy (CBT) is a recommended treatment by the NHS to support menopause-related low mood and anxiety and some physical symptoms, including hot flushes and joint pain (NHS, 2022b).

Mindfulness meditation has also been used to support menopausal symptoms. A meta-analysis of Randomised Controlled Trials (RCTs) on mindfulness-based interventions (Chen et al., 2021) showed significant improvements in total quality of life, and vasomotor and physical quality of life, with potentially long-term improvements. A recent eight-week at-home self-guided study with midlife women, preceded by a five-month centre-based meditation intervention used mindfulness-based meditation to reduce menopausal symptoms demonstrated that as self-efficacy increased (based on Coping Self-Efficacy Scale), menopausal symptoms decreased (based on Menopausal Rating Scale). The outcomes of the intervention indicate that a simple mindfulness-based meditation intervention can help menopausal women to better cope and alleviate their symptoms (Winges Conflitti, Hoffman and Mathiason, 2024). Bundling a mix of cognitive techniques and other therapeutics has also been explored. For example, an eight-week intervention of peri-menopausal women (N=21) using cognitive-behavioural techniques including relaxation, nutrition, exercise, and pelvic floor exercises found a significant reduction in most menopausal symptoms, including depression and anxiety (García and Gómez-Calcerrada, 2011). Although such multi-purpose packages may be tempting to implement to address many issues at once, it is unclear and challenging to determine which (combination of) components of the package were effective in reducing menopausal symptoms.

While menopausal symptoms are common among midlife women, their incidence varies according to the population that is studied (Levis and Griebeler, 2010) and can differ between individuals and cultures (Gold et al., 2000; Hall et al., 2007). The SWAN study concluded that ethnic differences in the prevalence of obesity of women in midlife (N=3,302; aged 40-55 years) were pronounced (Matthews et al., 2001). Additionally, increased adiposity (i.e., higher percentage of body fat) was associated with increased odds of reporting VSM, with African-American and Hispanic women having the highest BMI and therefore greater risk of VSM (Green and Santoro, 2009a). Hispanic and African-American women were also more likely to report depressive symptoms than Chinese and Japanese women (Bromberger et al., 2005). Additionally, poor sleep was reported more frequently in African American and Hispanic women (Green and Santoro, 2009a).

Moreover, an individual's health related quality of life (HRQoL) in midlife is influenced by many additional non-menopausal factors, such as physical inactivity and lack of social integration (Schneider and Birkhäuser, 2017). Therefore, lifestyle changes including increased physical activity (i.e., weight-bearing exercise), eating a balanced diet (including calcium and vitamin D supplementation), smoking cessation, and minimal alcohol intake are recommended for post-menopausal women to maintain BMD (Crosignani, 2010; Compston et al., 2017). In addition, physical activity is further associated with reduced frequency of hot flushes through thermoregulatory and cardiovascular adaptations (Bailey et al., 2016), while weight excess at midlife is associated with heightened risk of cardiovascular and metabolic disease and adversely impacts HRQoL (Davis et al., 2012). Although there is still much unknown regarding the effects of menopause on health (Roberts and Hickey, 2016), it is known that prevention of menopause-related complaints is important from a clinical and public health perspective (Lobo et al., 2014), as well as for improving women's quality of life (Ozcan, 2019). While there are increasing number of therapies for midlife women, individual approach to treatments must be considered to be effective (Palacios and Mejias, 2015).

2.5 Lifestyle Factors to Consider in Midlife for Women

Research shows that modifiable health behaviours (e.g., smoking, substance use, diet, physical activity, sleep, adherence to prescribed medical treatments, health care seeking behaviours), whether intentional or unintentional, are actions taken by individuals that affect their health or mortality (Short and Mollborn, 2015). Understanding how successful behaviour change occurs is the key to creating healthy behaviour, reducing the burden of chronic disease globally, and promoting health (Davidson and Scholz, 2020). Thus, behaviour change interventions (BCIs) are fundamental to the effetive practice of clinical medicine and public health (Michie, van Stralen and West, 2011). BCIs can be defined as coordinated sets of activities designed to change specified behaviour patterns, which are measured in terms of the prevalance or incidence of particular behaviours in specified populations (e.g., delivering healthy lifestyle advice by general practitioners) (Michie, van Stralen and West, 2011). Eating a healthy diet and staying physically active have been found to help reduce various symptoms experienced by women during peri-/post-menopause (Moilanen et al., 2010; Pimenta et al., 2012; Jaspers et al., 2015) and minimise gains in fat mass, undesirable changes in body composition, and body fat distribution (Quesenberry and Menopause, 2005). Furthermore, it's been established that individual's factors, including social determinants (e.g., discrimination, stress), and demographics (e.g., social class, gender, ethnicity) also influence people's health behaviours (Short and Mollborn, 2015). For example, more educated adults are more likely to initiate healthy behaviour change and smoke and more likely to be physically active (Margolis, 2013). Although health behaviours are often addressed as individual-level behaviours, they can also be measured for individuals, groups, or populations (Short and Mollborn, 2015). Moreover, besides being idiosyncratic, health behaviours are also dynamic, they vary over the lifespan, across cohorts, settings and over time (Short and Mollborn, 2015).

However, policies targeting health behaviours often focus on single behaviours and conclude that such behaviours are resistant to change. On the other hand, health lifestyle approach views behaviours as occurring in sets and that they influence each other (Williams, 1995), and therefore, focus on improvements in multiple behaviours (e.g., diet, physical activity) have the potential to be more effective. For example, a meta-analysis of weight loss interventions (k=10) that included both diet and physical activity interventions (k=2) resulted in a statistically significant subgroup differences for fat mass change between menopausal group and premenopausal group when comparing to diet only interventions (Thomson et al., 2021). However, at this point in time, there is lack of evidence of interventions for midlife women targeting multiple health behaviours. In the meta-analysis (Thomson et al., 2021), two studies that included both diet and physical activity behaviours involved overweight or obese breast cancer survivors (N=692) (Rock et al., 2015) and obese women (N=148) (Annesi and Whitaker, 2010). The following section is addressing nutrition and physical activity individually, including interventions that focused on these individual health behaviours in midlife women.

2.5.1 Nutrition

Optimisation of diet is a key factor in strategies aimed to reduce the risk of chronic diseases and to promote menopausal health (Cano et al., 2020). The NHS recommends a diet that addressed primarily bone health and consists of eating a healthy diet that includes plenty of fruit, vegetables, and sources of calcium (e.g., milk, yoghurt, kale) (NHS, 2022a). The BMS recommends eating a balanced diet (e.g., ¼ protein, ¼ carbohydrate, and ½ fruit, vegetables or salad) by structuring meals made up of major food groups (BMS, 2023). Additionally, reducing portion sizes, eating more slowly and planning meals, including snacks to increase nutrient intake (BMS, 2023), increasing consumption of fruit and vegetables (Yelland et al., 2023), and reducing alcohol drinking are also recommended (Peltier et al., 2020; BMS, 2023). Furthermore, eating carbohydrates rich in fibre and with low glycaemic index (e.g., types of fruit, vegetables, whole-grain foods, dairy products with no added sugar) have health-protective effects (Erdélyi et al., 2023). Although current evidence suggests that low-fat plant-based diets are associated with beneficial effects on body composition, further studies are needed to confirm these results in menopausal women (Silva et al., 2021).

Moreover, epidemiological evidence linking diet, as one of the most important modifiable lifestyle factors affecting the risk of AD (which is the primary cause of death for women in the UK (Prince et al., 2021)), is rapidly increasing (Mosconi and McHugh, 2015). A three-year Mediterranean diet (MeDi) intervention measured Alzheimer brain biomarker changes in midlife adults and included low MeDi and high MeDi diet and although no changes on MRI were observed, the high MeDi diet adherence was estimated to provide 1.5 to 3.5 years of protection against AD (Berti et al., 2018). According to the European Menopause and Andropause Society (EMAS) position statement and clinical guidelines, short-term adherence to the MeDi may improve vasomotor function, improve mood, and reduce symptoms of depression, while a long-term adherence in peri- and post-menopausal women may reduce all-cause mortality, risk of breast cancer, CVD incidence, improve bone mineral density (BMD), and prevent cognitive decline (Cano et al., 2020). However, most of the conclusions are based on studies that also included men, had wide age range with a small number of studies including perimenopausal women (Szmidt et al., 2023). In the cross-sectional study (FLAMENCO project), a cardioprotective influence of the MeDi in perimenopausal women (N=172) was observed, however no associated was observed with VSM (Flor-Alemany et al., 2020). Moreover, in a cross-sectional study of Spanish perimenopausal women (N=3,508), high level of adherence to the MeDi was inversely associated with overweight and obesity, as well as reduced menopausal symptoms (Sayón-Orea et al., 2015). In a prospective cohort study with Australian midlife women (N=6,040) followed up for over nine years found that adherence to the MeDi was inversely associated with VSM (Herber-Gast and Mishra, 2013). Furthermore, although the MeDi has been previously shown to have various health-related benefits for women's health (Cano et al., 2020), the association between MeDi and the onset age of natural menopause has not been studied (Szmidt et al., 2023).

Furthermore, other dietary outcomes have been found relevant in midlife (e.g., increasing fruit and vegetables intake, increasing hydration, reducing caffeine and alcohol consumption). Fruit and vegetables contain high levels of vitamins, antioxidants, flavonoids, phytochemicals and other bioactive substances and are positively linked to bone health (New et al., 2004). An eight-week feasibility study with midlife women (N=21) showed significant increase in urine pH after increasing fruit and vegetables portions from five to nine per day (Gunn et al., 2013a). Alkaline buffer precursors supplied in fruit and vegetables are one of the tenets of the link with higher BMD (Macdonald et al., 2005). Additionally, higher consumption of fruit and vegetables in young adulthood was shown to be associated with better cognitive function in midlife (Mao et al., 2019), and improved cognitive function in the elderly (Zielińska et al., 2017). The strongest association was observed for leafy greens (Morris et al., 2018). Additionally, consumption of Omega-3 fatty acids and fish (part of MeDi) has shown neuroprotective effects (Raji et al., 2014). Weekly consumption of fish was positively associated with structural brain integrity in healthy adults over 65 years old (Raji et al., 2014). Therefore, evidence suggests that there is an opportunity to address healthy diet in midlife to achieve better health outcomes in older age.

Alcohol consumption has increased in midlife women over the last two decades in high-income countries, including the UK (Miller et al., 2023). Alcohol consumption has been indicated to affect the age of natural menopause, although the pathways are not fully understood (Taneri et al., 2016). Evidence from meta-analysis suggests that low to moderate alcohol consumption (three or fewer drinks per week) appears to be associated with later onset of menopause than for non-drinkers (Taneri et al., 2016). This is also supported in a prospective longitudinal study with midlife women (N=107,817) having lower risk of early menopause than non-drinkers when consuming moderate amount of alcohol (particularly white wine) (Freeman et al., 2021). However, the study had several limitations, including self-reported alcohol consumption with only a few participants reporting consuming more than two alcoholic beverages per day, thus limiting statistical power to evaluate associations at higher intakes (Freeman et al., 2021). Moreover, in a cross-sectional study with Spanish midlife women (N=10,514), no association was found between alcohol consumption and VSM (Antonio Martínez Pérez et al., 2009). While the MeDi is characterised by a high intake of plant food (e.g., fruit, vegetables, legumes), olive oil, moderate intake of fish, it also contains a low to moderate intake of alcohol and dairy products, low intake of saturated fats, meat and poultry (Trichopoulou and Lagiou, 1997). On the other hand, alcohol intake has also been established a risk factor for breast cancer with greater risk beginning at consumption levels as low as one drink per day (Kungu, Hamajima and Hirose, 2002). Furthermore, despite a very limited research and publication on caffeine intake and its effects on menopausal symptoms, caffeine has been promoted by healthcare providers as having negative impact on VSM (Bouchard, 2015). In a cross-sectional study with midlife women (N=1,806) using the Menopause Health Questionnaire, caffeine was positively associated with mean VSM, and the findings remained significant after adjusting for smoking and menopause status (Faubion et al., 2015). Another systematic review also indicated an association between caffeine intake and the intensity of menopausal symptoms (Noll et al., 2020). However, other studies showed contradictory results (e.g., coffee and tea consumption was associated with a lower intensity of menopausal symptoms (Taher, Ben Emhemed and Tawati, 2012), which may be driven by the differences in the caffeine content of beverages and variations in metabolism of caffeine among individuals (Bouchard, 2015). A cross-sectional study with Norwegian midlife women (N=2,123) explored association between early menopause and lifestyle and found that caffeine and alcohol had no significant association with early menopause, however current smoking was significantly associated with early menopause. However, stopping smoking more than ten years before menopause considerably reduces the risk of early menopause (Mikkelsen et al., 2007). Furthermore, in terms of hydration, changes in oestrogen and progesterone have important effects on body fluid regulation (Stachenfeld, 2014). Additional dietary DHIs targeting midlife women are presented in a systematic review of this thesis (**Chapter 5**).

2.5.1.1 Precision (Personalised) Nutrition

In nutritional research, randomised, double-blinded, placebo-controlled trials are the gold-standard to assess intervention success whereby the effectiveness of a given diet intervention is determined by comparing the change in an outcome measure (e.g., body weight, fasting glucose) in the intervention group to the control group. However, by reducing the population level responses to averages (or generic cut-offs), the sometimes-considerable inter-individual response is often neglected (O'Donovan et al., 2024). Retrospective studies have demonstrated that subgrouping participants based on metabolic characteristics, including phenotypic features (e.g., tissues specific insulin resistance, glucose tolerance status, acetyl carnitine profile) may modulate intervention success (O'Donovan et al., 2024). Precision Nutrition (PN) represents an advancement from traditional one-size-fits-all dietary approach, which assumes that individual nutritional requirements and responses mimic the average response observed in study populations (Bush et al., 2020). Instead, PN is a data-driven approach to developing comprehensive and dynamic nutritional recommendations based on individual factors, including dietary (e.g., dietary preferences, meal composition, meal content and timing), lifestyle and environmental (e.g., physical activity, sleep, medication use, smoking), and biological (e.g., anthropometric measurements, genetics, microbiome, health status, including medical conditions, metabolic health, nutritional status) (Berciano et al., 2022). The PREDICT study (Bermingham et al., 2022), being the largest nutrition study with midlife women (N=1002; pre- N=366, peri- N=55, post-menopausal N=206) demonstrated that post-menopausal women had higher fasting blood glucose measures, sugar intake, and poorer sleep compared with pre-menopausal women. Postprandial metabolic responses for glucose and insulin were also higher in post-menopausal vs pre-menopausal women. In age-matched subgroups, postprandial glucose responses remained higher post-menopause. Therefore, the differences in postprandial response in subgroups suggest that different treatments would be suitable and PN would be beneficial. Additionally, women taking HRT had better outcomes in lower visceral fat, fasting (glucose and insulin), and postprandial measures (Bermingham et al., 2022). Associations were also observed between menopause and metabolic health indicators (e.g., visceral fat) that were in part mediated by diet and gut bacterial species (Bermingham et al., 2022).

Therefore, nutritional recommendations that are targeted toward specific characteristics (e.g., genotype, microbiome composition, metabolic traits) of an individual, may provide improved and more sustainable health outcomes for the individual (Ordovas et al., 2018; Blaak, 2020). The potential for PN and tailoring of nutrition based on phenotypic features was demonstrated by (Zeevi et al., 2015) revealing that gut microbiota composition could explain much of the observed inter-individual variation in the glucose excursions following a meal. Furthermore, in a follow up intervention (Ben-Yacov et al., 2021) involving personalised dietary recommendations based on microbiota composition demonstrated greater improvements in glycaemic control than a MeDi (O'Donovan et al., 2024). Although several studies found dietary intake to be associated with the severity of menopausal symptoms, evidence for the association between dietary intake and menopausal symptoms is inconsistent and inconclusive and is provided by a small number of studies (O'Donovan et al., 2024).

Furthermore, a recent study developed a physiology-based computational model to characterise an individual's metabolic health in silico (O'Donovan et al., 2024) by quantifying insulin resistance, β-cell function and liver fat. A population of 342 personalised computational models were generated based on a dataset consisting of overweight and obesity individuals from three independent interventions. The study concluded that the developed (Mixed Meals Models) models can be used to evaluate the impact of a dietary intervention on multiple aspects of metabolic health at the individual level (O'Donovan et al., 2024). As such, future healthy diet-promoting behavioural interventions should be enriched with data not only from self-reported dietary intake, but also with objectively measured metabolic health measures to provide personalised tuning of dietary recommendations.

2.5.2 Physical Activity

Ageing is associated with physiological decline, primarily due to a decrease in BMD and lean body mass, with a concurrent increase in body fat and central adiposity (Nassis and Geladas, 2003). Furthermore, many midlife women experience changes in body composition and the accumulation of intra-abdominal fat deposit and visceral fat (Fenton, 2021), which is driven by changes in energy expenditure and spontaneous activity (Kendall and Fairman, 2014). While physical activity is one of the key behavioural factors associated with improvements in physiological decline (Kendall and Fairman, 2014), during midlife, women reduce their physical activity levels (PAL) considerably (Davidson, Tucker and Peterson, 2010). In many developed countries (e.g., USA, Finland) up to 75% of women do not meet the physical activity guidelines (L. E. Davidson et al., 2010; Grammatikopoulou et al., 2022).

Exercise is considered a safe and low-cost non-pharmaceutical treatment option for the protection of musculoskeletal health and fracture prevention (Daly et al., 2019). With the increased risk of osteoporosis for women later in life, that is initiated during their menopausal transition and the corresponding decline of oestrogen (Christenson et al., 2012), several studies have focused on physical activity interventions and their effects on BMD. For example, in a recent meta-analysis of interventions (k=73) involving postmenopausal women (N=5,300) concluded that exercise training at midlife is effective on BMD even later in life in older women (aged over 65 years) (Shojaa et al., 2020). Although the review included studies with high heterogeneity in exercise protocols, exercise training was considered a cost-effective strategy to prevent osteoporosis in midlife (Shojaa et al., 2020). The NHS recommendations for physical activity focus primarily on bone health and include regular exercise, including weight-bearing exercises, walking, running or dancing, and resistance exercises using weights. Other types of NHS recommendation include relaxing movements such as yoga and tai chi (NHS, 2022a). Evidence suggests the use of meditative movement (e.g., Tai Chi, Qigong, yoga) to improve body composition (measured using DEXA) and weight control in midlife women (James et al., 2023). Multiple studies that used yoga interventions have shown improvements in weight-related outcomes and body composition (Larkey et al., 2018). Interventions involving yoga have also shown to be an effective way to reduce body mass index (BMI) among those overweight or living with obesity (Lauche et al., 2016). Additional DHIs targeting physical activity improvements in midlife women are described in the systematic review of this thesis (**Chapter 5**). There appear to be no other DHIs published since the review was completed.

2.5.3 Other Lifestyle Factors

Additional factors associated with health and wellbeing of women in midlife include psychological factors (e.g., stress and mood, mindfulness, self-compassion, body awareness), additional behavioural factors (e.g., sleep), and physiological factors (e.g., cortisol and oestrogen levels, gut hormones, the microbiome) (James et al., 2023). From other behavioural factors (in addition to diet and physical activity), sleep is also described in this thesis. Sleep disturbance is common, affecting 40-60% of menopausal women (Nelson, Covington and Rebar, 2005), and it is an important determinant of health and quality of life (Matteson-Rusby et al., 2010; Polo-Kantola, 2011). While sleep disturbance is often presented as difficulties initiating and/or maintaining sleep with frequent nocturnal and early morning awakenings, the cause is unclear (Gold et al., 2000), with several factors thought to play a role (Ameratunga, Goldin and Hickey, 2012). These factors include changing hormonal levels, VSM, circadian rhythms abnormalities, mood disorders, exacerbation of primary insomnia, coexistent medical conditions and lifestyle factors (Ameratunga, Goldin and Hickey, 2012). Sleep deprivation has been linked to medical conditions, such as obesity, CVD, T2DM, and mood disorders (Ameratunga, Goldin and Hickey, 2012). Sleep deprivation is further associated with fatigue and lower levels of physical activity in midlife women and may also lead to greater weight gain (Patel et al., 2006). Therefore, interventions targeting sleep disturbance in menopause need to consider several factors, including behavioural, circadian, and basic sleep history (Ameratunga, Goldin and Hickey, 2012). Although most interventions targeting sleep have been reported as qualitative in nature, the correlation between objective and subjective measures of sleep appears to be not high. In a UK study of midlife women (N=1200), the risk of sleep problems was higher by a factor of 1.5 for perimenopausal women and a factor of 3.4 for postmenopausal women (relative to that for premenopausal women) (Kuh, Wadsworth and Hardy, 1997). In a study of midlife women (N=400), poor sleep was associated with higher levels of both anxiety and depression (Hollandera et al., 2001). Furthermore, (Freedman and Roehrs, 2007) found that high anxiety scores predicted low subjective sleep quality in peri- and post-menopausal women (N=102). Considering the multifactorial origin of sleep problems in midlife and after, treatment can be challenging (Polo-Kantola, 2011). Good sleep hygiene (e.g., comfortable bed in a dark room, at suitable temperature, avoiding daytime naps and irregular bedtimes) (Davidson, 2008), avoiding intake of beverages (e.g., tea, coffee, some soft and herbal drinks), smoking, and alcohol before bedtime are recommended (Ancoli-Israel, 2000). HRT has been shown to be an effective treatment for menopausal sleep problems for women who have climacteric VSM or mood symptoms (Polo-Kantola, 2011), however, in women over age 60 years, side-effects outweigh the beneficial effects on sleep (Hays et al., 2003). Individual treatment options should therefore be considered (Sarti et al., 2005).

Furthermore, depressive symptoms are highly prevalent for women, with rates two times higher than those found in men, and more prevalent in peri- and post-menopause compared to pre-menopause (Pérez-López et al., 2014). Women experiencing depressive symptoms experience lower quality of life and lower work productivity (Whiteley et al., 2012). In addition, women with severe hot flushes are more likely to report depressive symptoms, anxiety, and sleep disturbances (Whiteley et al., 2012; Pérez-López et al., 2014; Borkoles et al., 2015). Although depressive symptoms can be managed with pharmacological or psychological interventions, biofeedback, and relaxation techniques, regular exercise, including walking, has benefits for women in midlife and beyond (Arakane et al., 2011). In a meta-analysis of 11 articles on physical activity RCTs on depressive symptoms in midlife women (N=1943) (age range 47-65 years) revealed that low to moderate intensity exercise significantly reduces depressive symptoms in midlife women (Pérez-López et al., 2017). Additionally, lower perceived stress and insomnia, after exercise, were also reported as secondary outcomes (Pérez-López et al., 2017).

2.6 Digital Health Behaviour Change Interventions (DHBCIs)

This thesis addresses the need to improve health in the population of midlife women, in the UK, through integrating behavioural science to systematically design a DHBCI. Behavioural sciences, through explicit use of theories and models, bring rigour and discipline to intervention designs, development, and evaluations and provide cumulative evidence base of what works (Public Health England, 2018). Furthermore, digital health innovations provide an opportunity to use problem-based and person-centred transdisciplinary approaches to deliver effective and efficient health behaviour change (Public Health England, 2018).

In 2023, over 5.4 billion people worldwide (i.e., 67% of the world's population) were estimated to be using the Internet in some form or another (ITU, 2023). With Apple's introduction of the iPhone in 2007, the reality of the connected world materialized (Greengard, 2021). Globally, 78% of people (6.2 billion people) aged 10 and over owned a mobile phone in 2023 and the percentage of individuals owning a mobile phone exceeded the percentage of Internet users (ITU, 2023). With the technologically connected world, DHIs to support the health of users of digital media are becoming increasingly prevalent (Pelly et al., 2023). Consequently, innovations in technology have facilitated more intensive, more frequent, more natural, less invasive, and simultaneous data collection of activities in real time, creating new opportunities to learn how individual's lifestyle health behaviours unfold (McNeish et al., 2021). Collecting data in real time through mobile or wearable devices reduces burden of collecting data and increases ecological validity because the data collection occurs in people's natural environments and not in a laboratory setting (de Haan-Rietdijk et al., 2017). Thus, responses are given in real time rather than recalled after the fact (de Haan-Rietdijk et al., 2017). As a result, research designs where data is collected in real time have increasingly become popular in behavioural and health sciences (Moskowitz and Young, 2006). Furthermore, methodological advances have allowed for collection of more refined data on health behaviours through intensive longitudinal data collection to achieve greater ecological validity in the measurements of psychological states and health behaviours (Walls and Schafer, 2006).

Digital behavioural interentions, which rely on digital technologies to promote behaviour change and maintain health have been growing rapidly in the past few decades (Marcu et al., 2022). Therefore, as more behavioural health interventions move from traditional (e.g., face-to-face, remote delivery via post or telephone) to digital platforms, applying evidence-based theories and techniques may be advantageous to expedite digital health intervention (DHIs) development, improve its efficacy, and increase reach These technologies can support health behaviour change by assisting to form, alter, or maintain health-related behaviours in interventions that employ them, and are commonly referred to as digital behaviour change interventions (DBCIs) (Hekler et al., 2016; Yardley et al., 2016; Michie, Yardley, et al., 2017), and also as DHBCIs (Kaveladze, Young and Schueller, 2022). Digital technologies include not only technologies that access the internet (e.g., smartphones, PCs, tables), but also automated healthcare and communication systems (e.g., mobile, wearables, environmental sensors), including Internet of Things (IoT) devices that can provide intelligent monitoring and feedback as and when needed (e.g., Just-In-Time Adaptive Interventions (JITAI), or Ecological Momentary Interventions (EMI)) (Yardley et al., 2016). DHBCIs are typically automated, interactive, and personalised, employing user input or sensor data to tailor feedback or treatment pathways without the need for human input (e.g., health professional) (Yardley et al., 2016).

At present, initiatives to develop cost-effective modalities (i.e., types of technologies) to support self-management, lifestyle modifications (e.g., smoking cessation, diet, obesity, physical inactivity), and medication adherence are leading priorities in healthcare (Khan et al., 2017). Digital health has rapidly emerged as technology with the potential to address these issues and transform the way healthcare has been traditionally delivered (Khan et al., 2017). The economic success of the digital health market can be attributed to the adoption of mobile health (mHealth) into people's lives (Steinhubl, Muse and Topol, 2015). Furthermore, leveraging digital health technology with the fastest growing segment of smartphone users (aged >55 years) is becoming increasingly prevalent (Khan et al., 2017). However, one of the barriers to adoption of technologies is limited clinical evidence and therefore the increasing need to evaluate the feasibility and efficacy of these technologies (Burke, Ma, et al., 2015), particularly with midlife and older populations. Both, further clinical research and healthcare policy change are needed to move the promising new digital health technologies (Khan et al., 2017) towards their implementation in public health. A review of digital health technologies to promote lifestyle change and adherence (Khan et al., 2017) highlighted the use of mHealth applications, text messaging using mobile phones, and web applications. Other DHI technologies that have been used more frequently in the past few years include Ecological Momentary Assessment (EMA) (Kwasnicka et al., 2021), and wearable devices (e.g., fitness trackers, biosensors) (Khan et al., 2017). Recent research in Artificial Intelligence (AI) (Nahum-Shani et al., 2018; Meskó and Topol, 2023) has also shown promising results in using AI chatbots to provide support to health intervention participants. Additionally, technological advances in AI and sensors (e.g., wearables) also have the potential to revolutionise how nutrition research is conducted and how personalised dietary recommendations are presented to and used by the public (Berciano et al., 2022). Aided by the wealth of data collected using mHealth apps, EMAs and wearable devices allows for analysing and integrating this data using computational methods to generate just-in-time nutritional recommendations for the individual (Berciano et al., 2022). Systematically integrating this data (consisting of biological, dietary, other lifestyle factors) allows for developing personalised and dynamic predictions on how an individual will respond to specific foods or dietary patterns (to personalise dietary recommendations to the individual's needs), which in turn can induce positive behaviour change, and ultimately result in improved health outcomes (Berciano et al., 2022). See **Figure 2** describing PN feedback loop based on advanced predictive analytics of individual-level data to provide optimised dietary recommendations leading to behaviour change and improved health outcomes.

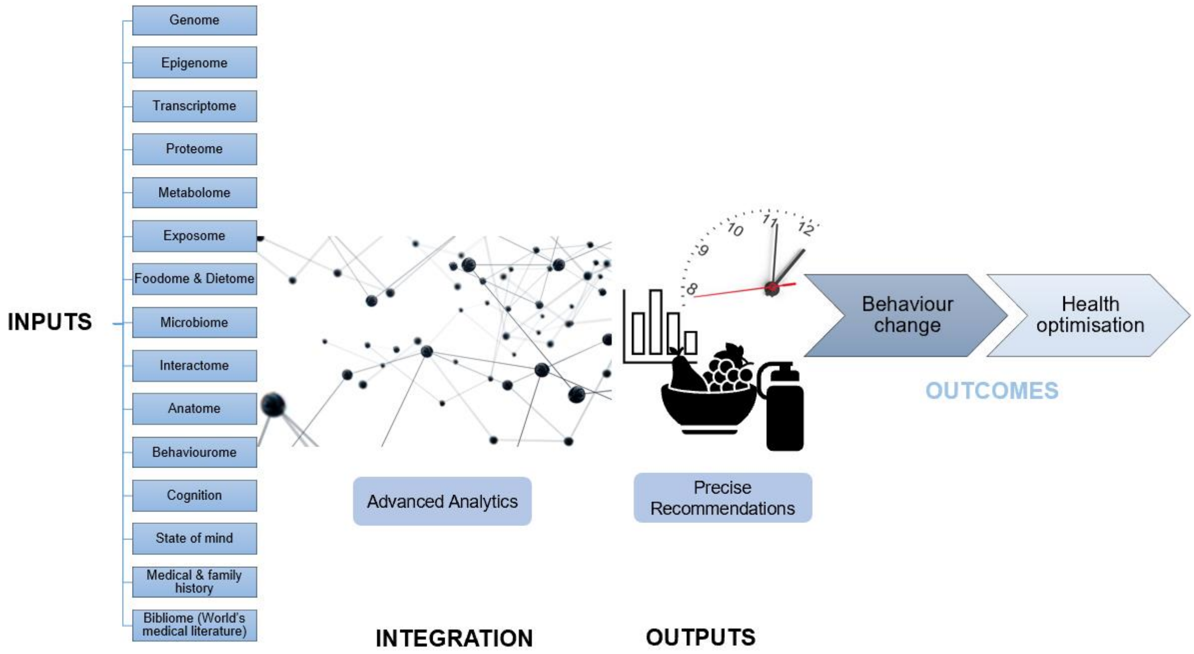


Figure 2: Precision Nutrition feedback loop, adapted from (Berciano et al., 2022)

Furthermore, it is important to note that both single-behavioural and multi-behavioural DHBCIs often include several technologies (i.e., multiple modalities) within a single intervention. Such multimodal interventions can leverage each technology's unique functionality to activate specific intervention components and collect wide-ranging data that each technology uniquely captures. For example, a combination of dietary MyFitnessPal website and a mobile app to monitor diet, Fitbit fitness tracker to monitor physical activity, and telephone coaching calls were used in a weight loss intervention with midlife women (Hartman et al., 2016). Thus, multiple modalities (e.g., telemedicine, web-based strategies, email, mobile phones, mobile apps, text messaging, monitoring sensors) can provide rich interaction but also data capture on different health behaviours (Triantafyllidis and Tsanas, 2019). Additionally, integrating these different data sources (i.e., multimodal data) allows for investigating an individual's potential risk factors and behavioural outcomes from a third-person observational perspective, promoting ecological validity (Nelson and Allen, 2018).

2.6.1 Personalisation of Digital Health Interventions

Given the historic one-size-fits-all approach to DHIs provided limited effects, personalised approach is necessary to promote healthy behaviours and prevent chronic conditions (Tong et al., 2021a). The current age of personalisation has created new expectations of personalised medical, health and care services, maps, news, and shopping experiences, to name a few (Lury and Day, 2019). Personalised (precision) nutrition (described earlier) has been explored for some time and it is based on considering individual differences in dietary, lifestyle, anthropometric, phenotype and genomic profiles, to be used to direct specific individualised dietary advice (Gibney, 2020). However, in order to be effective, personalised nutrition advice needs to consider the factors that influence variations in response to dietary interventions and implement such factors to support positive dietary and lifestyle behaviour change (Gibney, 2020). For example, a large multicentre study (Food4me) with adults (N=1269; mean age 39.8 years; 99% female) across Europe explored the impact of personalisation (based on genotype and phenotype) on changes in dietary intake and found that although there was greater positive change in dietary intake in the personalised groups compared to the control group, there was no difference in outcomes between groups consisting of different levels of personalisation (Gibney, 2020). This finding may suggest that individuals respond to any personalisation, regardless of the manner of personalisation (Celis-Morales et al., 2017). However, although there is evidence that individual differences in genotype and phenotype influence biological response to the consumption of nutrients, findings from studies that used personalised nutrition advice are often mixed as deriving dietary advice at individual/group level can be complex (Gibney, 2020). (Gibney, 2020) concludes that variation in response to personalised dietary advice is not only at a physiological level but also at a behavioural level. Research behind the Food4me project found positive associations between food choice motives (e.g., weight control, health, mood, ethical concerns) and attitudes towards intention to adopt personalised nutrition, however negative associations were found between food choice motives that are based on price of food and intention to adopt personalised nutrition (Rankin et al., 2018). Even for individuals with knowledge of risk (e.g., genetic variants) and a subsequent recommendation to increase consumption of a specific nutrient, the intervention did not result in a greater behaviour change (O'Donovan et al., 2016). However, these patterns also show mixed results in other studies (O'Donovan et al., 2017). Personalisation of nutrition advice is a complex topic that requires not only consideration of physiological factors (and phenotypic/genotypic variations) but also the underlying inter-individual variability in health perceptions, food beliefs, and other psychological factors that influence variability in response to personalised advice (Gibney, 2020). Therefore, these results suggest that personalisation of health-promoting interventions requires consideration of intra-individual (individual-level) variability at not only physiological level but also at behavioural level.

Generally, the degree of personalisation of tailored activities is assessed by the extent to which the interventions are tailored, individualised, or personalised for the target population (Hornstein et al., 2023). Although these terms are often used interchangeably, there are also differences in their definitions. For example, personalisation is defined as tailoring a solution for a specific individual, while individualisation is seen as integrating individual-level information, and therefore individualisation is perceived as being part of personalisation (Vesanen, 2005). Furthermore, while personalisation is used more commonly in biomedical and technological data-driven approaches, individualisation is used more generically (Mayer et al., 2023). Moreover, Hornstein et al. (Hornstein et al., 2023) is referring to personalisation when applied only to the level of the individual, while group-based adaptations (e.g., for a particular cultural context) are not considered personalisation. Further distinction is also made between personalisation and customisation, usage, and interactivity, none of which are considered personalisation (Hornstein et al., 2023).

Moreover, there are different levels of personalisation that have been implemented in lifestyle and mental health DHIs, including the type is personalised (e.g., intervention content, content order, level of guidance, communication with users) and the underlying mechanisms (e.g., user choice, provider choice, decision rules, ML-based approaches) (Hornstein et al., 2023) (**Figure 3**).

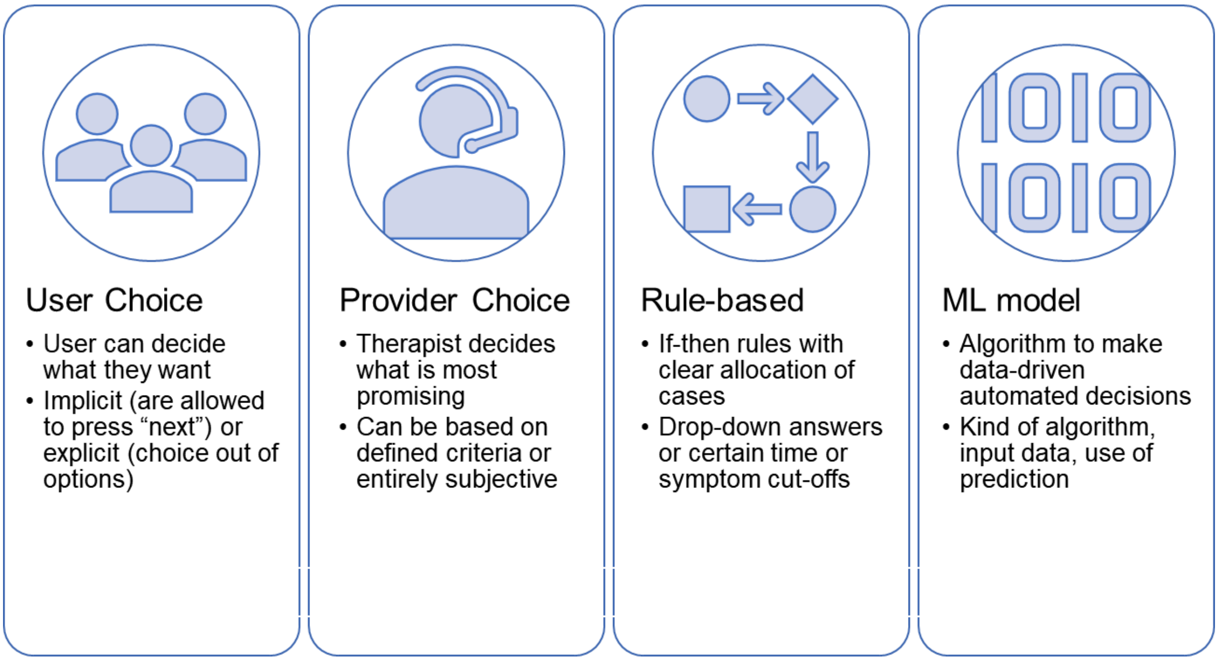


Figure 3: Types of DHI personalisation, adapted from (Hornstein et al., 2023).

For example, in a review of lifestyle DHIs, most interventions personalised their content but rarely personalised other features (Tong et al., 2021a). In a recent review of personalisation strategies in digital mental health interventions (DMHIs) (Hornstein et al., 2023), over one third of interventions equally focused on personalisation of the content, communication with the users, with the remaining third of interventions not being personalised. Personalisation in the DMHIs was delivered primarily via decision rules (48%), user choice (36%), while ML was rare (3%). The review concludes that future interventions could provide even more personalised experience and especially benefit from using ML models (Hornstein et al., 2023). Furthermore, to provide personalisation that is based on prediction of activities for each individual (e.g., by using ML models), it is vital to understand the components and features of interventions (Hwang and Jiang, 2023) that can be activated in the right time and context, in the right way, and for the right individual (Michie, van Stralen and West, 2011). A review of the degree of personalisation of tailored activities (Lu et al., 2021) revealed that interventions with a high-level of personalisation had a significant and moderate effect on intervention outcomes, followed by medium-level and lastly low-level of personalisation. Recommendations for improved personalisation included identifying characteristics of the target population and the intervention designs to allow for dynamic intervention adjustments in response to changing needs and circumstances of individuals (Lu et al., 2021). In a review of DHIs for older adults, the most personalised features included goal setting, motivating behaviour change, adjusting intervention plan, and data-driven approaches (Hwang and

Jiang, 2023). Although this thesis is using the term personalisation when exploring all types of personalisation in the design and optimisation of a DHBCI that is personalised at both individual-level (including user's preferences) and group-level (including intervention content and features) for UK-residing midlife women, it is also considering further refinements at the individual level of personalisation.

2.6.2 Adaptive and Continuous Digital Health Interventions

Ample evidence suggests that health behaviours are complex and that adaptive and continuous adjustment ("tuning") of interventions is necessary to support healthy behaviour changes over time and across contexts, similarly to what a clinician or a health coach would do with their patients and clients (Chevance, Perski and Hekler, 2021). Instead of delivering generic (i.e., without personalised components) and static (i.e., measured at single time point) interventions, tailored interventions are aimed to reach one specific individual, based on specific characteristics of that person that have been measured through formal assessments (Chevance, Perski and Hekler, 2021). Adaptative interventions take it a step further and provide dynamic decision-making over time, with pre-specified adaptive algorithms that are generated based on data from prior (other) individuals (Collins, Murphy and Bierman, 2004), and can be delivered via micro-randomised trials (MRT) (Chevance, Perski and Hekler, 2021). Continuous interventions are similar to adaptive; however, the tuning is based on previous data from the same individual, includes real-time optimisation algorithms, and delivers content based on the needs of a specific individual, using methods such as N-of-1 study design or reinforcement learning (Chevance, Perski and Hekler, 2021). Therefore, continuous tuning interventions, leveraging rapidly evolving technologies, and high-frequency assessments (using EMA and wearables) capturing individual-level observations, have the potential to better explain, predict, and promote health behaviour change (Riley et al., 2015; Chevance, Perski and Hekler, 2021).

2.6.3 Adherence to Digital Health Interventions

Despite the efficacy of DHBCIs to improve a range of health-related outcomes, adherence to these interventions is a major issue (Melville, Casey and Kavanagh, 2010; Meyerowitz-Katz et al., 2020; Torous et al., 2020; Jakob et al., 2022). Estimates for intervention dropouts in observed RCTs are up to 50% (Torous et al., 2020), nearly 80% of all participants engage at a minimum level (Meyerowitz-Katz et al., 2020), and response rates are unsatisfactory at less than 50% (Karyotaki et al., 2021). However, the reasons for such high dropout rates are still unclear (Torous et al., 2020). Evidence suggests that longer intervention duration and greater user engagement appear to be associated with improvements in intervention outcomes and overall greater effectiveness of DHIs (Vandelanotte et al., 2007). Some factors influencing attrition in DHIs have been attributed to ease of leaving the intervention, having unrealistic expectations on behalf of users, technology usability and interface issues, and the amount of workload required from the participants for them to benefit from the interventions (Eysenbach, 2005). A systematic review of factors influencing adherence to mHealth apps (Jakob et al., 2022) identified four intervention-related factors with positive effects on adherence across all health domains and included 1) personalisation or tailoring of the DHI content at the individual level, 2) providing individual-level reminders (push notifications), 3) the user-friendliness and technical stability of the digital technology used, and 4) personal support complementary to the digital intervention. Social features were also associated with greater adherence, as well as regular check-ins with the participants, and convenient intervention schedule (e.g., intervention starting on Mondays, not at the weekend) (Jakob et al., 2022). Therefore, these factors should be prioritised in intervention designs to improve DHI effectiveness.

2.7 Conclusion

This chapter highlighted that midlife for women is associated with increased risk of developing chronic health conditions and it is a public health issue. Women in midlife experience menopausal symptoms that negatively impact their quality of life and have profound societal consequence (e.g., loss of productivity, increased healthcare cost). This chapter demonstrates the need to address modifiable lifestyle health factors, including diet and physical activity, to support women's health and wellbeing in their midlife life stage. This chapter also highlighted that the use of technologies, such as wearables and mobile apps are rapidly increasing in people's lives, and utilising these technologies has the potential to deliver effective DHBCIs to support health behaviour change. Previous research demonstrated that personalisation of not only the intervention content but also of intervention features, utilising ML-driven predictions has the potential to improve individual-level effectiveness of DHIs. However, to personalise interventions, it is essential to understand individual components of interventions and linking theoretical constructs to features. In this respect, next chapter (**Chapter 3**) explores how designing DHBCIs that are theory informed and evidence-based has the potential to deliver more effective and sustainable interventions. The primary focus of the next chapter is to therefore review relevant theoretical approaches that may be helpful in designing DHBCIs to improve lifestyle health factors.

3. Theoretical Underpinning of the Thesis

3.1 Overview of Chapter

Support for adopting healthy behaviours to reduce the risk of ill-health, maintain health, and self-manage long-term health conditions is an important function of health care services (Public Health England, 2018). Systematic reviews of existing evidence demonstrate the effectiveness of applying behaviour change theory in health BCIs (Webb et al., 2010; Taylor, Conner and Lawton, 2012). Moreover, DHIs pose unique challenges and opportunities compared to non-digital interventions, including low levels of engagement and low adherence (Torous, Michalak and O'Brien, 2020). Thus, utilising design frameworks has the potential to increase efficacy of digital interventions for health-related behaviours (Pelly et al., 2023). Moreover, the Medical Research Council (MRC) (Craig et al., 2008) recommends that complex interventions should be based on behaviour change theory and appropriate evidence to clearly understand the intervention's process of change (Skivington et al., 2021). However, health behaviour change is a complex process, and although various guidelines and recommendations (NICE, 2007, 2014; Craig et al., 2008; Public Health England, 2019) have been proposed advocating the use of behaviour change theory to inform health BCIs, there is limited information about how this might best be achieved (Cowdell and Dyson, 2019). This chapter describes the theoretical underpinning of the thesis by applying behaviour change frameworks to guide a DHBCI design (presented in **Chapters 5, 6, and 7**) together with models and theories to identify specific intervention components.

3.2 Theoretical Frameworks for DHI Designs

To identify what type of intervention is likely to be effective, it is vital to systematically characterise and design BCIs (Michie, van Stralen and West, 2011). This includes identifying intervention features that are matched to the target behaviours, the target population, and the context in which the intervention will be delivered, underpinned by a model of behaviour and the factors that influence it (Michie, van Stralen and West, 2011). The process of designing BCIs usually involves determining firstly the broad approach that will be adopted and then working on the specifics of the intervention design (Michie, van Stralen and West, 2011). For example, when attempting to increase physical activity (e.g., steps count), the design of an intervention may focus on education as the appropriate approach, alternatively, the design may focus on providing incentives for completing planned activity or penalise incomplete activities. As such, the design of DHIs is a complex undertaking, which may involve many stakeholders, working within technical and time limitations, requiring significant expertise, planning, and financial resources (Sporrel et al., 2021; Farhat-Ul-Ain and Tomberg, 2023).

Moreover, theoretical frameworks are not often utilised, and interventions are commonly designed without evidence of having gone through the process of systematically characterising and designing BCIs and are merely based on implicit commonsense models of behaviour (Michie, Fixsen, et al., 2009). Even if one or more theories or models are chosen to guide the intervention, they do not cover the full range of possible influences on behaviour (Michie, van Stralen and West, 2011). For example, if guiding the design using only theories, such as the Theory of Planned Behaviour (Ajzen, 1991) or Health Belief Model (Rosenstock, 1974), these theories do not address the important roles of habit, self-control, impulsivity, emotional processing, or associative learning (West, 2009).

3.3 The Behaviour Change Wheel (BCW) framework

The Behaviour Change Wheel (BCW) (Michie, van Stralen and West, 2011; Michie S, Atkins L, 2014) framework was applied in the design of the DHBCI in this thesis. The BCW is a three-layered whole-system approach to intervention design, delivery and evaluation (Chater et al., 2022). It was developed from a synthesis of 19 behaviour change frameworks to provide a more comprehensive and conceptually coherent framework (Michie, van Stralen and West, 2011), covering nine intervention functions and seven policy categories that could enable those intervention functions (Michie, van Stralen and West, 2011). Behaviour change is key to addressing not only the challenges facing human health and wellbeing but also to promoting the update of research findings in health policy and practice (Michie, Thomas, et al., 2017). The BCW depicts this global view through its layers, consisting of the first centre layer identifying sources of behaviour (i.e., the COM-B model components), surrounded by the second layer of nine intervention functions, and a third layer of eight policy categories (see **Figure 4)**.

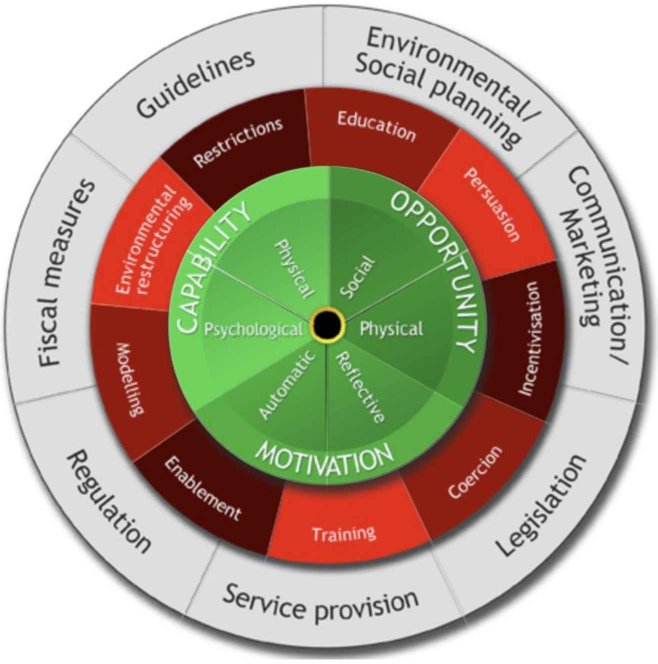


Figure 4: The Behaviour Change Wheel (BCW) (used with permission from authors) (Michie, van Stralen and West, 2011)

3.3.1 The COM-B Model Layer of the BCW

The COM-B model represents the inner layer of the BCW framework (see **Figure 4**). While COM-B is a model of behaviour, it also provides a basis for designing interventions aimed at behaviour change (Michie, van Stralen and West, 2011). The COM-B model depicts behavioural factors of capability, opportunity, and motivation that interact to generate behaviour that in turn influences these components (Michie, van Stralen and West, 2011). Capability (C) is defined as the individual's psychological and physical capacity to engage in the activity of concern, and it includes having the necessary skills and knowledge (Michie, van Stralen and West, 2011). Opportunity (O) is defined as all the factors that exist outside the individual that make the behaviour possible or prompt it (Michie, van Stralen and West, 2011). Motivation (M) is defined as all processes in one's mind that energise and direct behaviour, in addition to goals and conscious decision-making, and therefore includes not only analytical decision-making, but also habitual processes and emotional responding (Michie, van Stralen and West, 2011). The components can influence one other, for example, opportunity can influence motivation as can capability, while enacting a behaviour can alter all, capability, opportunity, and motivation (Michie, van Stralen and West, 2011). This means that an intervention can change one or more components in the COM-B behaviour system (Michie, van Stralen and West, 2011). Applying this model to intervention design could involve defining the behavioural target, and the components of the COM-B behaviour system that would need to be changed to achieve the behaviour (Michie, van Stralen and West, 2011). All components of the model are considered equal in controlling behaviour, and no priority is given to an individual, group, or environmental perspective, or to internal or external factors (Michie, van Stralen and West, 2011). Furthermore, the three components of COM-B are further broken down (see **Figure 5**, COM sub-constructs). Capability can be distinguished between physical and psychological (i.e., the capacity to engage in the necessary thought processes, including reasoning and comprehension). Opportunity can be further distinguished between physical afforded by the environment and social afforded by the cultural milieu (i.e., influencing the words and concepts that make up our language) (Michie, van Stralen and West, 2011). Motivation can be distinguished between reflective (i.e., involving evaluations and plans), and automatic (i.e., involving emotions and impulses) processes (Michie, van Stralen and West, 2011). According to the authors (Michie, van Stralen and West, 2011), all components, apart from reflective motivation, are necessary for a given behaviour to change, however, the intervention can target specific components to achieve the behavioural target.

3.3.2 TDF Framework Layer of the BCW

The Theoretical Domains Framework (TDF) (Atkins et al., 2017a) represents additional (fourth) layer of the BCW and it is mapped to the hub of the wheel (the COM-B) (Chater et al., 2022) (**Figure 5**). The TDF provides a conceptual framework for the design of interventions to enhance health care and to understand behaviour change processes (Cane, O'Connor and Michie, 2012a; Francis, O'Connor and Curran, 2012). It's been suggested that the strongest interventions may be built from multiple theories (Glanz and Bishop, 2010), that allow for unique contribution of different theories to the combined model (Glanz and Bishop, 2010). TDF is based on 128 constructs from 33 evidence-based theories and models of behavioural science and health psychology (Michie, van Stralen and West, 2011). It combines complex theories of behaviour into a simplified and accessible framework with 14 domains (Chater et al., 2022). Therefore, the TDF provides a theoretical lens to understand the determinants of behaviour (Chater et al., 2022). Particularly, it has been used in other studies to identify barriers and facilitators to behaviour change, for example to identify influences on nurses' engagement in antimicrobial stewardship behaviours where TDF explained 27% of the variance in behaviour (e.g., skills, behavioural regulation being the most predictive of AMS actions) (Chater et al., 2022). In this thesis, the TDF was applied to all three workstreams of the intervention design, specifically, in the systematic review, focus groups, and co-production, to extract, identify, and map specific intervention components.

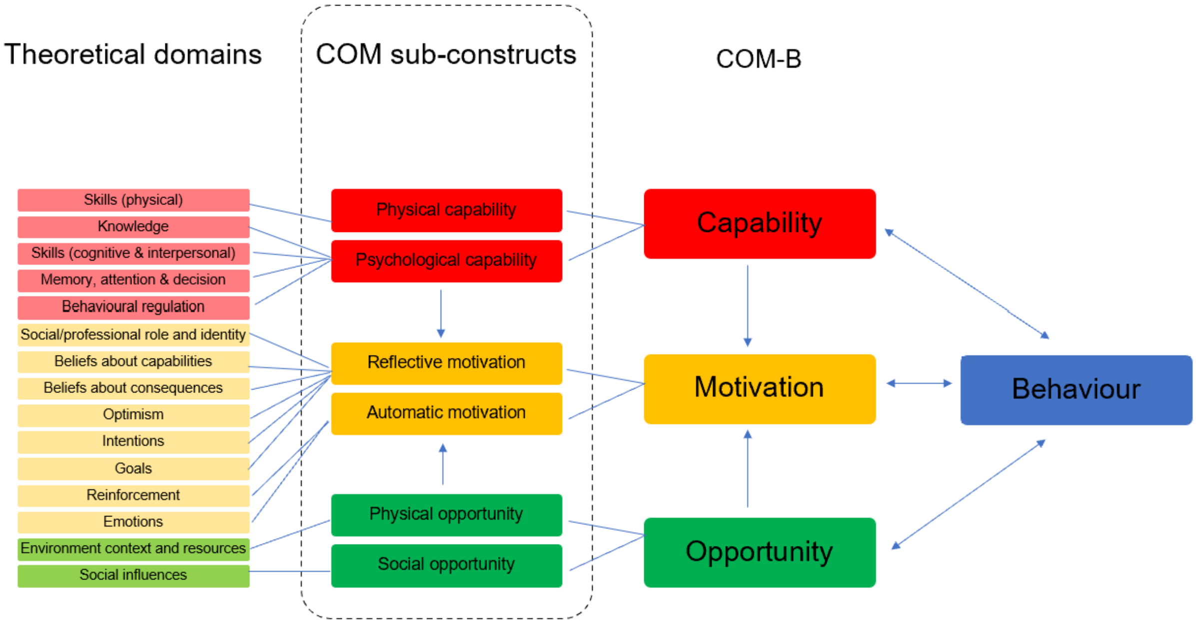


Figure 5: TDF and COM-B mapping, adapted from (Chater et al., 2022)

3.3.3 Intervention Functions Layer of the BCW

Intervention functions are broad categories of means by which an intervention can potentially change behaviour (Atkins and Michie, 2015). The BCW consists of nine intervention functions, including education, persuasion, incentivisation, coercion, training, restriction, environmental restricting, modelling, and enablement (**Figure 4**). Although the functions can be synonymous with types of categories, an intervention can have more than one function (Atkins and Michie, 2015). For example, promoting healthy eating may contain an element that is educational (e.g., benefits of healthy eating) but also be presented in a way that is persuasive (e.g., creating feelings of worry about the harmful effects of eating unhealthy foods) (Atkins and Michie, 2015).

Furthermore, the BCW forms the basis for a systematic analysis of how to make a selection of intervention functions and policies by providing links between the two (Michie, van Stralen and West, 2011). The intervention functions can also be explicitly linked to the COM-B model (Atkins and Michie, 2015). For example, if the intervention aimed to improve healthy eating in adults in the workplace which was identified as not being prioritised, the behaviour would be coded as reflective motivation in COM-B with several potential functions that are linked to these COM-B components, including education, persuasion, incentivisation, or coercion (Atkins and Michie, 2015). The APEASE (identifying affordability, practicability, effectiveness/cost-effectiveness, acceptability, side effects/safety and equity) criteria (Michie S, Atkins L, 2014) can be used to select the appropriate functions (Atkins and Michie, 2015). The intervention functions can be further linked to more fine-grained specific BCTs (Michie et al., 2013). For example, in the review of self-management interventions to increase physical activity and healthy eating (Michie, Abraham, et al., 2009a), the BCTs served five of the intervention functions (e.g., education, persuasion, incentivisation, training, and enablement) (Michie, van Stralen and West, 2011). The remaining intervention functions were seen to place more emphasis on external influences and less on personal agency (Michie, van Stralen and West, 2011).

3.3.4 The Policy Layer of the BCW

The policy layer consists of nine policy categories of communication/marketing, guidelines, fiscal measures, regulation, legislation, environmental/social planning, and service provision (Atkins and Michie, 2015) (**Figure 4**). With explicit links between intervention functions and policy categories, the appropriate policies can be selected to identify how the intervention will be delivered (Atkins and Michie, 2015). For example, if the intervention is to deliver healthy eating intervention in the workplace and the selected intervention function was persuasion (linked to the reflective motivation COM-B component), policy categories could be communication/marketing, guidelines, regulation, legislation, and service provision (Atkins and Michie, 2015). Using APEASE criteria (Michie S, Atkins L, 2014) can help selecting the most appropriate policies (Atkins and Michie, 2015).

3.3.5 Behaviour Change Techniques (BCTs)

The UK MRC guidance for developing and evaluating complex interventions recommends specification of the “active ingredients” of an intervention as the necessary step to investigate how interventions exert their effect so that more effective interventions can be designed and applied across target populations and settings (Craig et al., 2008). A BCT is defined as the smallest “active ingredient” of an intervention (Michie et al., 2013, 2021) and the previous developments within behavioural science has led to the definition of 93 BCTs and developed into the Behaviour Change Technique Taxonomy version 1 (BCTTv1) (Abraham and Michie, 2008; Michie et al., 2011, 2013). A BCT is an observable and replicable component that has the potential to change behaviour either independently or when combined with other BCTs (Michie et al., 2015). Thus, the correct choice of BCTs is crucial for behaviour change and for long-term sustentation (Bouton, 2014). The 93 BCTs are further grouped into 16 BCT clusters (e.g., 1. Goals and planning; 2. Feedback and monitoring; 3. Social support; 4. Shaping knowledge; 5. Natural consequences; 6. Comparison of behaviour; 7. Associations; 8. Repetition and substitution; 9. Comparison of outcomes; 10. Reward and threat; 11. Regulation; 12. Antecedents; 13. Identify; 14. Scheduled consequences; 15. Self-belief; and 16. Covert learning (Abraham and Michie, 2008; Michie et al., 2011, 2013)) that are used for grouping similar types of techniques (e.g., BCT 1.1 Goal setting (behaviour) is grouped under BCT cluster 1. Goals and Planning). Health behaviour change interventions typically use a set of techniques to facilitate behaviour change (Hankonen et al., 2015).

Furthermore, to aid the design of interventions and to optimise their efficacy, systematic reviews and meta-analyses have attempted to identify active ingredients of effective interventions by classifying intervention content to BCTs and examining associations between BCTs and outcomes (Hankonen et al., 2015). However, findings from systematic reviews on the optimal number of BCTs that are associated with better outcomes in lifestyle health intervention are inconsistent. For example, a systematic review of physical activity interventions for adults with T2DM showed that higher number of BCTs led to greater effects (in average improvement in physical activity minutes and steps, BMI, and haemoglobin A_{1c} (HbA_{1c})) (Avery et al., 2012), while another review of dietary and physical activity interventions for obese adults did not find this association (Taylor, Conner and Lawton, 2012). Another meta-analysis of complex behavioural interventions for obese adults suggested that increasing the number of identified BCTs are not necessarily associated with better outcomes (Dombrowski et al., 2012). A meta-analysis of BCTs in healthy eating (HE) and physical activity (PA) interventions (Michie et al., 2009) indicates that the technique of self-monitoring explained the greatest amount of among-study heterogeneity. Furthermore, if combined with at least one other technique derived from control theory, the HE and PA interventions were significantly more effective than other HE or PA interventions (Michie et al., 2009), although the specific number of BCTs was not associated with greater effects. Another review of HE and PA interventions for obese adults found techniques of goal-setting and self-monitoring to predict effects at short and long term (Samdal et al., 2017). A review of BCI's to increase intake of dietary fruit and vegetables and reduce dietary fat (associated with prevention of chronic diseases) identified two intervention components, including goal-setting techniques and using small groups, to be promising in modifying dietary behaviours (Ammerman et al., 2002). However, even when BCTs are identified, they are not always linked to the theory. For example, a review investigating application of theory using the Theory Coding Scheme (TCS) (Michie and Prestwich, 2010) found that only 10% of studies that were theory-based reported links between BCTs and theoretical constructs and only 9% reported that all the constructs in the interventions were targeted by BCTs (Davis et al., 2015). TCS is a methodology that provides a research tool to reliably describe the theoretical base of interventions, inform evidence synthesis within literature reviews, and potentially stimulate the use of empirical data for theory development (Michie and Prestwich, 2010).

However, identifying which BCTs or BCT combinations have the potential to be effective in a given context and population presents a major challenge (Michie, West, et al., 2018b). There may be several reasons for these discrepancies. For example, the effects of a single BCT may be very small (Michie, West, et al., 2018b) but may be amplified when delivered in a combination with other BCTs (Michie, West, et al., 2018b). However, while many BCTs typically occur together in a given intervention (Michie, West, et al., 2018b), not all included BCTs may be equally effective. Effectiveness also depends on how BCTs are delivered, how specific features that are not captured by BCTs are used, and the type of context (population and setting) the intervention involves (Michie, West, et al., 2018b). Additionally, reviews that attempted to identify BCTs from intervention reports also stated that descriptions of behavioural components in the reviewed studies were limited, which limited the ability to identify what techniques were used and how they were activated (Hankonen et al., 2015; Michie et al., 2018a). For example, this was reported in reviews of interventions promoting physical activity with midlife women (Arigo, Romano, et al., 2022a), healthy diet and regular physical activity (Michie et al., 2009) and physical activity in adults with T2DM (Avery et al., 2012). (Ammerman et al., 2002) also reported that behaviour change was more effective if interventions were based on principles drawn from evidence and theories of behaviour and behaviour change, implying that interventions that are not theory-based may include techniques that are less effective in behaviour change. Additionally, low or unknown fidelity of delivery of BCTs (Michie, West, et al., 2018b) also plays a role in the intervention effectiveness (McKenna, Flower and Ciullo, 2014; Ginsburg et al., 2021). Fidelity is referred to as the extent to which an intervention is implemented as intended (Dusenbury et al., 2003; Hankonen et al., 2015) and it provides a key information on why an intervention may or may not have achieved its intended outcome (Ginsburg et al., 2021). In this thesis, treatment fidelity was assessed using Bellg's fidelity measures (Bellg et al., 2004; Borrelli, 2011) in the systematic review (**Chapter 5**), consistent with other systematic reviews of BCIs (Avery et al., 2012; O'Shea et al., 2016; Timlin et al., 2020).

Moreover, attainment, or a person's use of BCTs in their daily life is rarely measured, with most studies that were identified in a review (Hankonen et al., 2015) reporting adherence to treatment conditions (e.g., attendance, self-monitoring), adherence to the intervention protocol (e.g., recording food and calories), self-reported behaviour change (e.g., time spent on an online intervention platform), or changes in clinical outcomes (e.g., weight loss, biomarkers) (Hankonen et al., 2015). Time spent online has also been measured by examining clusters of BCTs rather than individual BCTs (Hankonen et al., 2015). Furthermore, target behaviours (e.g., eating breakfast, exercising) are often assessed instead of BCT use (e.g., self-monitoring, planning) (Hankonen et al., 2015). This means that utilising existing methods of identifying effective BCTs (or BCT combinations) linked to target behaviour and context and that are associated with better outcomes all have important inherent limitations (Michie, West, et al., 2018b).

Nevertheless, latest advancements in AI/ML and multimodal data capturing have shown promising results in identify effective BCTs. For example, a recent multimodal lifestyle intervention measuring exposure time to each BCT (from a group of 35 BCTs used in the intervention) (Englund, Sommar and Krachler, 2024) revealed that during the five-week interventions the participants spent most of the time (126 h) on BCTs 8.1 Behavioural practice/rehearsal, 4.1 Instructions on how to perform the behaviour (98 h), and 6.1 Demonstration of the behaviour (65 h). Higher exposure was for physical activity compared to food habits, stress management and other unspecified lifestyle medicine (Englund, Sommar and Krachler, 2024). Other advancements in identifying effective BCTs are explored in the Human behaviour change project (HBCP) initiative (Michie et al., 2017). Currently, the HBCP Prediction tool is available for smoking cessation and a protocol has been developed for mental health ontology (Schenk, Hastings and Michie, 2024), which will also include stakeholder involvement with domain experts and co-production with people with lived experiences.

3.3.6 Mode of Delivery of DHIs

In addition to the intervention content identified in the previous sections (i.e., COM-B components, TDF domains, intervention functions, policy categories, BCTs), the BCW guide also suggests identifying how the intervention will be delivered (Atkins and Michie, 2015). For example, it could be delivered face-to-face, in groups or individuals, using digital media (e.g., website, mobile app) (Atkins and Michie, 2015). Using APEASE criteria (Michie S, Atkins L, 2014) can be used to select the most appropriate mode of delivery (Atkins and Michie, 2015). The mode of delivery systematically reviewed in DHIs targeting midlife women included primarily digital media (websites, apps, and wearables) focusing on passive delivery of health information or interactive health coaching with almost half (6/13) of the interventions also providing face-to-face option (**Chapter 5**).

3.3.7 Using the BCW Guide to Design DHIs

The BCW guide provides a practical way to use the BCW framework and it has been used to design real world complex interventions (Teixeira, 2016) and in the DHI design in this thesis. Based on the Cochrane handbook (Thomas et al., 2023), intervention complexity (rather than complex interventions) can be defined by three ways, including by the number of components in the intervention; interactions between intervention components and/or interactions between the intervention and its context; and the wider system within which the intervention is introduced. Furthermore, the MRC (Craig et al., 2008) defines the complexity of interventions by the number of interacting components within the experimental and control interventions; number and difficulty of behaviours required; number of groups or organisational levels targeted; number and variability of outcomes; and a degree of flexibility or tailoring of the intervention. For this reason, developing an intervention should be done systematically, using the best available evidence (including from systematic reviews), developing theoretical understanding, and modelling processes and outcomes, while using an iterative design process, following a formal framework (Craig, 2015) to identify intervention components.

The BCW guide provides an evidence based stepped approach to changing behaviours, while encouraging intervention designers to consider a full range of options (Ekberg et al., 2021). The BCW follows a three-step process of designing behaviour change interventions that are further divided into eight steps (Michie S, Atkins L, 2014) (**Figure 6**). The first stage (steps 1-4) is concerned with understanding the behaviour and it includes identifying the COM-B components. The second stage (steps 5 and 6) consists of identifying the intervention functions. In this thesis, intervention policies were not defined due to the limited scope of the thesis and should be considered in future feasibility studies. However, in other studies policy categories that aligned with the intervention functions were rated based on the APEASE criteria (Ekberg et al., 2021). The third stage (steps 7 and 8) is used to identify the content (i.e., BCTs) and implementation options (i.e., mode of delivery). These three stages can also be complemented or replaced by other frameworks or models. For example, in a study to identify facilitators and barriers to smoking cessation in a minority population (Daoud et al., 2018), the authors utilised a mixture of frameworks, including the Concept Mapping (CM) (Trochim, 1985), a participatory research method for public health research used in generating hypotheses and developing theory (Burke et al., 2005). CM was used in the initial step to brainstorm potential strategies for smoking cessation with participants, followed by performing thematic analysis (TA) using the Behavioural Ecological model, and finally, identifying intervention functions and policies using the BCW (Daoud et al., 2018) (representing step 2 in the BCW guide).

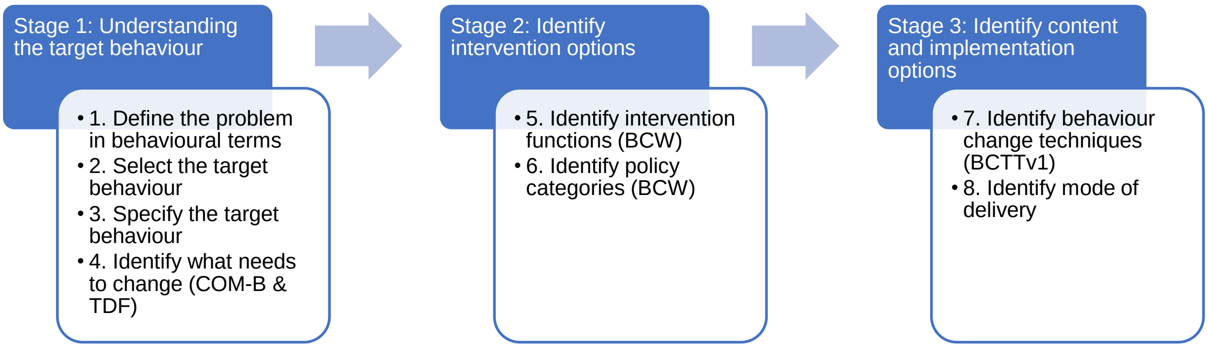


Figure 6: Behaviour change wheel (BCW) stages to designing an intervention, adapted from (Michie S, Atkins L, 2014)

The BCW guide (Michie S, Atkins L, 2014) has been used in other studies addressing behaviour change in the health contexts, including diet and physical activity interventions (Webb, Foster and Poulter, 2016; McEvoy et al., 2018; Nyenhuis et al., 2019; Kinnear et al., 2020; MacPherson et al., 2021), a digital intervention to reduce occupational sedentary behaviour (Stephenson et al., 2020), smoking cessation interventions (Gould et al., 2017; Passey et al., 2021; Mersha et al., 2023), and in co-designing a physical activity intervention for adolescent females (McQuinn et al., 2022). The BCW framework was also utilised in the design of a three-month long RCT to promote physical activity behaviour change for Australian midlife women (aged 50 years and older) (Wallbank et al., 2019, 2022). In the population of UK midlife adults, the BCW was used in qualitative studies to identify barriers and facilitators to adoption of a Mediterranean diet (Timlin, McCormack and Simpson, 2021; Simpson, Doherty and Timlin, 2023), and capturing views of UK midlife women on the association between alcohol consumption and risk of breast cancer (Davies et al., 2023a). However, there is no evidence of existing digital lifestyle health-promoting interventions targeting UK midlife women that were developed using the BCW guide or any other framework.

Furthermore, healthy eating and regular physical activity (targeted in this thesis) are complex behaviours consisting of many components and interactions between the components (Michie, Abraham, et al., 2009a). Intervention components are defined as the active ingredients, processes, intervention techniques, and element of an intervention that have the potential to causally influence intervention outcomes (Kühne et al., 2015). Components are directly related to the behaviour change theory that is proposing the mechanism by which an intervention works (Caldwell and Welton, 2016). The identification of intervention components helps to explain the heterogeneity of studies in systematic reviews, and in designing interventions it helps with understanding how the intervention works, and what are its core drivers of intervention effect (what components are essential for effectiveness) (Caldwell and Welton, 2016). With the identification of the components, interventions can be adapted without compromising effectiveness and be optimised for future studies (Caldwell and Welton, 2016).

3.4 The MOST Framework

The Multiphase Optimisation Strategy (MOST) framework is an engineering-inspired framework to support the development, optimisation, and evaluation of multicomponent behavioural (also biobehavioral, biomedical, or social-structural) interventions (Collins, 2018a, 2018b) to systematically, incrementally, and efficiently improve interventions (Collins, Murphy and Strecher, 2007; Collins, Dziak, et al., 2014; Collins, Trail, et al., 2014). MOST has been applied to a wide range of interventions targetting health behaviours, including weight loss (Thomas et al., 2021), smoking cessation (Collins et al., 2011), and digital health interventions (Collins, Murphy and Strecher, 2007; Marques and Guastaferro, 2022).

In addition to the BCW framework, the MOST framework was utilised in this thesis to guide the top-level intervention design through the first of its three phases consting of 1) preparation, 2) optimisation, and 3) evaluation phase (**Figure 7**). Within the preparation phase of MOST, the BCW framework can be overlayed (Marques and Guastaferro, 2022) to support designs and evaluation of interventions (feasibility studies) (**Figure 8**). The preparation phase can therefore be used to identify the conceptual model using COM-B and TDF (Atkins et al., 2017a). It can also be used to identify behaviours and behavioural components using the BCT taxonomy (BCTTv; (Michie et al., 2015)). Consistent with the MOST Preparation phase, experimental intervention components should be first evaluated with a small number of participants in a feasibility study (Thomas et al., 2021). The resulting refined components should be tested in future feasbility studies to maximise acceptability and feasibilty prior to a large-scale testing (Thomas et al., 2021). Subsequently, and according to the MOST Optimisation phase (Thomas et al., 2021), a factorial experiment can be conducted to determine what groups of intervention components contribute to improvements in intervention outcomes (Collins, Dziak, et al., 2014). Finally, the optimised intervention components can be tested in a future randomised controlled trial (RCT), according to the MOST Evalution phase (Thomas et al., 2021) to establish effectiveness of the intervention. One of the DHIs that combined the MOST with the BCW includes smoking cessation intervention (Tombor et al., 2016).

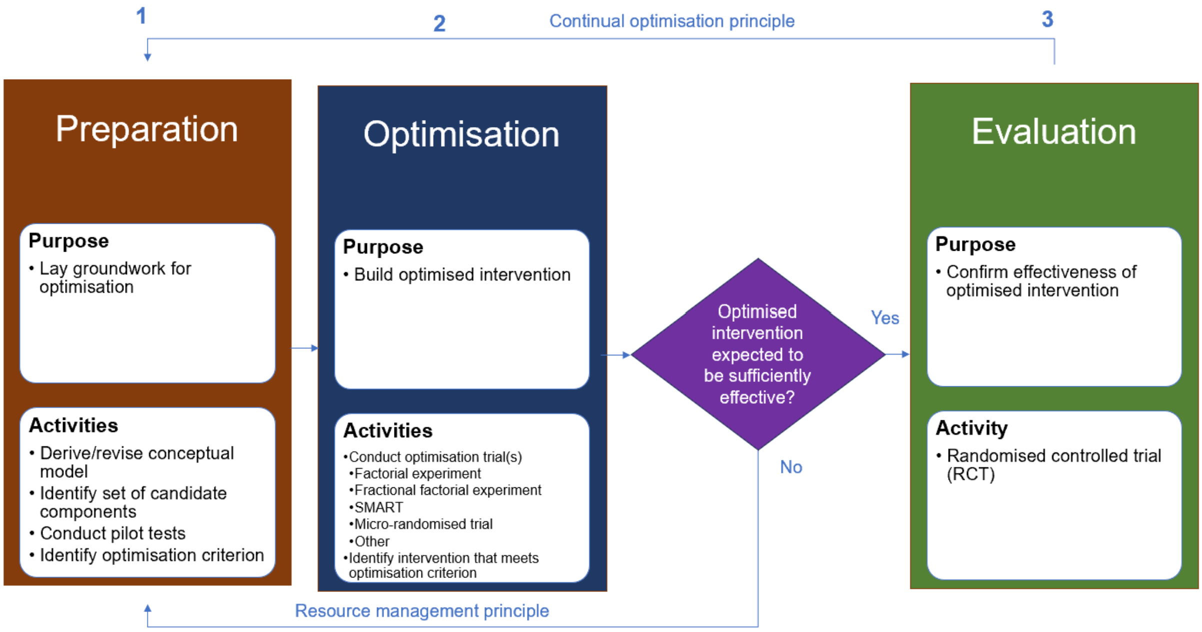


Figure 7: The MOST framework phases, adapted from (Collins, 2018a)

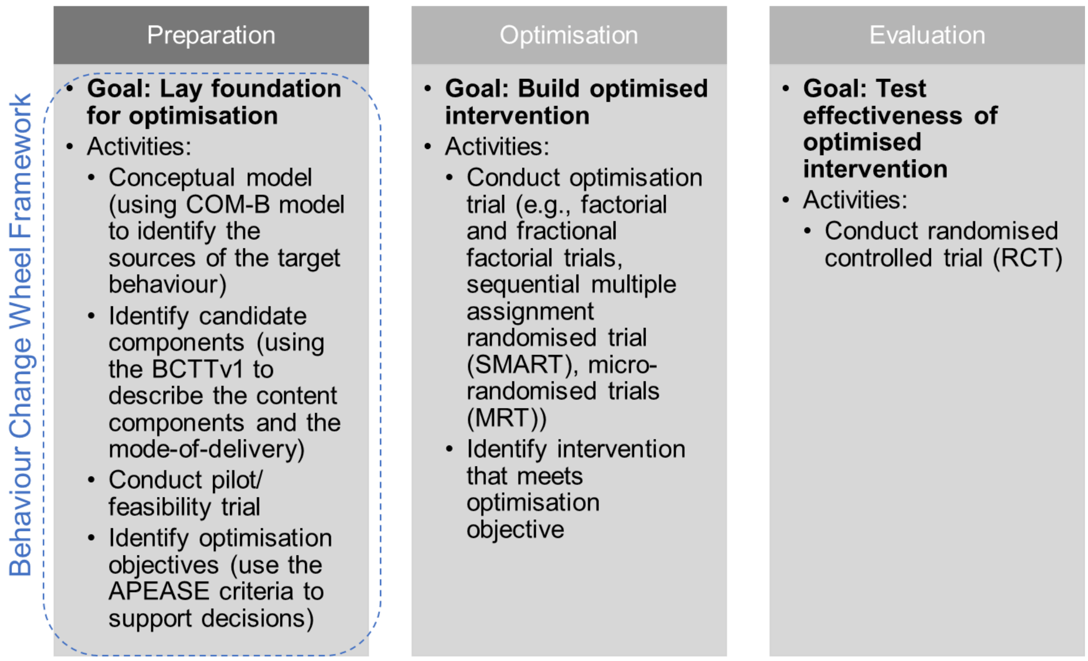


Figure 8: The MOST framework phases with embedded BCW framework adapted from (Marques and Guastaferro, 2022)

Although the MOST process is efficient, historically, a limitation of MOST is that it requires relatively large sample sizes and data collection across multiple waves (Moller et al., 2017). However, as more interventions move to digital platforms, the cost of data collection needed for running MOST designs can be reduced, making these techniques increasingly accessible to more researchers (Moller et al., 2017). Also, while performing an RCT is the gold standard for research questions evaluating whether a treament-package intervention performs better than standard of care or a control, a research question about optimisation (i.e., the process of finding one of the best interventions possible within given constraints) using factorial design can help in selecting the best performing intervention components (Collins, Trail, et al., 2014). It is important to note that this increase in experimental testing through optimisation increases the costs and logistics that need to be considered. The author therefore recommends using fractional factorial design to offset such constraits (Collins et al., 2011).

3.5 The Person-Based Approach (PBA)

The Person-Based Approach (PBA) is a framework for centralising users' experience throughout planning and development of interventions, via systematic and iterative exploration of target users' perspectives and tailoring of the intervention accordingly (Yardley et al., 2015). The PBA for developing health interventions consists of iterative methods and tools for developing effective, engaging, and easy to use interventions (Yardley et al., 2015). It consists of three phases of 1) planning, 2) optimising, and 3) evaluating and implementing behavioural health interventions intended to successfully engage diverse populations and support better health outcomes (Yardley et al., 2015) (**Figure 9**).

The PBA can be used flexibly, and it can be combined with other approaches to intervention development and evaluation (e.g., BCW), user centred design methods, and public/patient involvement (PPI) (Yardley et al., 2015). The PBA approach has been used in conjunction with the BCW in health-related interventions (Bowers et al., 2020; Arden et al., 2021; Reale et al., 2021). The MOST and PBA can also be conceptually overlayed, with the engineering-focused MOST targeting refinement of the intervention components, while the PBA ensures person-based approach by including inputs from various stakeholders, including PPI and the target population. Therefore, aligned with the previously described the MOST framework’s preparation phase, the PBA planning phase may include inputs from 1) reviews and synthesise of relevant literature, 2) qualitative studies, and 3) co-production to develop, describe, and refine the design of an intervention. A logic model (‘theory of change’) is developed to describe how the key intervention components should lead to behaviour change. The tools available in this phase include an intervention planning table, to capture intervention components, and guiding principles for intervention design, to capture what make the intervention feasible, acceptable, and engaging for the intervention participants (Yardley et al., 2015). The Optimisation phase of PBA is aimed to utilise feedback from the intended users of the intervention (e.g., PPI contributors, research participants) to make sure all elements of the intervention are as meaningful and useful as possible. Therefore, in this phase, the intervention elements may be evaluated by the intended users in terms of the intervention's ease of use, and whether the components can be understood, are enjoyable, engaging, informative and motivating. Some of the suggested methods for obtaining this feedback include think-aloud interviews, mixed methods process analyses, including qualitative (e.g., interviews, focus groups, observations) and quantitative process (e.g., intervention usage analysis, user engagement) analyses, which could be collected through feasibility studies. The feedback can be captured in the PBA's template for Table of Changes. Once the required feasibility and acceptability is achieved, the intervention can enter the Implementation and Evaluation phase, which may include an RCT.

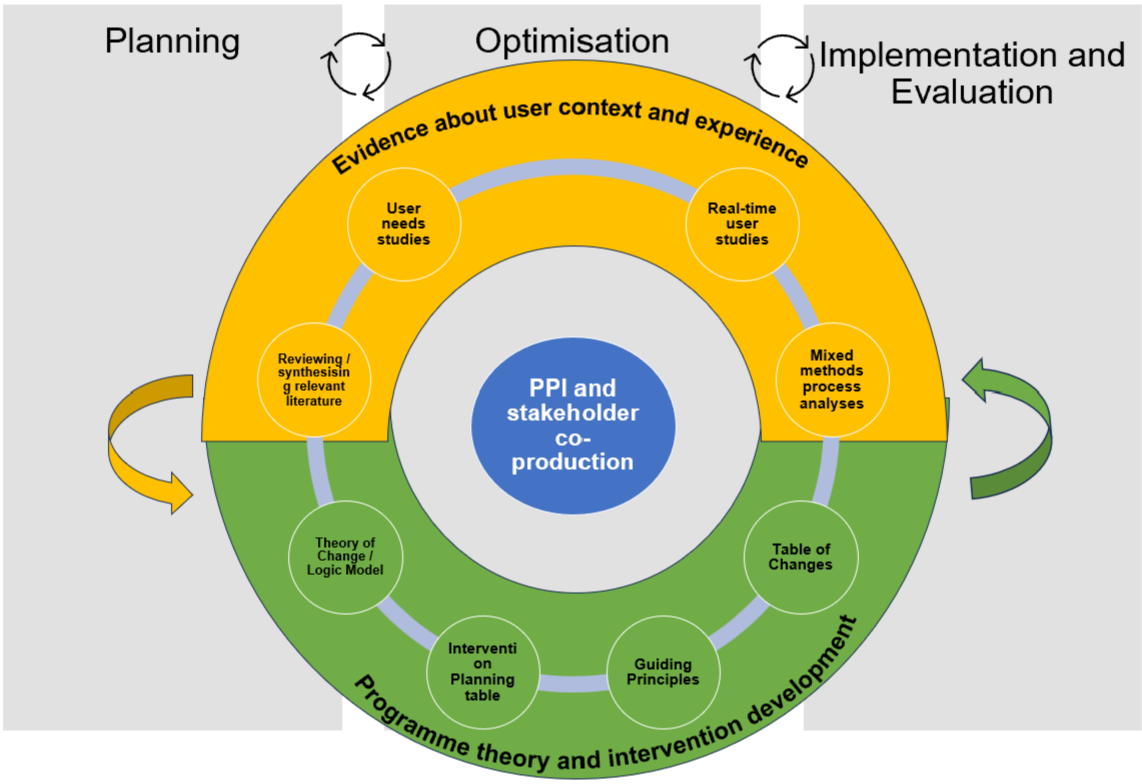


Figure 9: The person-based approach (PBA) adapted from (Yardley et al., 2015)

One of the strengths of the PBA is the amount of quality of input from the target population (both knowledge from existing literature and information provided directly from focus groups, diaries, think-aloud interviews) (Ferrey et al., 2018). However, similar to the MOST framework, because the process is so rigorous and the intervention is updated iteratively, there are additional expenses (for example related to time and compensation needed for think-aloud interviews) that must be costed in (Ferrey et al., 2018).

Other DHIs that used PBA include development of an online health application for the workplace to improve lifestyle habits (e.g., physical activity, diet, and sleep), enhance productivity, and increase wellbeing. The development included semi-structured interviews, think-aloud interviews and focus groups (Howarth et al., 2019). Another study involved development of a knee osteoarthritis lifestyle app, using inputs from literature review and qualitative data from focus groups during the planning phase, and usability testing with think-aloud sessions in the optimisation phase (Stevenson et al., 2024). PBA was also used in the development and optimisation of a DHI to support antidepressant discontinuation for patients in the UK's primary care (Bowers et al., 2020). In older populations in the UK, PBA was used to optimise an intervention to support home-living older adults at risk of malnutrition, using think-aloud and semi-structured interviews (Payne et al., 2021).

3.6 Critical Appraisal of Theoretical Frameworks and Theories

Utilising an intervention development framework has the potential to increase the efficacy of digital interventions for health-related behaviours (Pelly et al., 2023). However, different frameworks may be more or less useful in different circumstances (Michie, van Stralen and West, 2011) and for different types of interventions. According to the BCW authors (Michie, van Stralen and West, 2011), one of the strengths of the BCW framework is that it recognises that context (through the Opportunity component of the COM-B model) is key to the effective design and implementation of interventions, while it remains under-theorised and under-investigated compared to other approaches. Additionally, the authors of the BCW argue that none of the frameworks reviewed in their development of the BCW covered the full range of intervention functions or policies, and only a minority met the criteria of coherence or linkage to a model of behaviour (Michie, van Stralen and West, 2011). While the BCW provides a systematic and theory-guided method for intervention design, it does not provide a detailed blueprint for the design of specific behaviour change interventions, as acknowledged by its authors (Michie, van Stralen and West, 2011). The framework therefore provides only a starting point to an intervention design and designers should expect to apply the framework with some flexibility (Michie, van Stralen and West, 2011). As with the TDF, the application of the BCW requires subjectivity and inference and while identifying intervention functions and BCTs may be more straightforward, defining the content of the strategies may require some creativity, as acknowledged by others (Richardson et al., 2019). (Richardson et al., 2019) also suggested that stakeholder involvement in this process is essential for clarifying the feasibility and acceptability of the theory-based intervention strategies.

Others have pointed out that by attempting to reduce variability in theories (i.e., eliminating gaps in theories, reducing redundancy, and increasing parsimony (Hagger, 2009)), this resulted in the development of integrated systematised approaches that can be applied to all behaviours, creating approaches that are too generic and inclusive, which limits their utility (Ogden, 2016). This includes the BCW framework that has been described as too generic, broad, and inclusive, creating a false sense of theory simplicity when it is not simple (Ogden, 2016). More specifically, the BCW has been described as including everything from environmental planning to legislation, and that the BCT taxonomy recognises only the role of individual level factors (Ogden, 2016). On the other hand, such frameworks can also help to guide various stages of planning, implementing, and evaluating an intervention (Glanz K, 2005). Furthermore, it has been suggested that the BCW may be one of the best tools to guide the design of real-world interventions, and that it is one of the best tools for those researchers less experienced with designing interventions (Teixeira, 2016). As stated by the creators of the BCW guide, it is only a starting point for intervention design and should not be seen as a blueprint or a substitute for a detailed understanding of the behaviour in question (Michie S, Atkins L, 2014). The BCW has been instrumental in paving the way for changes in policy and practice and it has provided a framework for those practitioners wanting to design interventions (Ogden, 2016). A way forward suggested by (Ogden, 2016) is to celebrate variability in different frameworks but at the same time not to over systematise them across behaviours, theories, and practices.

Thus, to aid in the development of effective DHI interventions, numerous frameworks have been proposed, each offering a different approach (Sporrel et al., 2021). They range from guidelines for the development of public health interventions (Wight et al., 2016) and policies (De Zoysa et al., 1998) at the population level to behavioural health interventions (Michie, van Stralen and West, 2011; Michie S, Atkins L, 2014) and DHIs at the individual level (Kowatsch et al., 2019). For example, IDEAS framework (Mummah et al., 2016) and the MRC framework

(Craig et al., 2008) offer stepwise instructions to develop a DHI, while other models provide guidance for specific steps such as the translation of behavioural theories to persuasive strategies (e.g., the BIT model (Mohr et al., 2014)). However, the MRC framework (Craig et al., 2008) does not specify a particular theory to follow and although other frameworks, such as Intervention Mapping (Bartholomew, Parcel and Kok, 2016) or Mindspace (Dolan et al., 2012) can provide intervention development guidance, the comprehensiveness of these frameworks are limited (Owen et al., 2019). For example, they do not specifically link to a model of behaviour change and are not appliable to a broad range of behaviours (Michie, van Stralen and West, 2011). The BCW framework was developed to address these limitations (Owen et al., 2019).

While there are many theories, models, and frameworks in behavioural science that have been synthesised into 83 theories and models of behaviour change (Michie and Johnston, 2012), drawing on psychology, sociology, economics, and anthropology (Atkins and Michie, 2015), it is worth noting that no one theory can explain 100% of behaviour (Conner and Norman, 2022), even those based on integrative theories (Atkins et al., 2017a). Behavioural theories can be categorised in a variety of ways, for example, theories that describe determinants of behaviour (e.g., the health belief model), or a process of change (e.g., transtheoretical model (Prochaska and DiClemente, 1983)). Another way proposed by (Hekler et al., 2013) is to classify behavioural theories based on their generality compared to their specificity, and therefore described as ranging from the specific, detailed and focused to the generic, broad, and inclusive (Ogden, 2016). However, it's also been argued that specific theories may work well within limited domains and can be clearly operationalised in intervention designs (Ogden, 2016). On the other hand, the more generic theories have been labelled as 'a superfluous Theory of Everything', trying to cover too much while providing a false sense of simplicity (Peters, de Bruin and Crutzen, 2015). As a result, the choice of theory in a specific intervention may not be appropriate. In interventions targeting multiple health behaviours, behaviours typically do not happen in a silo, they interact with one another. For example, improving one's diet often has an impact on sleep, which can impact engaging in more physical activity. Therefore, accounting for these interactions and variance in behaviour has to some extent been achieved by combining theories or adding and extending them to include additional variables that may be relevant. In this respect, frameworks (e.g., TDF (Atkins et al., 2017a)) that are built on multiple behaviour change theories can potentially address multiple aspects of health behaviours. The TDF has been used in several qualitative studies focused on health behaviours (Alexander, Brijnath and Mazza, 2014; Lawton et al., 2016; Flannery et al., 2018; Rosário et al., 2021; Chater et al., 2022). A review of health BCIs using TDF (Cowdell and

Dyson, 2019) revealed that the majority of interventions using TDF were technology based, and were primarily designed to target diet and exercise, smoking, and sexual health, although, none of the interventions targeted the population of midlife women.

3.7 Conclusion

It can be argued that there is no public health intervention without behaviour change (De Zoysa et al., 1998). Thus, research needs to be guided by theory, else behavioural interventions will remain largely intuitive with limited opportunities for generalisations and repeatability (De Zoysa et al., 1998). Moreover, utilising conceptual frameworks provides researcher with steps in the development and evaluation of public health interventions (De Zoysa et al., 1998). A framework also helps to select appropriate research designs, ensuring research defines feasible, acceptable, and cost-effective approaches to delivering interventions, rather than developing a “quick-fix” solution (De Zoysa et al., 1998). In this thesis, the BCW framework provides an overall theoretical underpinning for the DHBCI design, with theory-and evidence-based BCTs representing the smallest active ingredients of the intervention aimed to improve healthy eating and regular physical activity in UK-residing midlife women. The next chapter (**Chapter 4**) presents the methodology used in the thesis overall, and in each individual study. Both qualitative and quantitative methods are discussed, contributing to the overall intervention design and outcomes of this research.

4. Methodology Applied Within the Thesis

4.1 Overview of Chapter

This thesis consists of four empirical studies and a co-production approach. The DHBCI design phase is based on mixed methods with three workstreams consisting of a quantitative systematic review (Study 1), mixed methods focus groups (Study 2), and a co-production approach. Quantitative methods are applied in the optimisation phase, consisting of a feasibility study ("intervention") to test the design (Study 3), and optimisation of the intervention features using predictive ML models (Study 4) (**Table 2**). This thesis therefore consists of both qualitative and quantitative approaches, forming a typology of a multi-strategy (mixed method) design (Robson and McCartan, 2019). The dominant research method (Morse, 2003) is quantitative, with all four studies containing a quantitative component. A set of questionnaires were utilised through surveys completed by the focus groups (Study 2) and intervention (Study 3) participants. The questionnaire methods used in the surveys are presented in detail in this chapter. Additionally, quantitative methods for analysing hierarchical longitudinal DHIs, and predicting intervention outcomes are described.

Table 2: Summary of the empirical studies presented in the thesis and their typology

Study identifier	**Title of the study**	**Typology of study design**
Study 1	Behaviour change techniques in digital health lifestyle interventions for midlife women: A systematic review	Quantitative, systematic review
Study 2	Hearing midlife voices: Designing a digital health behaviour change intervention for UK-residing midlife women using focus groups: A mixed-method study	Qualitative, thematic analysis Quantitative, survey
Study 3	The feasibility and acceptability of a co-produced digital health behaviour change intervention for UK-residing midlife women	Quantitative, longitudinal Qualitative (minor), survey (open ended) Co-production/co-design
Study 4	Predicting lifestyle health behaviours using machine learning with ecological momentary assessment, survey, and fitness tracker data: An exploratory study	Quantitative

4.2 Rationale for Using Mixed Methods

4.2.1 Characteristics of Qualitative and Quantitative Research

All research is built on certain underlying philosophical assumptions (acknowledged or unacknowledged) about what constitutes valid research and what research methods are appropriate for the development of knowledge in a given study (Krauss, 2005; Harrits, 2011; Scotland, 2012). Therefore, the use of research paradigm and theory provides specific direction for procedures in research design, and is linked to the concepts of ontology, epistemology, methodology and methods, in both quantitative and qualitative approaches (Madill, Jordan and Shirley, 2000). Ontological assumptions are concerned with what constitutes reality (i.e., how things really are how they really work), while epistemological assumptions are based on how knowledge can be created, acquired or communicated (i.e., what it means to know) (Scotland, 2012). Methodology is concerned with why, what from where, when and how data is collected and analysed, while methods are specific techniques and procedures used to collect and analyse data (Scotland, 2012). Research methods can be therefore tracked back, through methodology and epistemology, to an ontological position (Scotland, 2012). Thus, different ontological and epistemological position can often lead to different research approaches towards the same phenomenon (Scotland, 2012). Furthermore, different research approaches and choice of methods (and methodology) are also affected by the researcher's own underlying belief system of the research (ontological assumptions) (Krauss, 2005). Thus, the philosophical assumptions and theoretical paradigm about the nature of reality are crucial in understanding the overall study design perspective (Krauss, 2005).

4.2.2 Using Qualitative Approaches

Many qualitative researchers believe that the best way to understand any phenomena is to view it in its context and see all quantifications as limited in nature, in considering only a one small portion of a reality that cannot be split or unitised without losing the significance of the entire phenomenon (Krauss, 2005). Many qualitative researchers also operate under different ontological assumptions about the world, assuming there is no single unitary reality and therefore operate under the phenomenon of multiple realities (Krauss, 2005). Qualitative researchers use methods that take into account the individual and not attempting to aggregate across individuals on the grounds that each individual is unique (Krauss, 2005). Therefore, generally, qualitative research is based on interpretive paradigm of relativistic, constructivist ontology that postulates that reality is subjective, and differs from person to person (Krauss, 2005; Scotland, 2012). The interpretive paradigm's epistemology is subjectivism, which is based on real world phenomena (Scotland, 2012). According to subjectivism, knowledge about the world is created through interpretation of an individual's experience within their sociocultural context (Scotland, 2012). Interpretive methodology (e.g., case studies, phenomenology, hermeneutics, and ethnography) looks for an understanding of phenomenon from an individual's perspective, investigating interactions among individuals, including historical and cultural contexts. Therefore, the emphasis on an individual case, in which relativistic social world is embedded, is idiographic (Scotland, 2012) and qualitative data tends to be acquired inductively through focus groups and interviews (Scotland, 2012).

4.2.3 Using Quantitative Approaches

On the other hand, a positivism paradigm is often adopted in quantitative methodologies measuring independent facts about a single reality, in which data does not change (Krauss, 2005). In positivist epistemology, science is seen as the way to understand the phenomenon so that it can be predicted and controlled (Krauss, 2005). Within the positivist epistemology, researchers tend to have an ontological stance of realism which seeks a belief in a true, independent, and knowable reality (Madill, Jordan and Shirley, 2000; Scotland, 2012). Realists adopt the epistemological perspective that emphasises objectivity that is linked with the production of reliable findings producing consistency, stability, and repeatability of results (Madill, Jordan and Shirley, 2000). Positivism is aligned to deductive approach in research in which testable hypotheses are built, experiments are designed through operationalising variables, and empirical studies that are based on experimentation are conducted (Park, Konge and Artino, 2020). Therefore, positivist research often (although not always) relies on quantitative methods and its goal is to generate explanatory associations or causal relationships between causal and explanatory factors (e.g., independent variables and dependent variables) that ultimately lead to predictions and control of the phenomena in question (Park, Konge and Artino, 2020).

4.2.4 Pragmatic Stance on Using Mixed Methods

The pragmatism paradigm tries to move past the qualitative versus quantitative argument between both sets of purists (positivists and constructivists) who advocate incompatibility thesis and instead acknowledges values of both techniques in mixed method designs (Johnson and Onwuegbuzie, 2004). Pragmatists highlight the similarities between the various approaches in that both use empirical observations to address research questions, and both incorporate safeguards into their inquiries to minimise confirmation bias and other sources of invalidity (Johnson and Onwuegbuzie, 2004). Furthermore, in behavioural and social science, the goal is to understand many different phenomena, including intentions, experiences, but also macromolecules, nerve cells, and biochemical computational systems (Jong, 2003). Therefore, there is space in ontology for mental and social, as well as material reality (Johnson and Onwuegbuzie, 2004) to allow for a wide range of research questions to be addressed (Robson and McCartan, 2019). The choice of paradigm of pragmatism for mixed methods research therefore points to an inquiry process that is built around combining the different strengths of qualitative and quantitative methods (Allemang, Sitter and Dimitropoulos, 2022).

4.2.5 Potential Benefits of Using Mixed Method in Health Behaviour Change

Combining methods within a single study (mixed methods design) or a research programme (multimethod design), can provide a more complete picture of human behaviour and experience, when compared to using a single method (Morse, 2003). Moreover, combining research approaches can potentially offset weaknesses and neutralise limitations of each approach, while building on their strengths, leading to stronger inferences (Robson and McCartan, 2019). For example, in research projects in which the core strategy and main analysis is quantitative, supplementing ideas generated from qualitative data as well as incorporating qualitative textual data into statistical analysis can illuminate the main analysis of quantitative research by providing important context (Morse, 2003). Combining these approaches is particularly valuable in real world settings due to the complex nature of the phenomenon and the range of perspectives that are required to understand them (Robson and McCartan, 2019). Thus, corroboration between quantitative and qualitative data can enhance the validity of findings through triangulation (Robson and McCartan, 2019). Moreover, integration of quantitative and qualitative data can dramatically enhance the value of mixed methods research (Creswell et al., 2003), including utilising qualitative data to inform development of an intervention, or assessing the validity of quantitative findings, whereas quantitative data can explain findings from the qualitative data or help generate the qualitative sample (Fetters, Curry and Creswell, 2013).

4.2.6 Applying Pragmatism Paradigm and Mixed Methods Design in this Thesis

This thesis incorporates the pragmatism paradigm, which acknowledges values of both quantitative and qualitative methodologies in a mixed method design (Johnson and Onwuegbuzie, 2004). Mixed methods research in this thesis therefore draws upon the strengths of both quantitative and qualitative approaches with the aim to provide an innovative approach to address behaviour change research (Fetters, Curry and Creswell, 2013). Considering different methods to understand the complexity of human behaviour and experience can also provide different perspectives to answer particular research question (Morse, 2003). In this thesis, combining methods provided multimethod design, presenting a more complete picture of human behaviour and experience, compared to using a single method (Morse, 2003).

Furthermore, in developing complex behavioural interventions, the synthesis of multiple types of information, including data from individual interventions, systematic reviews of qualitative and quantitative evidence, and qualitative studies involving focus groups, interviews, or surveys, is often helpful (Richardson et al., 2019). Quantitative methodologies are often used to address research questions about causality, generalisability, or magnitude of effects, while qualitative methodologies are applied to research questions to explore why and how a phenomenon occurs, to describe the nature of an individual's experience, or to develop a theory (Fetters, Curry and Creswell, 2013). Both methodologies can complement each other (Yardley, 2000) and utilising mixed methods can be valuable in evaluation (in establishing feasibility and acceptability) and development of complex interventions (Yardley et al., 2015). Moreover, collecting both qualitative and quantitative data within this research study allows for more in-depth exploration of the participants' perspectives and experiences (Yardley et al., 2015). Qualitative study can provide rich insight into what participants think and feel in response to the design of the intervention, although, qualitative methods cannot articulate how the intervention design is associated with differences in satisfaction and engagement or changes in behaviours (Yardley et al., 2015). On the other hand, systematic quantitative approach (e.g., survey, systematic review) can supplement insights provided by the qualitative focus groups (Yardley and Bishop, 2007).

Additionally, as mixed methods research continues to pervade the field of healthcare, the paradigm of pragmatism and patient-oriented research as an engagement strategy are often combined to strengthen the process and outcomes of the research (Allemang, Sitter and Dimitropoulos, 2022). Patient-oriented research is an emerging healthcare research strategy that actively engages individuals with lived experiences across all stages of the research process (Allemang, Sitter and Dimitropoulos, 2022). Combining pragmatic and participatory research paradigms through co-production to co-design the DHBCI in this thesis supports the adoption of the scientific method of inquiry combined with person-centred research. In this thesis, the combined multiple methods of quantitative systematic review, mixed method focus groups, and co-production are utilised to identify constructs (e.g., BCTs) that are measured in the quantitative study (e.g., as variables linked to BCTs). Existing research demonstrates that in the design of interventions, synthesis that can identify evidence from multiple sources to inform the choice of intervention components is highly desirable (Richardson et al., 2019).

4.2.7 Implementing a Multi-Strategy Design within the Thesis

Overall, this thesis involves a multi-strategy design, in which the typology is more complex than the typical three basic designs (e.g., exploratory sequential, explanatory sequential, convergent) (Creswell et al., 2003). Moreover, this thesis is based on three advanced mixed method design frameworks (i.e., multistage, intervention, and participatory) (Creswell et al., 2003). The intervention mixed methods framework is focused on conducting interventions in which qualitative data are collected primarily to support the development of the intervention, to understand contextual factors that could affect the intervention outcomes or explain results (Fetters, Curry and Creswell, 2013). This involves identifying theoretical behavioural factors (Study 1, 2, and co-production) that are tested in the intervention (Study 3). Additionally, participatory framework (Fetters, Curry and Creswell, 2013) is used involving the voices of the target population (co-production) to inform the direction of the intervention design, including identifying the target behaviours and intervention content. The qualitative results from co-production usability testing informed the re-design of the intervention (Fetters, Curry and Creswell, 2013). The intervention was then delivered to the participants and qualitative data collected through questionnaire to assess acceptability. Therefore, the qualitative data in the thesis was collected to primarily support the development of the intervention and to understand contextual factors (e.g., BCTs) that explained quantitative results (e.g., identifying the most relevant predictors linked to groups of BCTs) after the intervention was completed. This involved identifying key behavioural factors (e.g., intervention components) in the three-workstream design phase (e.g., systematic review, focus groups, co-production) to be subsequently deductively mapped to an intervention framework and theory and measured in the feasibility study (Study 3) and predictive analytics (Study 4).

The multistage mixed methods framework is often used in longitudinal studies focused on evaluating the design, implementation, and assessment of a programme or intervention (Fetters, Curry and Creswell, 2013). It typically consists of multiple stages, and a combination of sequential components and convergent components. In this thesis, the sequence of steps begins with a systematic review (Study 1) to identify the initial set of intervention components. Next, a convergent design phase utilises focus groups and surveys (Study 2), and concurrently co-production. Third, primary data collection is completed in the intervention (e.g., merging data from EMA, fitness tracker, and survey data) and the data is tested quantitatively using

MLM (Study 3) and optimised using ML (Study 4) (see **Chapter 1, Figure 1**). Thus, the stages are sequential (both exploratory and explanatory) but also convergent. At present, the evidence of utilising a mixed method approach to lifestyle health intervention designs is limited, particularly for the population midlife women.

4.3 Quantitative Methods

4.3.1 Systematic Review (Study 1)

This thesis provides the first published evidence of constructing a systematic review of lifestyle DHIs targeting midlife women. The systematic review applied deductive approach to map descriptions from quantitative evidence (e.g., RCTs, feasibility studies) to the components of the BCW (Michie, van Stralen and West, 2011). This approach facilitated forming quantitative summaries of frequencies of identified BCTs (using BCTTv1 taxonomy (Michie et al., 2013)), COM-B components, and TDF domains. The deductively mapped intervention components from the review were used to inform the DHI design, combined with components identified in focus groups (Study 2), and co-production. Operationalising BCTs identified in a systematic review as also accomplished for example, in a design for a DHI aimed to reduce sedentary behaviour (Huang et al., 2023).

4.3.2 Questionnaire Methods (Study 2 and Study 3)

Questionnaires were used to collect data in both pre-focus groups (Study 2), and pre-/post-intervention (Study 3). Although both studies used mostly the same questionnaires, two questionnaires were replaced, and one questionnaire was added in the later intervention study. These changes were based on the data analysis obtained in the previous focus group study and were considered a better fit. The replacements involved specifically the Adult Eating Behaviour Questionnaire (AEBQ) (Hunot et al., 2016) and Technology Acceptance Model (TAM) (Davis, 1989), with the Dutch Eating Behaviour Questionnaire (DEBQ) and the Theoretical Framework of Acceptability (TFA) (Sekhon, Cartwright and Francis, 2017, 2022), which was published only after this focus group study was completed and therefore could not have been used in the focus group study. Additionally, Pittsburgh Sleep Quality Index (PSQI) (Buysse et al., 1989) was added in the pilot study as a result of the focus group participants describing sleep problems affecting their healthy eating and regular physical activity behaviours. Although all questionnaires are based on quantitative methods, the TFA used several open-ended questions in which the participants were able to freely provide their input, and therefore represent a minor qualitative method within the feasibility study (Study 3).

4.3.2.1 General Demographics and Lifestyle

The general demographics and lifestyle questionnaire consisted of 32 questions, including demographics (e.g., age, weight, height, county of residence, marital status, education level), types of therapies used to manage menopause symptoms (e.g., HRT, CBT, antidepressants), digital health technology types used (e.g., fitness tracker, apps for diet, apps for menopause symptoms, apps for exercise). Included were also open-ended questions specifically around the type of digital health technology the participants used. Additionally, seven questions were adapted from the North American Menopause Society Questionnaire (NAMS, 2005), including general health (4-scale item), additional diet items (e.g., number of meals per day, number of servings of fruit and vegetables per day, number of caffeinated beverages consumed per day, units of alcoholic beverages consumed per day), smoking (3-scale item), menopause perspectives and views (4-scale item), knowledge about menopause (4-scale item), and menopause stage (3-scale item).

4.3.2.2 Menopause-Related Quality-of-Life, using The Menopause-Specific Quality-of-Life Questionnaire (MENQOL™)

The MENQOL questionnaire (Hilditch et al., 1996; Lewis, Hilditch and Wong, 2005) is a validated research tool to measure health-related quality of life in midlife women (between ages 47 and 62 years) (Lewis, Hilditch and Wong, 2005). It consists of 29 items divided into four domains of vasomotor (three items), psychosocial (seven items), physical (16 items) and sexual (three items) (Lewis, Hilditch and Wong, 2005). All questions follow the same format, indicating either not experienced a symptom, or if experienced, then indicating how bothersome the experience is on a seven-point Likert scale (Lewis, Hilditch and Wong, 2005).

4.3.2.3 Food Frequency, using Short-Form Food Frequency Questionnaire (SFFFQ)

The SFFFQ questionnaire (Cleghorn et al., 2016) measures diet quality and consists of 24 questions about regular food consumption divided into main groups that focus on consumption of fruit, vegetables, fibre-rich foods, high-fat and high-sugar foods, meat, meant products and fish. It was developed based on nutritional guidelines for the UK adult population and it was validated and considered an effective method of assessing diet quality (Cleghorn et al., 2016). Consumption of one portion of each food is measured on a frequency scale from 1) never or rarely consumed, 2) weekly consumption (less than once a week; once a week; 2-3 times a week; 4-6 times week), and 3) daily consumption (1-2 times a day; 3-4 times a day; 5 and more times a day).

4.3.2.4 Adult Eating Behaviour Questionnaire (AEBQ)

The AEBQ questionnaire (Hunot et al., 2016) was developed and validated in a UK adult population and it measures appetite traits using 35 items measured along a five-point Likert scale (strongly disagree, disagree, neither agree or disagree, agree, strongly agree), constituting weight subscales, conceptually grouped into food approach and food avoidance scales, based on them being either positively or negatively related to weight (Hunot et al., 2016). Four food approach scales are comprised of hunger (five items), food responsiveness (four items), emotional over-eating (five items), enjoyment of food (three items). Four food avoidance scales include satiety responsiveness (four items), emotional under-eating (five items), food fussiness (five items), and slowness in eating (four items) (Hunot et al., 2016). The DEBQ (below) was used to assess convergent validity of the AEBQ (Hunot-Alexander et al., 2019). The AEBQ was used only in the focus group study and replaced with the below DEBQ in the intervention study. Other studies also acknowledged finding a better fit in the DEBQ that also demonstrates associations between weight and external eating and emotional eating in adults (Hunot-Alexander et al., 2022).

4.3.2.5 The Dutch Eating Behaviour Questionnaire (DEBQ)

The DEBQ is a validated measure of eating behaviour in adults using a 33-item scale. It was developed to assess three distinct eating behaviours in adults, including emotional eating (13 items), external eating (10 items), and restrained eating (10 items) (van Strien T., Frijters JER, Bergers JPA, 1986). Items within the questionnaire are scored using standard scale of a five-point Likert scale from 1 (never) to 5 (very often). Total scores are computed within a range from 33 to 165, with higher scores indicating higher levels of emotional eating.

4.3.2.6 Physical Activity Frequency, using Physical Activity Questionnaire (IPAQ-SF)

The IPAQ-SF (Craig et al., 2003) is a self-reported physical activity questionnaire with 9 items in its short form (IPAQ-SF), and with 31 items in its long form (IPAQ-LF). The short form questionnaire, used in this thesis, records the activity of four intensity levels, including vigorous-intensity activity (e.g., aerobics), moderate-intensity activity (e.g., leisure cycling), walking, and sitting (Lee et al., 2011). The authors recommend using the last 7-day recall (Craig et al., 2003) as the average time spent in the four activities. The recall period was adjusted in the intervention to reflect the timeline of the intervention of 14 days. Therefore, the participants were asked about their physical activity at baseline, and again after 14-days of intervention to reflect on the past 14 days.

4.3.2.7 Physical Activity Behaviours, using Behavioural Regulation in Exercise Questionnaire (BREQ-2)

The BREQ-2 questionnaire (Markland and Tobin, 2004) measures motivational regulation related to exercise participation, and it is comprised of five subscales, including intrinsic, identified, introjected, external, and amotivation. A five-point Likert scale ranging from 0 (not true for me) to 4 (very true for me) is used to rate each of its 19 items with the generation of each subscale score based on mean score across subscale items (Mahony et al., 2019). The BREQ-2 is one of the most widely used instruments (Sáez, Solabarrieta and Rubio, 2021) underpinned by the self-determination theory (SDT) (Deci and Ryan, 2004), that identifies motivational regulation (Mahony et al., 2019), and it has been used in a number of studies examining PA behaviours (Kovács et al., 2021; Sáez, Solabarrieta and Rubio, 2021; Videm, Hoff and Liff, 2022).

4.3.2.8 Physical Activity Readiness Questionnaire (PARQ)

The PAR-Q questionnaire (Shephard, 1988) was originally designed as a screening questionnaire with seven items to be self-administered before beginning physical activity, and it was intended to detect those participants who are at risk when increasing their exercise levels (Society and Ciety, 1999). The questionnaire was used prior in the intervention study (Study 3) at baseline, prior to the participants commencing the intervention to ensure it was safe for them to engage in a light physical activity, such as walking.

4.3.2.9 Pittsburgh Sleep Quality Index (PSQI) Questionnaire

The PSQI questionnaire (Buysse et al., 1989) is a self-rated measure for assessing sleep quality and disturbances over a one-month period. It consists of nineteen individual items that generate seven sub-scores (e.g., subjective sleep quality, sleep onset latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, daytime dysfunction) (Buysse et al., 1989), with the sum of scores yielding to one global score. The acceptable measures of internal homogeneity, consistency, and validity suggest its utility both in psychiatric clinical practice and research activities (Buysse et al., 1989). Similarly to the other questionnaires requiring a recall, the one-month recall period was changed to a two-week recall period to reflect the intervention period in Study 3.

4.3.2.10 Technology Acceptance Model (TAM) Questionnaire

The TAM (Davis, 1989) is a measure of technology acceptance, consisting of constructs of perceived of usefulness, perceived ease of use, attitude towards using, and actual current use. The TAM therefore suggests that intention to accept technology is determined directly by attitude, perceived usefulness and perceived ease of use. According to TAM, individuals' intention to use technology determines the actual use of the application, and attitudes toward technology affect the intention (Davis, 1989; Davis and Venkatesh, 2004; Venkatesh, Thong and Xu, 2012). Moreover, acceptability sits at the core of the widely used TAM, which posits that perceived ease of use and perceived usefulness of a given technology positively influence usage intentions, which in turn drive the adoption of new technologies (Perski and Short, 2021). This questionnaire was used in the design phase of the thesis (Study 2) to obtain information on how midlife women view using various technologies to support their lifestyle health behaviours. The intervention study (Study 3) utilised the following TFA instead, which is more appropriate to measure acceptability of an intervention.

4.3.2.11 Theoretical Framework of Acceptability (TFA) Questionnaire

The (TFA) questionnaire (Sekhon, Cartwright and Francis, 2017, 2022) is used to assess eight areas of acceptability, including affectivie attitutude, burden, ethicality, perceived effectiveness, intervention coherence, self-efficacy, opportunity cost, and general acceptabiity. In the TFA, affective attitude measures how an individaul feels about the intervention and includes six questions on how the participants like different components of the interventions (e.g., wearing fitness tracker, using the EMA app). Burden measures the amount of effort requried for the participants to participate in the intervention, and consists of eleven questions including one open-ended question to provide feedback on intervention burden. Ethicality measures the extent to which the intervention was a good fit with an individual's value system and consists of three questions. Perceived effectiveness measures the extent to which the intervention has achieved its intended purpose, and it is the longest section consisting of sixteen quesitons including one open-ended question. Intervention coherence measures the extent to which the participants understand how the intervention works, and consistes of four questions. Self-efficacy measures the participants' confidence that they can perform behaviours required to participate in the intervention using four questions. Opportunity cost measured the benefits, profits or values that were given up to engage in the intervention and consists of five questions. General acceptability asks for overall acceptability. In this thesis, additional question was added on whether the participants joined the study with a friend or someone they knew. This was added after the intervention recruitment (Study 3) was completed during which the participants shared joining the study with someone they knew, potentially facilitating social support for these participants.

4.3.3 Analysing Hierarchical Longitudinal Intervention Data (Study 3)

The intervention dataset (Study 3) was expected to resemble a typical longitudinal dataset in a longitudinal study, which often consists of unbalanced or missing data (Luke, 2011b). Many traditional longitudinal analysis approaches, such as repeated-measure multivariate analysis of variance (MANOVA), are unable to easily handle unbalanced longitudinal data that contains missing data or uneven time points (Luke, 2011b). Therefore, multilevel models (MLM) were utilised instead, providing more flexible and efficient way of using whatever data are available to model change patterns even for data that are collected at varying time points (Luke, 2011b). However, although MLM and other data analysis techniques that are used to investigate hierarchical data structures are equipped with procedures to deal with incomplete data (e.g., using multiple imputation (MI), maximum likelihood estimation (MLE)) (Grund, Lüdtke and Robitzsch, 2018), using incomplete data to investigate behavioural interventions in which the objective is to understand what components worked for whom, when, and how, may not be appropriate. Computing missing data (e.g., using MI or MLE) may potentially lead to a false conclusion that a particular BCT (i.e., component) influenced the target behaviour. For example, if a participant forgets to set their morning steps goal and the entry is computed based on the previous day's entry when the steps goals were set, and the participants achieves only a few steps on that day, we could falsely conclude that goal setting has no effect on the target behaviour of increasing steps count. For this reason, incomplete records were removed from the dataset and only records that contained responses to all EMA surveys and recorded steps and sleep were included for further statistical analysis.

MLM is specifically used in the analysis of data that has a hierarchical or cluster structure. Clustered data may result from a specific research design, for example, using a multistage sampling design and results in clustered design. Another example are longitudinal designs, in which repeated measurements are nested within individual subjects. The intervention data represents hierarchical longitudinal data with measures at different points in time (i.e., baseline and 14 intervention days) that are nested within an individual participant. The individual observations are not independent (they belong to the same individual in different time points), in which an individual's responses tend to be consistent across time (Cernat, 2023). Consequently, analysis of variance (ANOVA) cannot be used because it requires groups of variables that are not directly related to each other to determine whether any common means exist (Cernat, 2023). For this reason, MLM was used to predict values of intervention outcomes based on a function of predictors (independent variables) at more than one level (Luke, 2011a; Woltman et al., 2012). Furthermore, MLM are a form of ordinary least squares (OLS) regression models that can be applied to longitudinal data where the primary interest is in modelling the structure and predictors of change over time (Luke, 2011b). In the case of the intervention data, time (i.e., waves or intervention days) is nested within person (participant), and therefore the data structure has two hierarchical levels: 1) individuals and 2) time (i.e., intervention days, waves). Therefore, MLM embodies two types of research questions: level-1 questions about within-person change and level-2 questions about between-person differences in change (Singer and Willett, 2003).

Building multilevel models typically (and the intervention in **Chapter 7**) consisted of building both unconditional (without predictors) and conditional (with predictors) models. The first unconditional model is the simplest possible multilevel model that has no level-1 (within-person changes over time) or level-2 (between-person differences) predictors (Luke, 2011a). It is an unconstrained, unconditional, empty, null-model, and it is often used as a starting point for building more complex models. It is used to estimate between and within variation in the dependent variables (i.e., outcomes or target behaviours) and to determine the interclass correlation coefficient (ICC) (Luke, 2011a). The second unconditional model consists of building an unconditional change (growth) model to describe how the models change in time, during the intervention period (Cernat, 2023). Finally, the conditional models include predictors in blocks to determine how each predictor affects the model (Cernat, 2023) and in this thesis, conditional model is not explored using MLM. Instead, conditional models are explored using machine learning (ML) (**Chapter 8**), also described next.

4.3.4 Predicting Intervention Outcomes Using ML Models (Study 4)

4.3.4.1 Using ML for Predicting Intervention Outcomes

Although traditional statistical models (such as MLM) can be used to build numerous conditional models with different groups of predictors, this can be a lengthy and inefficient process when dealing with many predictors and outcomes as well as when implementing adaptive and dynamic interventions. Exhaustive search for optimal feature subset is infeasible in most cases and therefore many search strategies have been proposed in the literature to find accurate data models (Jović, Brkić and Bogunović, 2015). For example, to evaluate the optimal feature subset, feature selection method has to evaluate a total of $2^m - 1$ subset (where m represents the total number of features in a dataset, excluding the empty model) (Jović, Brkić and Bogunović, 2015). Given that the prediction algorithms in this thesis (Study 4) utilises a subset of the intervention data variables, specifically 22 time-varying predictors (e.g., goal setting for steps, goal setting for portions of vegetables, self-monitoring of water consumption, reading educational content) and 20 time-constant predictors (e.g., age, weight, ethnicity, menopause stage) across 10 outcomes, manual (i.e., using statistical methods) feature selection would involve evaluating 43 ($2^{22} - 1$) time-varying predictor combinations and 39 ($2^{20} - 1$) time-constant predictor combinations, one by one.

A better approach to identify best predictors for each outcome is to use ML algorithms, specifically supervised ML, which uses an automatic system to learn from a history of occurrences of a certain event and consequently makes predictions about future occurrences of that event (Ignatow and Mihalcea, 2018b) (e.g., setting specific steps goals by all participants each day, resulting in the recorded daily steps). The task of the ML algorithm is to learn how to make predictions efficiently, using features that characterise an event (i.e., 22 predictors selected most effectively in this study) along with specific instances of that event (Ignatow and Mihalcea, 2018b). Moreover, not every feature will have an impact on the outcome (i.e., output variable) and models that contain irrelevant features perform worse than models containing only relevant features (Bolón-Canedo, Sánchez-Maroño and Alonso-Betanzos, 2013). Generally, using only relevant and fewer features results in better performance and the objective of building an ML model is to find the right balance between the best-fit and simplicity of the model (Bolón-Canedo, Sánchez-Maroño and Alonso-Betanzos, 2013). This thesis utilised supervised ML approach to identify predictors to health behaviours linked to theoretical constructs (i.e., BCTs) (Study 4). The prediction was based on the collected intervention data (Study 3), incorporating multiple data sources (e.g., EMA, wearables, surveys), and a feature selection (FS) algorithm to identify groups of the most relevant predictors (and BCTs) predicting each target behaviour (Study 4).

4.3.4.2 Feature Selection Method Evaluated in the Thesis

The main goal of FS algorithms is to find the smallest subset of features that provides the maximum amount of beneficial information for prediction by eliminating redundant or irrelevant features in a specific dataset (Alshurafa et al., 2014). Applying effective FS algorithm not only increases the performance of the model (by removing irrelevant features) but it also decreases the computational complexity of the system by reducing dimensionality and redundancy

(Alshurafa et al., 2014). Although there are various FS methods available, most researchers agree that there is not a so-called “best method”, rather there are methods better suited for a specific problem setting (Bolón-Canedo, Sánchez-Maroño and Alonso-Betanzos, 2013). Furthermore, there are several methods to constructing and selecting features, including ranking all potentially relevant features based on their individual predictive power or selecting a subset of features that are useful to build a good predictor and that together have a good predictive power (Guyon and De, 2003). It can be argued that selecting the most relevant features is suboptimal for building a predictor, particularly if the features are redundant. On the other hand, selecting a subset of useful features may exclude many redundant, but relevant features (Guyon and De, 2003).

While starting with feature ranking models is recommended for reducing the number of features, the second objective of eliminating redundancy can be address with forward selection or backward elimination models (Fogelman-Soulié, 2008). This thesis (Chapter 8) explores feasibility of using both, feature ranking (e.g., correlation matrix, feature importance) and selecting a subset of features (e.g., univariate feature identification, recursive feature elimination) methods to make predictions. In feature ranking, features are assessed individually and assigned weights according to their degrees of relevance. Subset evaluation however produces subsets of the most relevant features, based on the metrics of the specific algorithm used. Although several ML models are explored, the reported results contain predictions based on recursive feature elimination (RFE) method (Chapter 8). The RFE algorithm starts with all features and removes features with lowest scores at each iteration (Khaire and Dhanalakshmi, 2022). The model trains with increasingly smaller sebset of features and finds the best group of features. This is done by recursively eliminating the weakest features until the specified number of features is left (Khaire and Dhanalakshmi, 2022). As the output of RFE is the best-subset of predictors, in addition to predictor ranking, it alings with the aim of this thesis (Chapter 8) to determine a group of predictors that best predict target behaviours.

4.3.4.3 Metrics Used in ML Model Performance

Among the key measures for model performance and selection of the best model from a set of potential models are root mean squared error (RMSE), the mean squared error (MSE), R-squared (R^2), and adjusted R-squared (adj R^2) (Pham, 2019). These metrics were also used in other supervised ML dietary intervention studies in predicting short-term body weight prediction (Babajide et al., 2020).

RMSE:

The RMSE measures the average difference (i.e., the average error) between the model's predicted values and the actual values. Mathematically, RMSE represents standard deviation of the residuals (i.e., the unexplained variance), which represent the distance between the regression line and the data points (Zhu, 2014). RMSE values can range from zero to positive infinity and uses the same units (e.g., steps, cups) as the outcome (dependent) variable. Because it assesses the amount of effort in the regression (or another statistical model), the lower the RMSE, the better the model (Huang and Carriere, 2006), the better the model fits the data, indicating a more precise prediction. MAE, similar to RMSE, measures the prediction error, although it is less sensitive to outliners.

Normalised RMSE:

To interpret the results of RMSE in models with different scales, normalised RMSE (NRMSE) is applied, using one of four normalisation methods (e.g., mean, difference between maximum and minimum, standard deviation, interquartile range) (Otto et al., 2018). The range method (RMSE/(y_{max} – y_{min})) with the difference between maximum outcome value and minimum of the observed outcome value in the dataset was applied in this research. While the best possible value for NRMSE is 0, acceptable values of (0 ≥ NRMSE ≤ 0.5) (Wang and Lu, 2018), corresponds to accuracy of ≥ 50% (1 - 0.5). However, as other studies in health (Agrawal, Jain and Joshi, 2022) achieved NRMSE ≤ 0.30 and therefore accuracy of at least 70% (1 - 0.30), this thesis considers higher accuracy of at least 70% (0 ≥ NRMSE ≤ 0.30) to be acceptable.

R-squared:

Whereas RMSE is the non-standardised goodness-of-fit assessment of the model, R-squared is the standardised assessment of goodness-of-fit. R-squared is a metric of correlation and it determines the proportion of variance in the dependent variable that can be explained by the linear model (i.e., the predictor variable included in the model). It shows how well the data fit the regression model (i.e., the goodness of fit). Generally, the higher the R-squared, the better the model fits data, and although higher R-squared (i.e., closer to 1) is generally desirable in life sciences research, studies that involve predicting human behaviour tend to have R-squared values lower than 0.5 (50%). This is due to the complexity in predicting human behaviour, which is often influenced by many factors. Although predicting human behaviour is challenging, the goal of most social science research modelling (and the goal of this study) is not to predict human behaviour, and rather, the goal is to assess whether specific predictors or explanatory variables have a significant effect on the dependent variable. Therefore, a low R-square of at least 0.1 (or 10 percent) and up to 0.50 is acceptable in social science research on the condition that some or most of the predictors or explanatory variables are statistically significant (Ozili, 2023). An R-squared between 0.50 to 0.99 is acceptable in social science research especially when most of the explanatory variables are statistically significant (Ozili, 2023).

Adjusted R-squared:

Choosing measuring criteria for model performance and selection has been a topic of discussion in the research community, since some criteria may place more emphasis on the number of parameters (predictors) while others put add penalties for sample size of the given data (Pham, 2019). For example, the shortcomings of RMSE and R-squared are in their insensitivity to adding additional predictors, even those that do not have significant contributions in explaining the outcome, and adding more predictors will increase R-squared and reduce the RMSE. To overcome these shortcomings, additional metrics are used in the evaluation of the regression models, specifically adjusted R-squared, Akaike's Information Criteria (AIC), and Bayesian information criteria (BIC) (G, 1978; Akaike, 1987). These metrics add a penalty for including additional variables to the model. Therefore, although R-squared assumes that every single predictor explains the variation in the outcome (dependent variable), adjusted R-squared provides percentage of variation explained by only the predictors that actually affect the outcome. Adjusted R-squared includes a penalty for including predictors that do not fit the model, and it will therefore always be less or equal to R-squared (Ivanescu et al., 2015). Similarly to R-squared, a cut-off point of 0.1 (or 10 percent) is deemed acceptable.

Spearman rank correlation coefficient:

Weighted Spearman rank correlation coefficient is used to evaluate strength of association between features, providing Rho (r_s) and p-values. Higher values are better, with a cut-off point with significance level of $p<0.05$ is used.

Cross-validation:

In the previous section, the most commonly used metrics (e.g., adjusted R-squared, RMSE, AIC, and BIC) were used for model comparisons and best-fit model selection. These metrics assess how well the models fit to the same data (i.e., training data) that was used to build the regression model. Typically, predictions that are based on training data are of less interest than prediction built on previously unseen data (test data). Cross-validation includes a set of methods for measuring the performance of a predictive model on a new, previously unseen, test dataset. Although the feature selection algorithm also incorporate k-fold cross-validation, future research should include larger dataset and perform thorough test data analysis on unseen data. A standard cross-validation method is 10-fold (k=10), and it is recommended to use 10 times 10-fold cross-validation method to reduce variance (Fogelman-Soulié, 2008). For illustration purposes, this research describes assessing performance of only the steps count model on unseen data using three most-commonly used cross-validation methods (e.g., leave one out cross validation, k-fold cross validation, and repeated k-fold cross validation), including 10-fold cross-validation (**Chapter 8**).

4.3.5 Quantitative Data Analysis Software

Statistical analysis of the survey data, including descriptive statistics, ML modelling, and multilevel modelling (MLM) was conducted in R statistical software (using R Studio 2023.06.0 build 421). In addition, feature selection was developed also in Python (version 3.9.13, using Jupyter notebook version 6.4.12). For comparison of different packages, feature selection was performed in both, R, using *Caret* package in R and also in Python using Scikit library (*SelectKBest* and *Extra Trees Classifier* libraries) in Jupiter Notebook (version 6.4.12). Weighted Spearman correlation coefficient (r_s) was used to measures the strength and direction of association between ranked predictors. R package “stats” was used to produce the weighted correlation matrix, and “Hmisc” package was used to produce Rho (r_s) and p-values using function cov.wt(). A linear mixed model (using the Ime4 package (Bates, 2018)) was used for all MLM estimations.

4.4 Qualitative Methods

4.4.1 Focus Groups (Study 2)

The mixed method focus group study incorporated both qualitative focus group discussions with the target population of midlife women, in the UK, and a quantitative survey (see questionnaires methods section) administered prior to focus group meetings. A focus group is a data-collection method that brings together a small group of individuals, typically six to eight people, to discuss a series of open-ended questions, in which the moderator asks the questions and moderates the discussion (Cyr, 2017). The goal of the discussions was to understand how people talk about the topics of interest, to extrapolate their individual or group attitudes and behaviours (Cyr, 2017). The focus groups in this thesis (Study 2) involved groups of UK-residing midlife women who discussed barriers and facilitators to healthy eating and regular physical activity. As the discussions took place in groups, the participants were able to react to one another's comments, which brought a synergistic quality to the social dynamics of the groups (Cyr, 2017). Furthermore, the discussions allowed for data to be captured at the individual level of analysis (with quotes from individuals being captured) and group level (group-level consensus and disagreements) (Cyr, 2017). In qualitative research, the focus is on thematic methods to identify themes within first-person accounts. The real-world phenomena, including healthy eating and physical activity behaviours, were captured and the text from the transcribed focus groups were used as the medium through which real-world can be understood and investigated. The qualitative data extracted from the focus group transcripts were deductively mapped to the BCW/TDF framework, in which the intervention components were identified, as described in the previous section.

4.4.2 Qualitative Data Analysis Software

Thematic analysis was completed in NVivo qualitative data analysis software (version 12, QSR International, Melbourne, Australia). Mapping of themes deductively to the BCW and BCTs were conducted in Microsoft Excel (Microsoft 365 version in 2022).

4.5 Co-Production (Chapter 7)

A recent population survey by the Department of Health and Social Care in England found that 84% of respondents (N=97,307) felt women's voices have not been listened to in matters pertaining to women's health and care (Department of Health, 2022). Co-production is used to improve quality and relevance of research (Greenhalgh et al., 2019; Oliver, Kothari and Mays, 2019). However, while researchers and clinicians are encouraged to involve the public and patients (PPI) as collaborators in research, clear understanding of what such involvement entails is not often clearly defined (Price et al., 2022). Health research includes many different collaborative and participatory methods, with co-production, co-creation, and co-design being used commonly and summarised as 'co' approaches (Cowdell et al., 2022). Despite the description of the fundamentals of 'co' approaches in the literature, there is little consensus about the type of approaches these three terms describe (Cowdell et al., 2022). In practice, these three terms are often used interchangeably with inadequate and ambiguous description (Pearce et al., 2020; Cowdell et al., 2022). Although this thesis is using the term co-production to as a 'co' approach (also in other similar studies (Hall et al., 2020b; Davies et al., 2023)), the term co-design may also be appropriate to use instead to describe designing a complex intervention (O'Cathain et al., 2019).

Despite the lack of clarity around the definition of co-production, what it comprises of, and what it means in practice, interest for co-production healthcare services and research is growing in the UK (Smith et al., 2022). One of the uses of co-production represents enhanced public patient involvement and engagement (PPI/E), a way to improve on its shortcomings by re-engaging with the principles of power-sharing, equality and social justice, and reinforcing the democratic right of citizens to influence healthcare (Paylor and McKevitt, 2019; Williams et al., 2020). Other ways of using co-production involves consulting the public and service users to provide instrumental inputs into health and social care services and research, demonstrating a more technocratic rationale (Martin, 2008). PPI typically join research teams to co-produce evidence for the practical use of interventions in clinical practice (Price et al., 2022). Although researchers are operationalising co-production in various ways, different approaches are needed to tailor co-production to context, different stakeholder groups and various stages of the research and implementation process (Smith et al., 2022). In this thesis, the PPI represented members of the public (i.e., UK-residing midlife women) who were involved in shaping key intervention components from the beginning of the intervention design to the end, including focus group content testing (Study 2) and usability testing of all intervention components (Study 3) prior to the intervention launch. In addition, a group of health experts (i.e., nutritionist, exercise physiologist, NHS GP) were involved to provide their expertise in the intervention education content development. The co-production approach in this thesis is guided by the BCW guide (see **Section 3.3.7**) and it includes group activities aligned to the three stages of the BCW guide, including identifying target behaviours (Workshop 1), COM-B components (Workshop 2), intervention functions and mode of delivery (Workshop 3), and mapping BCTs to each intervention feature (completed by the researcher).

4.6 Conclusion

This chapter highlighted the philosophical distinction between quantitative and qualitative paradigms and provided a methodological argument for combining quantitative and qualitative methods in a single study, which is widely practiced and accepted in many areas of healthcare research (Sale, Lohfeld and Brazil, 2002) and in social science research (Creswell et al., 2003). Combining methods in a multimethod design provides a more complete picture of human behaviour and experience, which is utilised in the design of the DHBCI within this thesis. The systematic review (Study 1) described in the next chapter (**Chapter 5**), is an essential step towards understanding the designs of DHIs. It is necessary to synthesise and evaluate existing evidence on components of DHIs aimed to improve health behaviours in midlife women. Overall, the findings from this study are used to inform the next phase of this research intervention design and general conclusions of this thesis.

5. Behaviour Change Techniques in Digital Health Interventions for Midlife Women: A Systematic Review

5.1 Introduction

This chapter includes published article and concludes with a short update on new research since the article publication in November 2022 (see **List of Presentations and Publications** for details on the publication).

Note: Relevant supplementary materials for this study are presented in ***Appendix A*** *of this thesis.*

BEGINNING OF THE PUBLISHED ARTICLE

5.1.1 Background

Around 3.5 million women aged 50 – 65 are employed in the UK and experience menopausal symptoms (e.g., hot flushes, disturbed sleep, depression, cognitive dysfunction) (Brinton et al., 2015) that can contribute to job dissatisfaction and decreased commitment to work (Griffiths, MacLennan and Hassard, 2013). The impact can be bidirectional with symptoms, such as poor concentration, poor memory and sickness absence, impairing job performance (Brewis et al., 2017) and the workplace exacerbating menopausal symptoms (Grandey, Gabriel and King, 2019). Moreover, an individual's health related quality of life (HRQoL) in midlife is influenced by many additional non-menopausal factors, such as lifestyle, physical activity, and social integration (Schneider and Birkhäuser, 2017). Evidence suggests that midlife for women represents a critical window for preventing chronic disease and for optimising health and functioning, while it is increasingly recognised that a healthy lifestyle may mitigate such health risks (Harlow and Derby, 2015). Improvements in diet, physical activity, and lifestyle can provide an effective intervention to manage menopause symptoms, improve HRQoL (Imayama et al., 2011) and reduce menopause-related health risks (Crosignani, 2010; Scheyer et al., 2018) (e.g., neurodegenerative diseases, particularly Alzheimer disease (Brinton et al., 2015; Mosconi et al., 2018a) and increased cardiovascular disease risk (Thurston et al., 2008), low bone-mineral density, fractures, and osteoporosis (Johansson, Mellström and Milsom, 1993; Compston et al., 2017)).

BCIs aimed at promoting population-level participation in key behaviours have been widely applied in the general population (Hagger et al., 2020) and to some degree also in midlife women (Pérez-López et al., 2017; Noll et al., 2020). Women in midlife are willing to make positive health behaviour changes but need support (e.g., social connectivity (Arigo, 2015)) to have those changes be effective (Anderson, Anderson and Hurst, 2010a). Changing established behaviour patterns can however be challenging as it requires addressing a strong psychological, environmental or social gradient (Michie S, Atkins L, 2014). BCIs are typically complex and involve many interacting components, and therefore, a theoretical understanding of how the intervention causes behaviour change is needed to strengthen their effects on clinical outcomes (Craig et al., 2008). A recent scoping review (Arigo, Romano, et al., 2022a) identified limitations in describing physical activity interventions in midlife women, with only 59% of the 51 studies specifying an underlying theoretical model. Many studies provided a limited description of how BCTs were activated to achieve desired outcomes and provided limited insight into how the BCTs were received by midlife women (Arigo, Romano, et al., 2022a). As a result, interpreting designs and evaluations of complex interventions can be challenging without sufficient description of key intervention content (Glidewell et al., 2018), and therefore characterising interventions by BCTs can be insightful in understanding the effectiveness of interventions (Michie, Abraham, et al., 2009b).

The use of psychological theory in the development of BCIs (including digital BCIs) is associated with greater intervention effects (Abraham et al., 2008; Webb et al., 2010; Michie, Carey, et al., 2018). Although there are a wide range of theoretical models of behaviour, (e.g., the Theory of Planned Behaviour (Ajzen, 1991), the Health Belief Model (Rosenstock, 1974)), health-promoting interventions that are based on a single theory have generally been shown to be more effective in changing behavioural intentions than actual behaviour (Webb and Sheeran, 2006; Sniehotta, Scholz and Schwarzer, 2007). Integrated theories have therefore been proposed to overcome this limitation by drawing their hypotheses from several different theories with the aim to provide a more comprehensive explanation of behaviour (Hagger and Chatzisarantis, 2014). Theoretical frameworks, such as the Theoretical Domains Framework (TDF) (Cane, O'Connor and Michie, 2012b) integrate insights of multiple behavioural theories to identify relevant constructs that may be implicated in various health behaviours. Together with the COM-B model ('capability', 'opportunity', 'motivation', and 'behaviour') (Michie, van Stralen and West, 2011) that aims to identify the sources of target behaviour, they form the BCW framework. The BCW framework provides a systematic and theoretical basis for understanding and changing behaviour. It has been used extensively to develop and evaluate the implementation of interventions in healthcare settings (Alexander, Brijnath and Mazza, 2014; Barker, Atkins and de Lusignan, 2016; Mc Sharry, Murphy and Byrne, 2016), in lifestyle (e.g., smoking cessation (Fulton et al., 2016), alcohol use prevention (Rosário et al., 2021), sedentary behaviour (Ojo, Bailey, Brierley, et al., 2019), physical activity (Flannery et al., 2018), dietary patterns (Timlin, McCormack and Simpson, 2021)) but also in other areas such as personal transportation habits (Arnott et al., 2014).

Behavioural interventions to promote physical activity in midlife women have been traditionally delivered face-to-face or in group settings (Arigo et al., 2019). However, the use of digital technology to change health behaviours has increased exponentially in recent decades, primarily after the introduction of smartphones in 2009 (Taj, Klein and Van Halteren, 2019). Moreover, digital health technology (i.e., apps, wearables, websites) has the potential to increase scalability through broader user reach (Arigo et al., 2019) throughout the day, improve intervention effectiveness (Arigo, 2015) and achieve greater cost efficiency (Iribarren et al., 2017; Jiang, Ming and You, 2019). Indeed, DHIs are both feasible (Cadmus-Bertram et al., 2015; Steinberg et al., 2020) and acceptable among midlife women (Im et al., 2012; Arigo, 2015; Joseph et al., 2021). Digital health technologies (including therapeutic interventions, online support communities, and virtual consultations) can provide important means for midlife women to obtain evidence-based menopause-related health information and recommendations, social and health-practitioner support, and symptoms tracking (Cronin, Hungerford and Wilson, 2020).

5.1.2 Objectives

The development of the BCT taxonomy (Abraham and Michie, 2008; Michie et al., 2013) and methods for assessing the extent to which behavioural interventions are theory-based, allow for more sophisticated coding of intervention content and insight into how and why the intervention promoted behaviour change. Thus, the primary aim of this systematic review was to 1) assess the frequency and type of BCTs and BCT categories (representing groups of BCTs) used in DHIs with midlife women, 2) understand the mechanism of action proposed to affect changes in the behavioural outcome, and 3) appraise the intervention functions or broad categories of means by which the studies proposed to change behaviour, using the BCW. In addition, this review will identify the theoretical grounding (or the extent of behaviour change theory used) in the DHIs, using the Theory Coding Scheme (TCS) (Michie and Prestwich, 2010) and determine the technological features (mode of delivery) used in these studies.

5.2 Methods

The structure of this document follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021), as the basis for reporting findings from the selected trials. The study protocol was registered with the International Prospective Register of Systematic Reviews (PROSPERO reference: CRD42021259246).

5.2.1 Selection Criteria

In accordance with PRISMA, the Population, Intervention, Comparison, Outcome (PICO) and study design tool was deployed.

5.2.1.1 Population

Women aged 40-65 years, of all ethnicities and health conditions, healthy, overweight, and obese, as well as breast cancer survivors and women with high risk of hypertension were included. These broad criteria were used to explore the impact of behaviour change theory on lifestyle improvements rather than the interaction with these disease states.

5.2.1.2 Interventions

Studies describing interventions where the stated aim was to improve diet, physical activity, sleep, menopausal symptoms, and body composition by promoting changes in health behaviours including healthy eating (single nutrients or whole dietary patterns) and/or physical activity (frequency or intensity). Only studies with participants randomised to a group explicitly asked to use digital technology (e.g., wearables, mobile apps, websites) as a mode of intervention delivery were considered. No other restrictions were placed on intervention type and delivery or duration.

5.2.1.3 Comparison

Control group or other treatment groups, involving health education, assignment of no digital health technology, or altered (i.e., frequency, intensity) or no physical activity or diet intervention were included.

5.2.1.4 Outcome

The primary health outcomes were changes in physical activity (i.e., frequency, intensity), diet (i.e., fruit and vegetables intake, single nutrient intake), body composition (i.e., body weight, lean muscle mass, waist circumference), and frequency or intensity in menopausal symptoms (i.e., VSM, sleep, bone health, anxiety, depression). Although these health outcomes were included in the search criteria, they were not part of this review's assessment of study designs (described in the study aims). However, when available, the outcomes of the interventions were extracted as part of the description of the studies to allow for the main outcomes to be presented in the relevant context.

5.2.1.5 Study design

Both experimental (i.e., RCTs, quasi-experimental) and non-experimental (i.e., observational studies) were included, with a minimum of 2-arm RCTs, pilots and feasibility studies.

5.2.2 Search Strategy

Literature searches were conducted by HS and SD between February 2021 and April 2021. Articles published prior to April 2021 and available in English were searched in the following databases: MEDLINE/PubMed, Web of Science, PsycINFO, Cochrane Central Register of Controlled Trials (CENTRAL) in The Cochrane Library. The search criteria included the following terms: ("midlife") AND ("mHealth" OR "eHealth" OR "digital") AND ("diet" OR "physical activity" OR "menopaus* symptom*" OR "lifestyle" OR "'weight loss" OR "mental health" OR "depression" OR "sleep"). The filters used were 'Randomised Controlled Trials', and 'Clinical Trials', and the species selected were 'Humans' only, and language 'English' only. The search was limited to studies published between January 2009 and April 2021, reflective of the increased use of digital technology to change health behaviours after the introduction of smartphone in 2009 (Taj, Klein and Van Halteren, 2019). Interventions published before 2009 focusing on older technologies, such as such as pedometers were not considered. Additional hand searches of relevant journals were performed, which included JMIR mHealth and uHealth, Menopause, and Climacteric.

5.2.3 Data Extraction and Collection Process

The studies were screened using title and abstracts and those that did not meet the inclusion criteria were excluded. The following information was extracted from each study: author, behaviour change theory, intervention type, study design, country, ethnicity, intervention length, participant age and health risk, comparison group, main outcome significance between group differences. Data from each eligible study was populated into a prepared Microsoft Excel template to evaluate their eligibility and observe any missing data. Two reviewers (HS and SD) independently extracted the data, and this was checked for accuracy. Any disagreements were resolved through a discussion and a third reviewer was not required.

The first template included key information on each study, such as the intervention type, length, behaviour change theories used, outcomes, and mean age of the participants. Multiple studies from the same trial were merged and information extracted to gain a full picture of the intervention, ensuring reported descriptive statistics were not double counted. Authors of the original reports were contacted to obtain further details if insufficient information was included in published documents. A reminder was sent if no responses were received after two weeks. The use of BCTs and clusters of BCTs as defined by The Behaviour Change Techniques Taxonomy v1 (BCTTv1) (Michie et al., 2013) was synthesised (and coded) for each included study. The number of individual BCTs included in each study was counted (range 0-93) and the mean value and standard deviation are reported. Furthermore, the use of behaviour change categories (BCCs), and combinations of techniques and categories or clusters were investigated for each included study. Each study and groups of related studies (i.e., weight loss, lifestyle, and menopause symptoms) were mapped into this framework. The overarching synthesis bringing the studies together by providing a systematic and theoretical basis for understanding behaviour was based on the COM-B model (Michie, van Stralen and West, 2011), the TDF (Cane, O'Connor and Michie, 2012b) and the BCW (Michie S, Atkins L, 2014). The BCW links to theory-based frameworks (i.e., TDF, and BCTTv1) to understand behaviour for specifying intervention content (Atkins and Michie, 2015) Using the TDF and/or the COM-B model, intervention designers can make a behavioural diagnosis of what needs to change in order for the desired behaviour to occur, and in the evaluation of interventions, the framework can help to identify the mechanism of action (i.e., how an intervention is working) (Atkins and Michie, 2015). Explicit links between the COM-B model and TDF domains are provided in the BCW Guide (Michie S, Atkins L, 2014).

The BCW also supports evaluating intervention functions (consisting of education, persuasion, incentivisation, coercion, training, restriction, environmental restructuring, modelling, and enablement) by identifying broad categories of means by which interventions can change behaviour (Atkins and Michie, 2015). For example, a digital health app designed to promote healthy eating may contain an educational element (e.g., providing new information about the benefits of healthy eating) but also be presented in a way that is intended to be persuasive (e.g., generating feelings of worry about the health consequences of eating unhealthy foods) (Atkins and Michie, 2015).

The use of psychological theory in the studies was examined using the Theory Coding Scheme (TCS) (Michie and Prestwich, 2010) to assess the extent to which behaviour change theory was used to design the interventions within each study. This data was extracted by HS and reviewed for accuracy by SD. The overall scoring for each study was assessed as having weak (score 0 – 7), moderate (score 8 – 15), or strong (score 16 – 23) levels of theory use (Willmott et al., 2019). Lastly, the technological and non-technological components from each study were extracted and mapped into pre-defined categories that were created based on the review of the included studies. Frequencies of individual modes of delivery were reported together with frequencies of related groups of passive and interactive components. The quality assessment was completed using the Physiotherapy Evidence Database (PEDro) scale (Cashin and McAuley, 2020) and the Cochrane risk-of-bias tool for randomised trials (RoB 2) (Sterne et al., 2019) was used to assess the risk of bias in randomised trials (**Appendix A**, **Figure 68** and **Figure 69**).

5.2.4 Treatment Fidelity Assessment

Treatment fidelity facilitates theory testing, with high levels often associated with alteration in the mechanism(s) of change (e.g., increased physical activity, healthier eating) hypothesised to affect the outcomes (Borrelli, 2011). According to Borrelli (Borrelli, 2011), high fidelity constitutes 80 – 100 percent integrity, whereas 50 percent constitutes low fidelity scoring. By describing methodological strategies that are applied to monitor and enhance the reliability and validity of health behaviour change interventions (Bellg et al., 2004), treatment fidelity helps to increase scientific confidence that the changes in the outcome of interest (dependent variable) are due to the manipulation of other variables (independent variables) by the researchers (Borrelli, 2011). This is achieved through assessment of the degrees to which the intervention is implemented as intended and the study arms differ along critical dimensions, respectively (Borrelli, 2011). In interventions that produce non-significant effects, treatment fidelity helps to uncover whether these effects are due to the omission or addition of active/inactive components or due to an ineffective treatment (Borrelli, 2011). The treatment fidelity of the studies included here was assessed utilising a 29-item checklist (Borrelli, 2011) grouped into 5 domains. These are 1) Design of study (6 items), 2) Monitoring and improving provider training (7 items), 3) Monitoring and improving delivery of treatment (9 items), 4) Monitoring and improving receipt of treatment (5 items), and 5) Monitoring and improving enactment of treatment skills (2 items) (Bellg et al., 2004), termed henceforth as Study design, Training, Delivery, Receipt, and Enactment (Timlin, McCormack and Simpson, 2021).

5.3 Results

5.3.1 Study Selection

Initial searches highlighted 1324 records from databases and an additional five records from Menopause, Climacteric, and JMIR journals. Screening the titles highlighted 341 duplicates and an additional 85 records which were excluded for other reasons. Full text reviewed 53 eligible studies provided the remaining fifteen studies (investigating 1661 women) comprised of thirteen intervention designs (involving 1308 women) were included in the systematic review. **Figure 10** illustrates the study selection process based on PRISMA flow (Page et al., 2021).

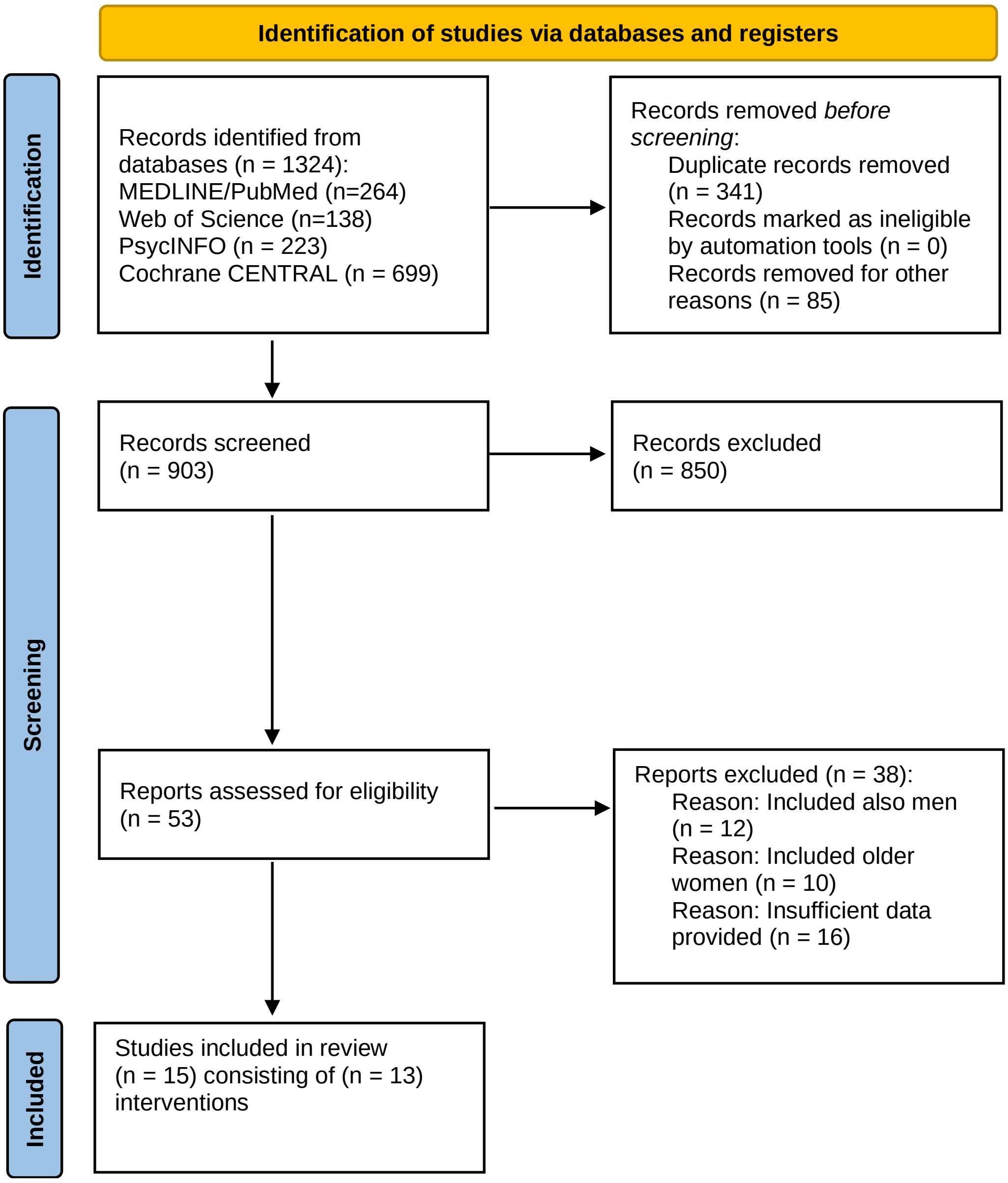


Figure 10: Study selection flow diagram based on PRISMA statement (Page et al., 2021)

5.3.2 Study Characteristics

The included studies consisted of three studies with weight loss (Park and Kim, 2012; Hartman et al., 2016; Grossman, Arigo and Bachman, 2018) as their primary aim. Eight studies focused on improving lifestyle factors, including two studies on diet (Ryan et al., 2013; Steinberg et al., 2020), six studies on physical activity (PA) (Finkelstein et al., 2015; Cadmus-Bertram et al., 2015; Fukuoka et al., 2019; Lynch et al., 2019; McGuire et al., 2019; Nguyen et al., 2021) (with one study on PA and diet (McGuire et al., 2019) and one study on PA and sleep (Nguyen et al., 2021)). Four studies focused on improving menopausal symptoms (Anderson et al., 2015; Im et al., 2017, 2019; P Ryan et al., 2020), such as VSM (e.g., hot flushes and night sweats), and bone health (Ryan et al., 2020). Characteristics of two interventions (the ACTIVity And TEchnology (ACTIVATE) (Lynch et al., 2019; Nguyen et al., 2021), and the Women's Wellness Program (WWP) (Anderson et al., 2015; McGuire et al., 2019)), were each reported in two papers and are described once only (**Table 3**). Of the 13 interventions, nine originated in the USA, three in Australia, and one in South Korea. The length of the studies ranged from 8 weeks to 12 months (median 12 weeks). In nine (69%) of the studies, the participants were overweight or obese, and four (31%) were breast cancer survivors. One study reported having participants with a high risk of hypertension. The ethnicity of the participants was 69% (9/13) white, 23% (3/13) Asian, and one study had a mix of white and African American participants.

The average age of subjects was 52.25 ± 4.79 years (range 45.7 – 61.6). The inclusion criterion required a minimum of 2 participant groups/ arms, with three studies (i.e., ACTIVATE (Lynch et al., 2019; Nguyen et al., 2021), WWP (Anderson et al., 2015; McGuire et al., 2019), and STBS (Ryan et al., 2020)) consisting of 3-arms. Comparison groups were either a control group or groups with reduced behaviour change intervention frequency (e.g., diet tracking with no feedback (Steinberg et al., 2020)), technology (e.g., no technology (Anderson et al., 2015; McGuire et al., 2019), or no text messages (Finkelstein et al., 2015)), or physical activity type (e.g., endurance group (Grossman, Arigo and Bachman, 2018)). Where appropriate, additional review of the studies is provided in 3 categories (i.e., weight loss, lifestyle, and menopausal symptoms) to allow for a more meaningful comparability of the interventions. The outcomes of the studies provided mixed results, with 33% (5/15) studies reporting statistically significant differences between the intervention group and the control group in the primary measured outcomes. This represents 31% (434/1308) of all the intervention participants combined (**Table 3**). Finally, all studies combined had a mean retention rate of 84±12.6% (range 59–100%).

Table 3: Characteristics of the studies included in the review (n=1308)

Study	Behaviour change theory [a]	Intervention									
		Type [b]	Study Design	Comparison group	Length (weeks)	Country	Ethnicity	Health risk [c]	N [d]	Mean Age (SD) [e]	P [f]
(Grossman, Arigo and Bachman, 2018)	Several BCTs	Weight loss	2-arm feasibility pilot	Endurance group	16	USA	White	Obese	11	59.0 (5.33)	No
(Hartman et al., 2016)	SCT	Weight loss	2-arm pilot	Usual care	6 months	USA	White	Breast cancer, Overw / obese	54	45.7 (4.0)	Yes*
(Park and Kim, 2012)	Several BCTs	Weight loss	2-arm quasi-experimental RCT	Control group	12	South Korea	South Korean	Abdo obesity	67	51.3 (11.31)	Yes*
(Cadmus-Bertram et al., 2015)	CALO-RE framework	Lifestyle (PA)	2-arm RCT	Control group	16	USA	White	Overw / obese	51	58.6 (6.5)	No
(Finkelstein et al., 2015)	Several BCTs	Lifestyle (PA)	2-arm crossover pilot	No text msgs group	8	USA	White, African American	Obese	27	52.0 (12.0)	Yes*

(Fukuoka et al., 2019)	SCT (Bandura), SCM	Lifestyle (PA)	3-arm parallel RCT	Control group	12	USA	White	Overw/ obese	215	52.4 (11.2)	Yes*
(Lynch et al., 2019) and (Nguyen et al., 2021)	MI, several BCTs	Lifestyle (PA) Lifestyle (sleep)	2-arm RCT	Control group	12	Aust ralia	White	Breast cancer, oberw / obese	83	61.6 (6.4)	Yes* No
(McGuire et al., 2019) and (Anderson et al., 2015)	SCT (Bandura)	Lifestyle (PA), Meno Sympt	3-arm equivalency RCT	No tech group (Group B)	12	Aust ralia	White	Breast cancer, overw / obese	225	50.9 (5.9)	No
(Ryan et al., 2013)	ITHBC	Lifestyle (Diet)	2-arm repeated measure experiment al RCT	Usual care	6 months	USA	White		148	50.11 (5.53)	No
(Steinberg et al., 2020)	Several BCTs	Lifestyle (Diet)	2-arm feasibility RCT	Control group (active)	12	Aust ralia	White	Hyper-tension	59	49.9 (11.9)	No
(Im et al., 2017)	SET (Bandura)	Meno sympt	2-arm repeated measure RCT	Control group	12	USA	Asian - American		29	45.7 (4.0)	No

(Im et al., 2019)	SET (Bandura)	Meno sympt	2-arm repeated measure RCT	Control group	12	USA	Asian - American	Breast cancer	91	51.3 (11.31)	No
(Ryan et al., 2020)	IFSMT	Meno sympt	3-arm prospective repeated measure longitudinal RCT	Wait list	12 months	USA	White	Overw	260	50.57 (5.19)	No

[a] Behaviour change theory consisted of 1) several behaviour change techniques (BCTs), 2) Social Cognitive Theory (SCT), 3) Coventry, Aberdeen, and London-Refined (CALO-RE) framework, 4) Social Cognitive Theory (SCT), 4) Self-efficacy theory (SET), 5) Integrated Theory of Health Behaviour Change (ITHBC), 6) The Individual and Family Self-Management Theory (IFSMT).

[b] Intervention outcome types included 1) Weight loss 2) Lifestyle physical activity (PA), 3) Lifestyle (Diet), 4) Lifestyle (Sleep), 5) Menopausal symptoms (Meno sympt).

c Health risks included 1) Obesity (obese) 2) Breast cancer 3) Overweight/obesity (overw/obese), 4) Hypertension, 5) Overweight 6) Abdominal obesity (Abdo obesity).

[d] Number of participants in the intervention.

[e] Mean age, standard deviation (SD).

[f] Statistically significant between group differences.

*$p < 0.05$.

5.3.3 Behaviour Change Techniques and Categories used

Overall, the thirteen interventions used a range of 6–21 BCTs (mean 13.0 ± 4.3; median 13), representing 6–23% (median 14%) of all the available 93 BCTs from the BCTTv1 taxonomy (Michie et al., 2013) (**Table 4**). Nine BCTs (i.e., 'instructions on behaviour', feedback on behaviour', 'habit formation', 'behavioural practice/rehearsal', 'action planning', 'prompts/cues', 'goal setting (behaviour)', 'self-monitoring of behaviour', and 'graded tasks') were used by more than half (54%; 7/13) of the studies. Additionally, two BCTs (i.e., 'instructions on behaviour', and 'feedback on behaviour') were used by 92% (12/13) and 85% (11/13) of the studies, respectively (**Appendix A, Table 47**). Examples of 'instructions on behaviour' included providing participants with DVD-guided training instructions, coaching calls that included instructions on meal planning and increasing vegetable intake, or daily video clips about healthy diet and weight maintenance. Examples of 'feedback on behaviour' included receiving individualised weekly feedback on activity recording and adherence to the dietary program, and upon recording food intake receiving immediate feedback on how many calories are left until the participant's daily goal is reached. The next two frequently implemented BCTs of 'habit formation' and 'behavioural practice/rehearsal' were each implemented by 77% (10/13) of the interventions. Examples of 'habit formation' included researchers providing three messages per week or reinforcing content through daily messages and videos. 'Behavioural practice/rehearsal' was delivered by providing weekly activity planning with participants to identify and reflect on their barriers to exercise behaviour change through journal activities, reflections, and discussion. Finally, approximately 69% (9/13) of the studies used 'action planning, or 'prompts/cues' BCTs.

Table 4: Number of BCTs and BCT categories used across all studies

BCT categories	(Grossman, Arigo and Bachman, 2018)	(Hartman et al., 2016)	(Park and Kim, 2012)	(Cadmus-Bertram et al., 2015a)	(Finkelstein et al., 2015)	(Fukuoka et al., 2019)	(Lynch et al., 2019) and (Nguyen et al., 2021)	(Anderson et al., 2015) and (McGuire et al., 2019)	(Ryan et al., 2013)	(Steinberg et al., 2020)	(Im et al., 2017)	(Im et al., 2019)	(Ryan et al., 2020)	BCTs per category, n (%) [a]	Mean (SD), n [c]
1.Goals and planning (n=9)	4	5	1	3	-	4	4	3	5	2	-	-	3	34 (20)	2.62 (1.85)
2.Feedback and monitoring (n=7)	4	2	4	3	2	2	2	1	2	4	-	-	2	28 (17)	2.15 (1.34)
3. Social support (n=3)	1	-	-	-	-	1	1	1	1	2	2	1	1	11 (7)	0.85 (0.69)
4. Shaping knowledge (n=4)	1	1	1	1	1	1		1	1	1	1	1	1	12 (7)	0.92 (0.28)
5.Natural consequences (n=6)	-	-	-	-	-	1	1	1	-	-	1	1	-	5 (3)	0.38 (0.51)

6.Comparison of behaviour (n=3)	1	-	-	-	-	-	-	1	1	1	-	-	1	5 (3)	0.38 (0.51)
7.Associations (n=8)	-	2	1	-	1	1	2	1	1	2	-	1	-	12 (7)	0.92 (0.76)
8.Repetition and substitution (n=7)	3	1	5	1	2	3	2	3	3	-	2	2	3	30 (18)	2.31 (1.25)
9.Comparison of outcomes (n=3)	1	1	1	-	-	-	-	1	1	-	-	1	-	6 (4)	0.46 (0.52)
10.Reward and threat (n=11)	2	-	-	2	-	2	-	-	2	2	-	-	3	13 (8)	1.00 (1.15)
11.Regulation (n=4)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
12.Antecedents (n=6)	3	1	1	1	1	1	1	-	-	-	-	-	1	10 (6)	0.77 (0.83)
13. Identity (n=5)	-	-	-	-	-	-	-	-	-	-	-	-	-		

14. Scheduled consequences (n=10)	1	-	-	1	-	-	-	-	-	-	-	-	1	3 (2)	0.23 (0.44)
15.Self-belief (n=4)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
16. Covert learning (n=3)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BCTs per study, n (%) [d]	21 (12)	13 (8)	14 (8)	12 (7)	7 (4)	16 (9)	13 (8)	13 (8)	17 (10)	14 (8)	6 (4)	7 (4)	16 (9)	169 (100) [b]	13.00(4.30)

[a] The total number of behaviour change techniques (BCTs) used across all 13 interventions for each behaviour change category (BCC). In the table, the number of BCTs in each study is represented by a number. Studies with absent BCTs in within each BCC are marked with -.

[b] The sum of the total number of BCTs used across all 16 BCC and all 13 interventions.

[c] The average number of BCTs used within each BCC across all 13 interventions and the standard deviation (SD) of the mean number of BCTs used in within each BCC.

[d] The total number of BCTs used within each intervention and the percentage of BCTs each study used from the total number of BCTs across all studies.

There was no single cluster of BCTs from which all thirteen interventions selected at least one BCT (i.e., no BCC reached 100%) and only 44% (7/16) of the BCCs were used by more than half (7/13) of the studies (**Table 5**). The most frequently used seven categories or clusters of BCTs (from which more than half of the interventions used at least one BCT), were 'shaping knowledge', 'repetition and substitution', 'feedback and monitoring', 'goals and planning', 'social support', 'associations', and 'antecedents'. Furthermore, 57% (7/13) of the studies used at least one BCT in 13 of the available BCCs, while four clusters of BCTs (i.e., 'regulation', 'identify', 'self-belief', and 'covert learning') were not utilised by any study. Further review of different intervention groups suggests that the majority (more than 50%) of the BCTs selected within each BCC were used by 44% (7/16) and 25% (4/16) of the weight-loss or lifestyle, and menopause symptoms interventions, respectively.

Table 5: BCT categories results by study type where at least one BCTs was used in each BCT category

BCT categories	All studies scoring ≥ 1 BCT, %	Weight-loss studies scoring ≥ 1 BCT, %	Lifestyle studies scoring ≥ 1 BCT, %	Menopause symptoms studies scoring ≥ 1 BCT, %
1.Goals and planning	77	100	88	50
2.Feedback and monitoring	85	100	100	50
3. Social support	69	33	75	100
4. Shaping knowledge	92	100	75	100
5.Natural consequences	38	0	50	75
6.Comparison of behaviour	38	33	38	50
7.Associations	69	67	88	50
8.Repetition and substitution	92	100	88	100
9.Comparison of outcomes	46	100	25	50
10.Reward and threat	46	33	50	25
11.Regulation	0	0	0	0
12.Antecedents	62	100	63	25
13. Identity	0	0	0	0
14. Scheduled consequences	20	33	13	25
15.Self-belief	0	0	0	0
16. Covert learning	0	0	0	0

5.3.4 Behaviour Change Wheel Mapping

Eight of the nine BCW intervention functions were used in the interventions. The most commonly used intervention functions were 'enablement' (36%; 60/169), 'training' (19%; 32/169), 'persuasion' (14%; 23/169), and 'education' (11%; 189/169). 'Incentivisation' (8%;14/169), 'environmental restructuring' (4%; 7/169), and 'coercion' (1%; 2/169) were used to a smaller degree. 'Restriction' and 'modelling' were not used by any intervention. The COM-B model at the core of the BCW shows that 50% (49/98) of the interventions focused on increasing 'capability', 42% (41/98) on increasing 'motivation', and 8% (8/98) on providing 'opportunity'. Furthermore, a breakdown of the 'capability' component suggests that 42% (41/98) was linked to 'psychological capability', and 8% (8/98) to 'physical capability'. The 'opportunity' components shows that 3% (3/98) and 5% (5/98) were related to 'social' and 'physical opportunity', respectively. Finally, expanding the 'motivation' component suggests that 35% (34/98) and 7% (7/98) were linked to 'reflective' and 'automatic motivation', respectively. The TDF framework components in within the COM-B model of the BCW indicates that the mechanism of action for the BCTs used most frequently was 'behavioural regulation' (15%;15/98), primarily in the 'goals and planning' BCC (6/15) (e.g., instructions to rotate through five different workouts before progression, setting initial weight loss goal), and in the 'repetition and substitution' BCC (6%;6/15) (e.g., progression from 60 minutes of exercise in week 1 to 250 minutes of exercise in week 15, providing three text messages per week). Additional TDF domains used most frequently within the 'repetition and substitution' BCC were increasing 'knowledge', 'skills', and 'cognitive and interpersonal skills'. 'Motivation' was increased primarily through 'beliefs about capabilities' (e.g., providing daily feedback on steps walked to help the participants to monitor and adjust goals), and 'professional or social role and identify' (e.g., providing monthly face-to-face group meetings, access to online forum to discuss experiences and receive individual and group coaching support). 'Opportunity' was increased primarily by 'physical environmental restructuring', such as providing instructions on modifications to food and exercise environments (e.g., stocking the kitchen with healthy foods, packing exercise clothes ahead of time) (**Appendix A, Table 48**).

5.3.4.1 Weight-loss Interventions Group

Three studies aimed to induce weight loss in midlife women (Park and Kim, 2012; Hartman et al., 2016; Grossman, Arigo and Bachman, 2018), with all using exercise and diet interventions. The mean frequency of BCTs across the three weight loss studies was 16±4.36 (range 13–21). The BCT categories of 'goals and planning', 'feedback and monitoring', and 'repetition and substitution', were used most frequently, with 10, 10, and 9 BCTs, respectively. The BCW mapping suggests that increasing 'capability' was implemented in 55% (42/77) of the behaviour change interactions, followed by increasing ‘motivation’ in 36% (28/77), and lastly by increasing ‘opportunity’ in 9% (7/77). Furthermore, the ‘psychological capability’ TDF domain was used the most frequently, specifically through ‘behavioural regulation’.

5.3.4.2 Lifestyle Interventions Group

Of the eight studies included in the lifestyle group of interventions, three studies aimed to improve physical activity through a physical activity program (Finkelstein et al., 2015; Cadmus-Bertram et al., 2015; Fukuoka et al., 2019). Two studies aimed to improve wellbeing through diet (Ryan et al., 2013; Steinberg et al., 2020). The WWP trial’s McGuire et al (McGuire et al., 2019) study aimed to improve physical activity through diet and exercise. Two studies from the ACTIVATE trial aimed to improve sleep by improving physical activity (Nguyen et al., 2021), and physical activity through exercise and coaching (Lynch et al., 2019), respectively. The mean frequency of BCTs across the lifestyle studies was 13.13± 3.00 (range 7–17). The BCT categories of ‘goals and planning’, ‘feedback and monitoring’, and ‘repetition and substitution’, were used the most frequently, with 25, 18, and 16 BCTs, respectively. The BCW mapping shows that motivation was used in 45% (31/69) of BCTs, similar to capability at 46% (32/69), and lastly by increasing ‘opportunity’ at 9% (6/69) of BCTs. ‘Psychological capability’ TDF domain was used the most frequently, with ‘behavioural regulation’, followed by increasing ‘knowledge’ (e.g., self-monitoring food intake and physical activity), and ‘building competencies’ (e.g., encouragement to enter consumed foods in real time and receiving immediate feedback on goal progression).

5.3.4.3 Menopause Symptoms Interventions Group

Four studies were included in the menopause symptoms intervention group (Anderson et al., 2015; Im et al., 2017, 2019; P Ryan et al., 2020). One study (Anderson et al., 2015) measured menopausal symptoms, such as depression, anxiety, somatic, VSM, using the Greene Climacteric Scale (Greene, 2008). The intervention was based on promoting healthy lifestyle behaviours, emphasising healthy diet and regular physical activity. (Im et al., 2017) aimed to improve menopausal symptoms by emphasising physical activity. On the other hand, the aim of (Im et al., 2019) study was to decrease menopausal symptoms by education and coaching. (Ryan et al., 2020) measured bone mineral density among three groups (2 intervention and one control). The study used an Ecological Momentary Assessment (EMA) software to encourage the participants to increase their calcium intake, physical activity, balance and strength (Ryan et al., 2020). The frequency of BCTs across the 4 menopause symptoms studies was 10.50±4.80 (range 6–16). The BCT categories of ‘repetition and substitution’, ‘goals and planning’, ‘social support’, and ‘shaping knowledge’, were used the most frequently, with 10, 6, 5, and 4 BCTs, respectively. The BCW mapping shows that ‘motivation’ was used in 44% (24/55) of BCTs, similarly to ‘capability’ at 47% (26/55), and lastly by increasing ‘opportunity’ at 9% (5/55) of BCTs. The BCW mapping suggests that ‘psychological capability’ TDF domain was used the most frequently, specifically through ‘behavioural regulation’.

5.3.5 Extent of Theory Used

The overall mean total use of theory score (based on TCS) for all interventions is 7.85/23±3.87 (min = 4; max = 15), which represents a weak level (score 8–15) (**Appendix A, Table 49**). Individual studies were scored, with 62% (8/13) categorised as weak (score 0–7), with the remaining 38% (5/13) scoring moderate levels (score 8–15). No study achieved a strong score (score 16–23). Of 13 interventions, 7 (54%) explicitly reported that they were based on theory (I5) (**Appendix A, Table 50**). Of these, 7 (54%) were based on a single theory (I3); none reported using theory to recruit study participants (I4), and 3 (23%) reported using theory to tailor BCTs to recipients (I6). Of these 13 interventions, none explicitly reported links between all BCTs within the intervention and the targeted theoretical constructs (I7), while 4 (31%) interventions reported targeting all the constructs within a specified theory with specific BCTs (I10). Eight (62%) studies reported measuring theoretical constructs postintervention and eight (62%) measured constructs both pre- and postintervention (I12). However, only 8 (62%) tests of interventions reported statistically significant mediated effects (I16d). Only three (23%) interventions reported suggestions for theoretical refinement on the basis of their findings (I19). The review of the six TCS categories suggests that 77% (10/13) (mean 1.69/3±1.25) of the interventions stated or suggested rather than demonstrated theoretical base (being based on theory) (C1). All thirteen studies targeted theoretical constructs that predicted behaviour (C2) (mean 2.69/7±1.84).

5.3.6 Behaviour Change Theories Used

Although all thirteen interventions mentioned behaviour change, a specific behaviour change theory was mentioned by 69% (9/13) of the interventions. The most frequently used behaviour change theories included Self-Efficacy Theory (SET) and Social Cognitive Theory (SCT); each being implemented in the design of 15% of the interventions (2/13), respectively. Stages of Change Model (SCM), Individual and Family Self-management Theory (IFSMT), the Integrated Theory of Health Behaviour Change (ITHBC), Motivational Interviewing (MI), and Coventry, Aberdeen, and London-Revised (CALO-RE) (Michie et al., 2011) framework were each used in one study, respectively. The remaining 4 studies that mentioned behaviour change reported using several behaviour change techniques.

5.3.7 Modes of Delivery Used in the Studies

The studies used a combination of technological and non-technological components. Websites were used in 69% (9/13) of the studies, phone/text was used in 62% (8/13) of the studies, followed by wearables, which were used by 54% (7/13) of the studies (**Appendix A, Table 51**). Apps, email, electronic documents, and EMA were used in 46%, 23%, 15%, and 8% of the interactions, respectively. Additionally, 63% of the technology interactions with the participants in all studies were provided in a passive manner without the participant's active involvement (e.g., providing health and lifestyle information such as recipes, tips, and frequently asked questions). On the other hand, 37% of the interactions were provided in an interactive manner. Evaluation of technological features provided in the interventions shows that the top 3 interactions included health or lifestyle information that was provided in 24% (16/68) of all the interactions, activity tracking in 19% (13/68), and health or lifestyle lessons in 10% (7/68) of the interactions. Furthermore, social media and support provided 7% (5/68) of the interactions, online health coaching provided 6% (2/68), while barrier's tracking, activity tracking, and health education, each provided 3% (2/68) of the interactions. Other technological features, such as reminders/prompts, social support, health information, health feedback, health activity, social support, practical support, diet tracking, and follow-up, each provided 1% (1/68) of the interactions. Non-technological components, such as face-to-face interactions and providing hard copy intervention material were used by 38% (5/13) and 46% (6/13) of the studies, respectively.

5.3.7.1 Weight-loss Interventions Group

In addition to technical components, two studies (Hartman et al., 2016; Grossman, Arigo and Bachman, 2018) also used non-technological components, such as face-to-face meetings, and providing a hard copy of the intervention material. From the technical components, 67% (8/12) components were passive, while 33% (4/12) of the components were interactive.

5.3.7.2 Lifestyle Interventions Group

From the technical components, 69% (24/35) of the components were passive, while 31% (11/35) of the components were interactive. The majority (75%; 6/8) of the studies also used non-technical components, such as face-to-face meetings and hard copy study documentation.

5.3.7.3 Menopause Symptoms Interventions Group

From the technical components, 62% (16/26) of the components were passive, while 38% (10/26) of the components were interactive. Only the WWP study (Anderson et al., 2015) used non-technical components, such as face-to-face meetings and a hard copy of the program book.

5.3.8 Fidelity of the Studies

Of the 13 included interventions, 62% (8/13) included an assessment on all five domains (**Appendix A, Table 52**). The greatest average proportion of adherence to treatment fidelity across all thirteen interventions was in 'Enactment' domain at 50% (0.50). The lowest mean proportion of adherence to strategies was found in 'Receipt' domain where on average only 26% (0.26) of strategies were reported among the studies. Finally, the mean proportion of adherence to strategies in the 'Treatment', 'Training', and 'Delivery' domains was 45% (0.45), 34% (0.34), and 32% (0.32), respectively. The mean proportion of adherence to treatment fidelity strategies included across all 5 domains for all studies was 0.39±0.14 (median 0.41). Based on the fidelity scoring (Borrelli, 2011), where 50 percent constitutes low fidelity scoring, 85% (11/13) of the studies scored low treatment fidelity across all five domains. Two studies (Ryan et al., 2013; Ryan et al., 2020) scored above 0.50, in the medium treatment fidelity range (i.e., 0.51 to 0.79) with 0.62 and 0.59 treatment fidelity, respectively. For details of scoring for each component of the treatment fidelity domain, see (**Appendix A, Table 53**).

5.4 Discussion

This review systematically reviewed 13 interventions that aimed to improve weight loss (20%; 3/15), lifestyle (53%; 8/15), and menopause symptoms (27%; 4/15) through DHIs with midlife women. Six BCTs (i.e., 'Feedback on behaviour', 'Prompts/cues', 'Action planning', 'Instructions on behaviour', 'Behavioural practice/rehearsal', 'Habit formation') were used in at least 80% (4/5) of the studies. This group of studies used on average 12.6 BCTs (range 7-16; median 13), representing 14% (169/1209) of all BCTs available from the BCTTv1 taxonomy. The most frequently used six clusters of BCTs (i.e., 'Feedback and monitoring', 'Associations', 'Repetition and substitution', 'Antecedents', 'Shaping knowledge', 'Goals and planning') were used by more than 80% (4/5) of the studies. Four clusters of BCTs (i.e., 'Social support', 'Natural consequences', 'Comparison of outcomes', 'Reward and threat') were used by only 20-40% (2/5) of the studies. Six other clusters (i.e., 'Regulation', 'Identify', 'Self-belief', 'Covert learning', 'Comparison of behaviour', 'Scheduled consequences') were not used, which may indicate that the BCTs within these clusters were unexplored or potentially found inappropriate for these interventions. Although the findings indicate what BCTs are used more frequently in health-enhancing DHI with midlife women, the high level of heterogeneity in the design of the interventions and selection of specific BCTs suggests that the designs of these interventions cannot be generalised across various contexts. DHIs should consider the unique experiences and needs of women in midlife, including marginalised women to improve their sociodemographic diversity.

In this review, seven (78%; 7/9) BCW intervention functions were identified with a strong emphasis on 'enablement' (e.g., encouragement to set initial weight-loss goal, self-monitoring food intake and physical activity) by increasing capability beyond education and training. 'Training' and 'persuasion' were also commonly used, while 'restriction' and 'modelling' were not used at all. In a non-digital lifestyle behaviour change intervention (involving adult men and women), five (56%; 5/9) intervention functions were used (i.e., 'enablement', 'training', 'persuasion', 'restriction', 'education'), while 'incentivisation', 'coercion', and 'modelling' were not used and were found to be inappropriate in the context of the intervention (Richardson et al., 2019). In another non-digital lifestyle behaviour change review, education (e.g., nutritional label reading, a resistance training booklet for exercise) was the most commonly used intervention function, being present in 81% of the interventions (Evangelidis et al., 2019). 'Enablement' (e.g., self-management techniques to foster self-efficacy, arranging support from friends and family) and 'training' (e.g., home-based exercise training, guided exercise training, interactive cooking classes) were also emphasised, while 'coercion' and 'restriction' were not used in any of the interventions (Evangelidis et al., 2019). Overall, 'education', 'enablement', and 'training' are used commonly across digital and non-digital intervention types, while 'coercion' or 'restriction' are used less commonly.

When comparing digital to traditional face to face (i.e., non-digital) lifestyle health-enhancing interventions, there are apparent commonalities and differences in the BCT clusters typically used within interventions. Previous reviews highlight that only a fraction (34%; 32/93) of the BCTs were used across all interventions, with 'Feedback and monitoring', 'Goals and Planning' BCT clusters used more commonly in traditional lifestyle interventions (Johnson et al., 2018; Evangelidis et al., 2019), which aligns with that observed in this review. Contrary to previous reports in traditional lifestyle interventions, this study demonstrated that DHI's in midlife women were more likely to utilise 'Repetition and substitution' (i.e., habit formation) techniques (Johnson et al., 2018; Evangelidis et al., 2019). This difference may be due to the just-in-time nature of digital technologies, which allows for implementation of behaviours that may emerge rapidly, unexpectedly, and ecologically, and that are usually less accessible with in-person approaches (Diez-Canseco et al., 2015).

In other DHIs, certain BCTs were found to be more frequently applied in particular technological platforms. For example, the most frequently used BCTs in lifestyle interventions using mobile apps were 'feedback on behaviour' (84%; 26/31), 'self-monitoring of behaviour' (77%; 24/31), and 'goal setting' (61%; 19/31) (Tong et al., 2021b). While these BCT features were apparent in mobile app-based interventions included in this review they were not universally applied. Equally, digital physical activity behaviour change interventions used primarily a combination of 'goal setting', 'self-monitoring', and 'motivation', while digital healthy eating interventions were primarily targeted by 'self-monitoring', 'goal setting', and 'feedback on behaviour' (Tong et al., 2021b). Similarly, in this review, 'feedback on behaviour' (83%; 11/13), goal setting (62%; 8/13), and 'self-monitoring' (62%; 8/13) were in the top ten BCTs used across all technological platforms by all studies. In gamification platforms for example, the most frequently used BCTs were 'education' and 'reward', as these are important features of gamification (Taj, Klein and Van Halteren, 2019). This highlights that almost all the key BCTs can be used on a mobile platform, most likely due to the flexibility and accessibility of this technology (Taj, Klein and Van Halteren, 2019), therefore interventions can be easily tailored to the context they are being applied. Health interventions for midlife women must be cognisant of the multiple co-occurring stressors that are borne from psychosocial and physiological transitions during this period (Thomas, Mitchell and Woods, 2018). Interestingly, DHI's have been suggested to be most effective in facilitating problem solving, encouraging self-efficacy and also reducing the impact of stress associated with behaviour change (Webb et al., 2010).

This review highlighted a varied use of theories of behaviour and behaviour change to design DHI's, with SET and the SCT most commonly used in DHI's research to date. Interventions informed by these theories can effectively enhance physical activity in midlife women (Anderson, Anderson and Hurst, 2010b; White, Wójcicki and McAuley, 2012), however, the application of theory to BCT intervention functions has been poorly reported and/or utilised (Michie and Prestwich, 2010; Willmott et al., 2019). In this review, although 69% of interventions mentioned behavioural theory, more than half had weak scores (based on TCS) in applying theory to the intervention. In cases where the intervention was reportedly based on theory (i.e., SCT, SET, SCM), none of the studies in this review explicitly linked all theoretical constructs with BCTs and vice versa. As such, having a theoretical understanding of behaviour change is necessary to maximise the potential efficacy of interventions (Davis et al., 2015).

A critical component of intervention delivery is establishing theoretical fidelity and ensuring that a theory is adequately reflected in the intervention's design and implementation (Borrelli, 2011). The overall poor reporting of treatment fidelity in the current review (with only 2 studies reporting medium treatment fidelity (Ryan et al., 2013; Ryan et al., 2020)) is similar to other reviews considering fidelity (Borrelli, 2011; JaKa et al., 2016; Timlin, McCormack and Simpson, 2021). Although 69% of interventions in this review mentioned a theory, the treatment-design domain achieved only a low mean proportion for treatment fidelity. When intervention effects are not significant, treatment fidelity helps to understand whether this is due to the omission or addition of active/inactive components or whether they are due to an ineffective treatment (Borrelli, 2011). However, it is important to highlight that lack of effect may reflect implementation failure rather than genuine ineffectiveness and through the evaluation process, implementation problems can be identified (Craig et al., 2008). Although this review combined treatment fidelity for studies that did and did not achieve statistically significant group differences, an accurate estimate of the relationship between theory use and intervention effectiveness can only be obtained from studies that reach high fidelity of delivery (Prestwich et al., 2014). DHIs incorporating behaviour change theory offer a unique opportunity to refine and strengthen the theory. Unfortunately, none of the studies in this review reported refining or developing a theory to strengthen the intervention effectiveness. (Moller et al., 2017) explored potential improvements for applying behaviour change theories in the context of digital health and suggests that digital technologies may potentially provide high fidelity of delivery due to their ability to measure engagement levels objectively. Furthermore, digital technologies can also access large datasets generated by ecologically valid measures of behaviour, emotion, physiology, and thinking in real-time and everyday contexts (Moller et al., 2017) . Considering treatment fidelity in DHIs is therefore essential to estimate the confidence in which intervention effects can be attributed to BCTs.

Although extending the interpretation of the findings to the effectiveness of certain BCTs was outside the scope for this review, it should be noted that identifying effective BCTs and a combination of BCTs for a given behaviour, in a given context presents a major challenge (Michie, West, et al., 2018b). Research evaluating the effectiveness of BCTs and BCT combinations uses a range of observational and experimental methods, each with strengths and limitations (Michie, West, et al., 2018a). For example, van Rhoon et al (Van Rhoon et al., 2020) made conclusions on the effectiveness of specific numbers and types of BCTs in weight-loss DHIs based on the BCTs that were present in interventions producing clinically significant weight loss outcomes. However, this method led to the inability to identify the mechanisms in which the BCTs and digital features influenced the target behaviour. Additionally, this method also runs the risk of including BCTs that do not add to effectiveness but happened to be included in the effective interventions (Michie, West, et al., 2018a). Furthermore, although other evaluation methods, such as meta-analyses, can provide generalisable conclusions (Michie, West, et al., 2018a), poor quality in intervention description and high heterogeneity in the designs may not allow for statistical analysis of the effectiveness of individual BCTs or a combination of BCTs on the intervention outcomes (Walsh et al., 2018; Richardson et al., 2019; Taj, Klein and Van Halteren, 2019; Ahmed et al., 2021; D Arigo et al., 2021). Making confident estimates on the effectiveness of BCTs and BCT combinations for a given behaviour, delivered in a particular way, in a given setting, to a given target population requires synthesis of information from diverse sources (Michie, West, et al., 2018a). This challenge provides an opportunity for future research to develop a strategy that systematically combines the strengths of the different methods and that links these constructs in an ontology of behaviour change interventions (Michie, West, et al., 2018a).

The outcomes of this review suggest that the effects of BCTs on behaviour are difficult to determine due to high heterogeneity in the designs of the interventions, low level of treatment fidelity and theoretical grounding. It is also important to note that although the BCW provides a systematic and theory-guided method for identifying components of interventions and types of interventions that are expected to be effective, it does not provide a detailed blueprint for the design of specific behaviour change interventions (Michie S, Atkins L, 2014). The BCW framework should therefore be applied with a level of flexibility, as acknowledged by its authors (Richardson et al., 2019). Furthermore, although theory-based intervention design is critical for intervention effectiveness (Craig et al., 2008), involvement of key stakeholders in the development process of interventions through co-production increases the likelihood of the intervention meeting user needs and their implementation (Craig et al., 2008; Wight et al., 2016). While the ethnicity of the participants in studies in this review was primarily white (69%; 9/13), research shows that menopausal symptom experiences vary in women of different sociodemographic characteristics, including ethnicity, income, and education (Hall et al., 2007; Green and Santoro, 2009b; Im, Lee and Chee, 2010). The lack of diversity in the sociodemographic characteristics of the studies and the apparent lack of evidence of how to culturally adapt digital health interventions provides an opportunity to explore these topics in future research. Additionally, co-designing theory and evidence-based interventions with Patient and Public Involvement (PPI) in all stages of the design process (O'Hara et al., 2017;

Walsh et al., 2018; Muller et al., 2019; Hall et al., 2020b) would be beneficial to ensure that digital health lifestyle behaviour change interventions with midlife women are acceptable, feasible, and more effective. To-date there has been no such study undertaken and therefore, this represents an opportunity for researchers to advance the field by improving both the quality and replicability of such interventions.

5.4.1 Strengths and Limitations

The process of identification of the BCTs requires classification and coding intervention descriptions (Michie et al., 2011) using the BCT taxonomy v1 (Michie et al., 2013) for each study. The level of detail necessary for BCT coding was limited in the studies. As such, this review contains a possible subjectivity limitation in categorising, reviewing, and mapping behaviour change theories and techniques. To mitigate this limitation, two researchers (HS and SD) interpreted and coded the BCTs to reduce any bias (also acknowledged in other research (Taj, Klein and Van Halteren, 2019)). Similarly, to reduce bias in interpreting and coding the TCS items (also acknowledged in other research (Timlin, McCormack and Simpson, 2021)) was completed by two researchers. Improving the description of intervention design and delivery is essential for improving BCT coding to better facilitate scientific evaluation and translational processes in future studies.

Furthermore, the number of health-promoting studies designed specifically for midlife women is limited. This review contains a small number of studies with limited sociodemographic (i.e., 69% of the participants being white) and socioeconomic (i.e., all included studies come from high income countries) backgrounds and attempts to assess the quality of evidence that may not be generalisable to all digital health behaviour change interventions with midlife women. Future research should consider the unique needs of women of diverse sociodemographic and socioeconomic backgrounds in their intervention designs to make their findings applicable to more women.

5.4.2 Conclusions

This review identified studies aiming to promote lifestyle improvements in midlife women using digital technology and assessed their designs through the application of the BCW framework. The assessment identified gaps in the process of designing digital health behaviour change interventions. The studies scored weak to moderate in their theoretical grounding, and their description of intervention components, intervention functions, and BCTs was also weak. The low level of treatment fidelity suggests that the interventions may not have delivered what the researchers intended to deliver (also acknowledged elsewhere (Timlin, McCormack and Simpson, 2021)) and that the interventions may not be replicable. This suggests, as also highlighted by (Michie, West, et al., 2018b) that there is a need for better tools and intervention design guidelines to facilitate better selection and utilisation of behavioural theories. Although the findings indicate which BCTs are used more frequently in specific groups of interventions, the high level of heterogeneity in the design of the interventions and selection of specific BCTs suggests that the designs of these interventions cannot be generalised across different contexts. Instead, applying the principles underlying the design of these groups of interventions through systematically co-designing theory and evidence-based interventions with midlife women may be more efficacious. Further research is needed to validate such intervention designs and its application in feasibility and acceptability studies. A closer collaboration between behavioural science and solution design is needed to bridge the gap and increase the effectiveness of digital health behaviour change technologies.

END OF THE PUBLISHED ARTICLE

5.5 Updated Literature Since the Publication of The Chapter

Since the publication of this review in which the researcher self-developed templates for annotating the content of the reviewed articles to the BCW framework and the BCTs (using BCTTv1 taxonomy (Michie et al., 2013)), the Behaviour Change Techniques Ontology (BCTO) (Marques et al., 2023), which is part of the Human Behaviour-Change Project (HBCP) (Michie et al., 2017) has been published, providing additional BCTs for annotating intervention content. Behaviour Change Intervention Ontology (BCIO) prototype templates (Norris et al., 2024) are being developed to enable researchers to extract contents of their reports and upload these to the HBCP repository. HBCP's goal is to synthesise evidence about BCIs and develop an automated knowledge system to identify patterns in the published literature and generate new, up-to-date evidence (Michie et al., 2017; Norris et al., 2017). This growing repository (currently available only for smoking cessation) can provide a systematic and efficient way of consolidating evidence from literature in the future (see **Appendix E** for more information on the Ontology). In the process of the development of the repository (and as noted by the authors), while success was achieved in using ML to extract information from reports of RCTs, challenges were identified that could be addressed by improved standardisation in the way studies are reported (West et al., 2023).

Additionally, although this systematic review is at the time of writing this thesis was the only review of its type targeting midlife women, another recently published scoping review of BCTs in physical activity interventions for midlife women (Arigo, Romano, et al., 2022a) provided similar conclusion that designs of the reviewed articles had limited theoretical grounding and description on whether and how BCTs were activated. The review identified a set of most frequent BCTs that were present in the reviewed 38 interventions (not specifically digital), including BCT categories of goals and planning, feedback and monitoring, social support, and comparison of behaviour (Arigo, Romano, et al., 2022a). Another recently published systematic review of BCIs in physical activity behaviours in the population of older migrants (Jagroep et al., 2022) identified 13 BCTs (e.g., goal setting (behaviour), self-monitoring of behaviour, problem solving, social support (unspecified), behavioural contract, instruction on how to perform the behaviour, information about health consequences, information about social and environmental consequences, demonstration of the behaviour, social comparison, behavioural practice/rehearsal, adding objects to the environment) that showed promising effects in at least one outcome cluster (Jagroep et al., 2022). This review also identified 24 studies that included cultural adaptation (e.g., using linguistic and socio-cultural strategies), which showed to be promising in all outcome clusters (Jagroep et al., 2022). Individually delivered interventions were less effective than interventions delivered to a group (Jagroep et al., 2022), which may indicate the relevance of social support in a group setting, as confirmed also in the systemic review (Sediva et al., 2022) and the scoping review (Arigo, Romano, et al., 2022a). Including subgroups of migrants (e.g., 'generation British') in future studies may provide more insight into what behavioural strategies are better suited for these population.

6. Hearing Midlife Voices: Designing a Digital Health Behaviour Change Intervention for Midlife Women in the UK: A Mixed Method Study

6.1 Introduction

Components of BCIs, including BCTs, such as goal-setting and self-monitoring, show positive effects on health behaviours (e.g., physical activity) (Murray et al., 2017; Arigo, Romano, et al., 2022b; Sediva et al., 2022), however, these techniques are not widely effective for improving health behaviours among midlife women (Murray et al., 2017; Arigo, Lobo, et al., 2022). To identify techniques that are relevant and potentially effective, it is essential to understand the needs and experiences of the target population (Syundyukov et al., 2021), and therefore be person-centred (Yardley et al., 2015). Furthermore, the fundamental aim of such person-based approach is to ground the development of BCIs on understanding the perspectives of the people who will use the BCI, and it is essential in maximising the acceptability and effectiveness of interventions (Yardley et al., 2015). This was explored for example in the development of a smartphone application to support health behaviour change in young adults in the UK, in which focus group discussions were centred on young adults' experiences in using smartphone apps (Dennison et al., 2013). Therefore, lived experiences of the impact of menopause on diet and physical activity behaviours are one of the most important inputs in designing BCIs that addresses the needs of the target population of midlife women (Arigo, Lobo, et al., 2022).

However, at this point in time, little is known about modifiable behavioural factors affecting healthy eating and regular physical activity in midlife women, in the UK. Although other studies explored barriers and facilitators to these behaviours in midlife women (Kowal and Fortier, 2007; Teixeira et al., 2010; McGuire, Anderson and Fulbrook, 2014; Chopra et al., 2022) and midlife adults (Kelly et al., 2016), the application of the BCW framework (Michie, van Stralen and West, 2011) and identification of BCTs to systematically describe lived experiences of UK-residing midlife women on both healthy eating and physical activity is novel. Only a few recent studies (outside of the UK) followed the BCW framework to identify a set of BCTs to inform the development of a BCI, for example to improve diet in patients with metabolic syndrome in China (Chen et al., 2023).

This study was conducted to address the methodological limitations highlighted in the previous chapter (Study 1) by identifying theory and evidence-based DHBCI components in the context of healthy eating and regular physical activity behaviours. Instead of applying generic population-level design components (identified in Study 1), this study aims to identify a more granular, group-level personalisation of a DHBCI's design components, specific to the target population of midlife women in the UK. Thus, the aim of this study is to identify intervention components in the following three sequential steps, using a mixed method approach of inductive thematic analysis based on a series of focus groups with midlife women, and a deductive approach based on the BCW framework:

1) Identifying factors (i.e., barriers and enablers) influencing healthy eating and regular physical activity in UK-residing midlife women using focus groups.

2) Annotating reported barriers and enablers to the COM-B model (Michie, van Stralen and West, 2011) and TDF (Atkins et al., 2017a) of the BCW framework to identify a broad spectrum of theoretically derived influences on lifestyle behaviours.

3) Mapping of the theoretically derived behavioural influences from the COM-B/TDF to the BCTs using standard taxonomy (BCTTv1) (Michie et al., 2013) to identify the smallest components of the DHBCI.

The design process in this study is guided by the BCW guide (Michie S, Atkins L, 2014) (see **Chapter 3** for more details on the guide) and the group-level personalisation is to be operationalised (actioned) in a DHBCI (Study 3, Chapter 7).

*Note: Relevant supplementary materials for this study are presented in **Appendix B** of this thesis.*

6.2 Methods

6.2.1 Study Design

The study followed a mixed method design, consisting of a structured survey (comprised of seven questionnaires), and qualitative semi-structured focus groups with midlife women (aged 40–65), between March 2022 and June 2022. This approach was selected based on existing evidence suggesting that focus groups are especially suited for women who are generally willing to share experiences of a somewhat personal nature, such as menopause, in a setting where others are sharing similar experiences (Ruff, Alexander and McKie, 2005). Previous research that highlighted the benefits of utilising focus groups with this population included: enabling discussions of otherwise taboo subjects, primarily as less inhibited members of the group break the ice for shyer participants (Kitzinger, 1994), and providing mutual support for participants, enabling them to express, develop, and clarify perspectives (Morgan, 2003). Additionally, in a group setting, individuals may query and explain themselves to each other, allowing the researcher to identify potential areas of disagreements and consensus within the group (Wadsworth, 2000). Furthermore, women from minority groups are more likely to participate in group activities if other women like themselves are also participating (Ruff, Alexander and McKie, 2005). Other studies that used focus groups with midlife women to explore women's health issues and priorities for health benefited from collecting rich qualitative data rapidly, enabling exchanges of views between participants, as well as providing a useful method for conducting prioritisation exercises (Adler et al., 2000; Essex et al., 2021).

6.2.1.1 Methodological triangulation

Between-method triangulation was supported by combining qualitative data from focus groups with quantitative data from a pre-focus group surveys completed by the participants individually, to identify group-level intervention components. Collecting data from multiple methods has been beneficial particularly in the research involving women's experiences of menopause, in the UK (Wadsworth, 2000). Qualitative interviews can provide access to rich and detailed data not available within quantitative research (Wadsworth, 2000), while quantitative methods help to identify attitudes of women's experiences in midlife and add complementarity to the qualitative data.

6.2.2 Sampling and Recruitment

The study participants were identified using non-probability purposive sampling, which is often used in focus groups where the participants have experience with the phenomenon of interest

(Bourne et al., 2021). In this study, the primary participants were identified having real-life experience with lifestyle health behaviours and peri-/post-menopause. Other focus group studies (Wadsworth, 2000; Essex et al., 2021) with midlife women in the UK discussed women's experiences of menopause, health and midlife, utilised purposive sampling recruitment method. Initial recruitment was conducted on social media platforms (e.g., Twitter, Instagram, Facebook) using a study recruitment flyer. Snowball sampling was used to recruit participants known to those who were already interviewed in a focus group. Snowballing was used in other qualitative focus groups with women experiencing menopause (Wadsworth, 2000).

Inclusion criteria included cisgender women aged 40–65 years, living in the UK, able to converse in English, and having access and ability to use Microsoft Teams platform for the online focus group meeting. Although the inclusion criteria initially included self-reported assessment of menopause stage (i.e., women experiencing peri-menopause, menopause, or post-menopause), this requirement was removed after a few discussions with potential participants who raised concerns with being uncertain of their menopause stage and therefore being unsure whether they could qualify for the study. Therefore, only the age range (of 40 – 65 years) corresponding to midlife for women (who are therefore assumed to experience hormonal changes associated with the menopause), was used. (See **Chapter 2** for definition of midlife and menopause stages).

Exclusion criteria comprised of items that were likely to alter lifestyle and menopause experiences for women, including: being under treatment for a serious mental health condition, having a serious life-threatening illness (i.e., cancer, heart failure), and being unable to perform the minimum 150 mins of moderate-intensity physical activity per week (NHS, 2021) (and who may therefore require establishing physical activity instead of discussing ways to improve physical activity). Additionally, women currently enrolled in another lifestyle study (and might have been possibly asked to change their lifestyle health behaviours).

Although based on other studies (Duffy, Iversen and Hannaford, 2011) recruitment of 15–20 midlife women was expected for study planning purposes, representing 4–5 focus groups, data collection was planned to continue until saturation was achieved and no new information or themes were uncovered (Ruff, Alexander and McKie, 2005). There is evidence suggesting that 3–5 focus group meetings are usually sufficient to achieve data saturation (Morgan, 1998), and some focus-group studies with midlife women achieved data saturation after the 4th and 5th focus group was conducted (Ramakuela 2015; Ruff, Alexander and McKie, 2005). The participants were self-selected and subsequently scheduled for an individual 20-minute telephone or Microsoft Teams meeting with the researcher to ensure they met the inclusion criteria and understood what the study involves. At the same time the participants had an opportunity to ask questions and select their potential availability to attend a focus group. The participant information sheet (PIS) and the informed consent (IC) form were provided to each potential participant by email following the initial discussion with the researcher. Signing the IC and sending it electronically by email confirmed the intent to participate in the study. No incentives were offered for participation. Prior to commencing the research, ethical approval was obtained from the University of Westminster's local ethics committee (reference number: ETH2122-0583), approved on 14/2/2022.

6.2.3 Co-Production Involvement

The pre-focus groups survey content and appropriateness of the questions was reviewed by a public/patient involvement (PPI) group of UK-residing midlife women who were involved in co-designing additional intervention components and participated in workshops simultaneously to this focus group study. The PPI reviewed the survey questions, and their feedback was captured at the end of the survey and collected electronically in JISC. For example, clarifications were added to questions on household income (to specify whether two co-living friends formed a household), adding non-applicable options for pregnancy age questions, clarification on self-assessment of menopausal stage, specification on whether sitting in a car while driving counts for sitting time. Suggestions on changes to the Likert scale to a standardised questionnaire (e.g., MENQOL) were not implemented to retain validated scoring scale. The average time to complete the survey by the PPI was recorded to be 13 minutes. Additionally, prior to conducting focus groups, the PPI group participated in a pilot focus group session with the researcher where the semi-structured focus group questions were tested. The feedback was positive with the group enjoying the flow and the content of the discussion.

6.2.4 Data Collection Procedures

6.2.4.1 Pre-Focus Group Survey

Prior to attending the focus group, the participants were asked to complete a 33-question online survey (using secured JISC online survey platform licensed by the University of

Westminster). The purpose of the survey was to understand idiographic dietary and physical activity behaviours and technology use that were not specifically discussed in the focus groups and to allow for participants to anonymously share their individual perspectives and experiences. The survey consisted of seven structured and standardised questionnaires that are described in more detail in **Chapter 4**. The questionnaires were aligned to each focus group discussion topic (**Table 6**) and individual responses to the questionnaires were used to further support identification of barriers and enablers during data analysis and consequently intervention components.

6.2.4.2 Focus Group Discussions

Semi-structured focus groups were used to identify barriers and enablers to healthy eating and regular physical activity in the target population. The focus-group interviews were informed by the BCW guide's three-step process of designing behaviour change interventions, including 1) understanding the target behaviour, 2) identifying intervention options, and 3) identifying content and implementation options (Michie, van Stralen and West, 2011; Michie, Atkins and West, 2014). The BCW guide is a widely used approach that provides a structured method for determining which evidence-based behaviour change strategies are applicable to a particular context (see **Chapter 3** for more details on the BCW guide). The guide provides a systematic process for analysing available options for intervention strategies (Farrell et al., 2023). Although the focus groups were following a predefined process, the discussions were open-ended and aimed to gather lifestyle and menopausal symptoms experiences of midlife women by reflecting on dietary and physical activity challenges associated with menopause, discussing optimal diet, physical activity, and ways to improve them. The focus groups began with a general introduction and explanation of what the focus group entailed. The participants were informed that their participation was voluntary and that they were free to withdraw at any time without giving reason. They were assured of confidentiality regarding any personal information they provided to the researcher. With participants' permission, focus groups were audio recorded (using Microsoft Teams application) to be transcribed. The discussion began with general experiences with menopause and how this experience affects the way women eat and exercise. Experiences with using digital media for lifestyle health support and how technology could potentially be better utilised to support women's health was discussed last (**Table 6**). The duration of each focus group was on average 90 minutes.

Table 6: Focus group topic areas following the BCW stages to designing an intervention

Topic	Questions	BCW stage	Survey link
Menopause experiences	What is your own experience with menopause? How has the menopause affected the way you eat and exercise? Describe if you are experiencing difficulties with maintaining optimal body weight, sleeping, maintaining healthy diet, or exercising regularly?	1.1. Define the problem	MENQOL (Hilditch et al., 1996; Lewis, Hilditch and Wong, 2005); General demographics, lifestyle, and technology use.
Barriers and enablers to healthy eating and physical activity	**Physical activity** When is it difficult or challenging to exercise, go for a walk, or keep fit and healthy physically? When do you find it easiest to stick to a routine with exercise and keeping fit and well? **Diet** When is it difficult or challenging to eat healthily? When do you find it easiest to stick to a routine with healthy eating?	1.2 Select the target behaviour 1.3 Specify the target behaviour 1.4 Identify what needs to change	**Physical activity** IPAQ-SF (Craig et al., 2003); BREQ-2 (Markland and Tobin, 2004) **Diet** SFFFQ (Cleghorn et al., 2016); AEBQ (Hunot et al., 2016)
Technology support	**Technology** Do you use technology? If so, describe what apps/ website (i.e., Balance app, the Menopause Charity, Strava, Facebook groups) or wearable devices (i.e., Garmin, Whoop, Fitbit, Apple Watch) in general you visit or use most frequently? Specifically, those that are related to managing menopausal symptoms, diet, or exercise support. If not, how do you feel about using technology to support your lifestyle? Can you think/ describe any app/ wearable support that could better help you with healthier eating habits and regular physical activity? How could it be best provided to you (i.e., through education, reminders, tips, communities, group challenges), when, and how often?	2.5 Identify intervention functions 3.8 Identify mode of delivery	TAM (Davis, 1989); General demographics, lifestyle, and technology use.

6.2.4.3 Data Analysis Procedure (Thematic Analysis and Deductive Approach)

Responses to the surveys were extracted from JISC online platform and exported into a Microsoft Excel. Each row in Excel represented a participant with JISC assigned unique identifier, while each column represented a survey question. Initial exploration of the data was conducted using Excel Pivot Tables, providing useful and adaptive functionality that helps to analyse raw data efficiently and discern underlying patterns and trends (Johri, 2021). Each questionnaire was analysed separately, with trends and comments reported for each questionnaire separately. After initial exploration, the raw data file was loaded into R Studio statistical software and a short script was developed to obtain descriptive statistics for each questionnaire. The Microsoft Teams' recorded semi-structured focus groups were anonymously transcribed verbatim and then analysed using NVivo qualitative data analysis software. All transcripts were completed by a professional transcription service (UK Transcription). Thematic analysis (TA) following Braun & Clarke's (Braun and Clarke, 2006) six stages of analyses was conducted in NVivo in groups of barriers and facilitators. The six-stage process involved reviewing transcripts for initial data familiarisation, inductive line-by-line coding of all data for barriers and enablers and describing the meaning of each line of text. Additionally, initial codes were grouped, and initial themes were generated.

The barriers and facilitators were extracted from NVivo into Microsoft Excel for the deductive phase of coding. Excel templates were prepared for annotating barriers and facilitators to the BCW (consisting of the target behaviour, COM-B, TDF, reported barriers, reported enablers, intervention functions, and BCTs). On the broadest level, the BCW mapping commenced with identification of the COM-B components that need to change in order to achieve the target behaviours (Michie, van Stralen and West, 2011). The themes were then mapped to the TDF components that extended from the COM-B model, by following the TDF guide. For example, a COM-B component of 'physical capability' was expanded into the corresponding TDF domain of 'physical skills', with an enabler for 'gradually increasing frequency of walking to work' mapped to it, representing three corresponding BCTs of Behavioural practice/rehearsal (8.1), Habit formation (8.3), and Instructions on how to perform the behaviour (4.1). A similar approach to qualitative data analysis that commenced with inductive analysis and continued with deductive mapping of themes to the COM-B and/or TDF framework was used in other lifestyle health-promoting studies (Curtis, Atkins and Brown, 2017; Ojo et al., 2019; Bondaronek et al., 2022; Brown et al., 2022). Finally, the themes were annotated to the BCTs using the Theory and Techniques tool (TaTT) (linking 74 BCTs and 26 mechanisms of action) (Bohlen et al., 2018; Johnston et al., 2021) and the BCTTv1 taxonomy (Michie et al., 2013) (see **Chapter 3** for details on the frameworks and models).

6.2.4.4 Inter-Coder Reliability (ICR) Procedure for the Deductive Phase

To improve the systematicity, communicability, and transparency of the coding process (O'Connor and Joffe, 2020), inter-coder reliability (ICR) of the coding (of themes and BCTs) for the deductive phase was performed by a second reviewer (DA). DA is an experienced assistant professor in psychology and has had an extensive experience in conducting qualitative research to improve physical activity behaviours in midlife women. DA was provided with a copy of the NVivo project containing all transcripts and completed TA of the focus group transcripts grouped into barriers and enablers. Additionally, a Microsoft Excel template was provided and included the researcher's (HS) defined barriers and enablers mapped to the TDF and COM-B with an empty column for BCTs to be independently annotated by DA. DA conducted an independent mapping of all 100% focus group themes to BCTs (using the BCTTv1 taxonomy (Michie et al., 2013). The TaTT (Johnston et al., 2021) was also utilised for triangulation of the mappings. ICR on BCTs has been conducted in other studies, including the creators of the taxonomy (Michie et al., 2015), and in several systematic reviews of health lifestyle behaviours (Black et al., 2019; Sediva et al., 2022).

6.2.4.5 Reflexivity

Reflexivity is vital to qualitative research, and it is a recommended approach to TA by (Braun and Clarke, 2006), to reflect and thoughtfully engage with data and reflexively and thoughtfully engage with the analytic process (Braun and Clarke, 2019). I maintained a reflexive journal throughout the TA process, and also in the ICR process of reviewing BCT codes with the second reviewer Dr Arigo. The ICR involved a process that was collaborative and reflexive, in which not only consensus on the mapping of BCTs was pursued, but also richer and more nuanced reading of the data was sought and achieved.

6.3 Results

6.3.1 Participant Characteristics

Seven focus groups with midlife women (N=33) were formed with 4-5 participants in each group. The participants had an average age of 50 years (range 41–64), weight of 67 kg (range 50-99), and height of 166 cm (range 152-182) (**Table 7**). The majority were aged younger than 54 years (75.9%; 22/29), married (78.5%; 22/30), White British ethnicity (76%; 22/30), and had college/university education (45%; 13/30). The majority also worked full-time (72%; 21/30), and over 41% (12/30) had higher household income of between £52,000 and £100,000 (**Table 8**). The majority (over 85%) self-assessed their health status as good to excellent. Their self-assessed menopausal status indicated that 10% (3/30) were pre-menopausal, 52% (15/30) perimenopausal, and 34% (10/30) menopausal or post-menopausal (one participant was unsure of their menopausal status). Over 41% (12/30) were currently taking Hormone Replacement Therapy (HRT) to manage their menopausal symptoms. One participant was a current smoker and 44% (13/30) had smoked in the past (see **Appendix B, Table 54** for additional demographics, and **Appendix B**, **Table 55** for reported general technology use).

Table 7: Group-level demographics (age, weight, height) of focus group participants

Characteristic	n	Percentage of sample (%)	Mean	SD	Range
Age	29	(96.66)	50.31	6.13	41.0 - 64.0
Weight (kg)	28	(93.33)	67.04	9.97	50.0 - 99.0
Height (cm)	29	(96.66)	166.10	8.15	152.0 - 182.0

Table 8: Demographics of focus group participants (N=30)

Characteristic		n	Percentage of sample (%)
Age group			
	40 - 44	7	(24.10)
	45 - 49	8	(27.60)
	50 - 54	7	(24.10)
	55 - 59	5	(17.20)
	60 - 64	2	(6.90)
Marital status			
	Married, or living as married	22	(78.60)
	Divorced, separated, or widowed	3	(10.70)
	Never married	3	(10.70)
Number of children			
	0	6	(20.70)
	1-2	17	(58.60)
	3 or more	6	(20.70)
Living with children under 18 years old			
	Yes	13	(46.40)
	No	15	(53.60)
Ethnicity			
	White British	22	(75.90)
	Other White background	5	(17.20)
	Indian	2	(6.90)
Education			
	Lower Secondary (GCSE)	2	(6.90)
	Upper Secondary (A-levels)	3	(10.30)
	College or University	13	(44.80)
	Post-graduate degree	11	(37.90)
Employment type		29	
	Full-time (30 hrs and more each week)	21	(72.40)
	Part-time (under 30 hrs each week)	5	(17.20)
	Fully retired from work	1	(3.40)
	Looking after the family or home	2	(6.90)
Household income level			
	less than £18,000	1	(3.45)
	£18,000 to £30,999	2	(6.90)
	£31,000 to £51,999	5	(17.24)
	£52,000 to £100,000	12	(41.38)
	more than £100,000	9	(31.03)

6.3.2 Thematic Analysis of Barriers and Enablers

TA conducted in NVivo resulted in 95 enablers and 64 barriers across 69 themes of which 44 were unique (and 14 were non-unique). Therefore, 14 themes were mapped to the TDF more than once. For example, depending on the type of motivation, motivation related to beliefs about capabilities was coded separately from motivation related to optimism, intentions, reinforcement, or emotions. Additionally, the type of social support was also coded multiple times, for example, depending on if it was related to beliefs about capabilities, reinforcement, emotions, or social influences within social opportunity COM-B component.

6.3.3 Annotating Themes to the BCW

Themes from the transcripts provided data for all 14 TDF domains, representing relevant mechanisms of action (means to changing behaviour), and for all three components (i.e., capability, opportunity, motivation) of the COM-B model. The Capability component of COM-B consisted of 20 themes (29%; 20/68) that were further linked to 19 barriers and 38 enablers. The Motivation component resulted in 37 themes (54%; 37/68) with 33 barriers and 37 enablers, and the Opportunity component resulted in 11 themes (16%; 11/46) with 11 barriers and 18 enablers.

6.3.3.1 Annotating Enablers to BCTs

The 95 enablers were further annotated to a total of 39 BCTs representing 42% (39/93) of all BCTs available in the BCTTv1 taxonomy, with 16 BCTs (35%; 16/46) in the Capability component, 20 BCTs (44%; 20/46), and the Motivation component, and 10 BCTs (22%; 10/46) in the Opportunity component. The TDF mapping within the COM-B model revealed that most (21%; 8/49) BCTs were annotated to each, Behavioural regulation, and Reinforcement, followed by Beliefs about capabilities (18%; 7/39). Knowledge, Emotions, and Social influences had 6 BCTs each (15%; 6/39), followed by Skills (13%; 5/39), Environmental context and resources (10%; 4/39), Beliefs about consequences, Intentions, and Goals with 3 BCTs each (8%; 3/39). Lastly, three domains of Optimism, Memory attention, and decision processes, and Social/professional role/identify had 2 BCTs each (5%; 2/39). No BCTs were mapped to Cognitive and interpersonal skills. The majority of the BCTs were grouped in the Behaviour Change Category (BCC) of Social support (100%; 3/3 BCTs), Self-belief (100%; 4/4 BCTs), and Repetition and substitution (86%; 6/7 BCTs). Additionally, two BCCs of Goals and planning (6/9 BCTs) and Natural consequences (4/6 BCTs) had also most (67%) of their group's BCTs selected.

6.3.3.1.1 Inter-coder reliability (ICR) of BCT Annotations

Two reviews of annotations were completed between the researcher (HS) and the second reviewer (DA) with two discussions to clarify the themes and to agree on the final annotations of themes to BCTs. There were 14 (23%; 14/60) discrepancies and generally, HS included more BCTs than DA across all TDF domains, with most of the discrepancies (11) in one domain of Beliefs about capabilities. The discrepancies were discussed and agreed on. In other studies where an attempt was to map 35 BCTs to 11 TDF domains from original TDF mapping showed good reliability across four researchers with 71% agreement (Michie et al., 2008), which is in line with this study that resulted in a 77% agreement.

6.3.3.2 Annotating Themes to the COM-B Model and TDF Domains

In this section, the themes, barriers, and enablers are presented separately for each component of the COM-B model and its corresponding TDF domains within it. Where appropriate, quotes from the focus group participants and survey results are also included.

6.3.3.2.1 Capability

TDF domain: Physical Skills

Physical skills domain consisted of four themes, including having skills to cook more at home to prepare healthy meals, being physically fit, and menopausal symptoms affecting one's physical activity. Additionally, challenging one's existing physical activity with new, more intensive practices, or replacing one physical activity type with another type (e.g., replacing running with swimming if unable to run) (**Table 9**). Experiencing menopausal symptoms (e.g., anxiety, low energy, sleep disturbance, lack of strength) and their impact on lifestyle behaviours and overall health related quality of life, were discussed extensively. Based on the survey (general questions), the participants slept seven hours per night (range 4–8 hours).

> *"For me, the most debilitating symptom has been the sleep disturbance, and that went on for quite a few years. Obviously, when you don't sleep, you don't eat well, or I didn't, and you don't exercise well. So, it's a vicious circle."* (age 47, FG7)

Physical activity improved with gradually increasing frequency of walking to work, speed walking instead of running (if unable to run), walking to work instead of taking public transportation). Additionally, based on the survey's reported physical activity frequency (based on IPAQ-SF), almost half of the participants (48%; 14/30) walked seven days per week, with 57% (17/30) walking for at least 1hr on those days. The enablers were annotated to five unique BCTs (e.g., instructions on behaviour, behavioural practice/rehearsal, habit formation, habit reversal, and graded tasks). Training was identified as the primary intervention function to strengthen physical skills.

Table 9: Physical skills TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Having the skills to cook more at home. 2) Challenging existing physical activity with new, more intensive, or replacing physical activity. 3) Menopause symptoms affecting physical and psychological functioning. 4) Being physically fit.	1) Unable to exercise due to injury (also fear of injury). 2) The effects of menopausal symptoms (physical and psychological). 3) Complicated recipes. 4) Lack of strength and cardio stamina. 5) Low energy levels or fatigue.	1) Gradually increasing frequency of walking to work (8.1)(8.3)(8.4)(8.7) 2) Speed walking instead of running if unable to run (8.1)(4.1) 3) Walking to work instead of taking public transportation (8.4) (8.3) 4) Ability to prepare meals based on recipes, variety of foods (4.1) 5) Cooking more at home (8.1) 6) Replacing driving with cycling (8.3)(8.4) 7) Weight training for bone health (4.1)	Instructions on how to perform the behaviour (4.1) Behavioural practice/rehearsal (8.1) Habit formation (8.3) Habit reversal (8.4) Graded tasks (8.7)

TDF domain: Knowledge

Knowledge domain consisted of four themes, including understanding the impact of menopause on one's health and wellbeing, knowledge of the impact of diet and physical activity on health and wellbeing, understanding the types of effective exercises for midlife women, and knowledge of healthy dietary aspects (types of foods, frequency, portion sizes) (**Table 10**). Physical movement through the day (e.g., also when cleaning and vacuuming), tracking physical activity using wearables and apps, and receiving personalised biofeedback on sleep to adjust one's physical activity, accordingly, were found to be useful to the participants. Knowledge and understanding of different types of physical activity (e.g., weight training, running, walking) that are recommended for midlife women was also useful.

> *"I found, probably about five years ago, that the weight started creeping on, and it wasn't easy to get rid of. And I couldn't understand that…what I've realised now is, yes, exercise is very important, and my exercise has changed. It's been more weight bearing, kettlebells, which I do enjoy, and I realise the benefits that I'm getting from it."* (Age 46, FG7).

Information about what healthy foods are and credible sources of information about the types of foods and supplements recommended for women in midlife were discussed extensively. The enablers were annotated to six unique BCTs (e.g., feedback on behaviour, information about health consequences, information about emotional consequences, instructions on how to perform the behaviour, biofeedback, behaviour substitution). Education was identified as the primary intervention function to enact the desired behaviour.

Table 10: Knowledge TDF domain mapping

Themes	Reported barrier	Reported enabler	BCTs
1) Understanding the impact of menopause on health and wellbeing. 2) Knowledge of the impact of diet and physical activity on health and wellbeing. 3) Understanding the types of effective physical activity. 4) Knowledge of healthy diet (types of foods, frequency, portion sizes).	1) Not knowing the effects of the menopause on health and wellbeing of midlife women. 2) Lack of information about what to eat in midlife. 3) Eating the same meals (lack of variety). 4) Obsessive behaviour about food (feedback from apps may cause distress).	1) Feeling better physically and mentally after exercising and eating healthy (5.1) (5.6) 2) Moving throughout the day (cleaning, housework) (4.1) (2.2) 3) Weight training for bone health (5.1) 4) Personalised biofeedback information on sleep (2.6) 5) Tracking physical activity using wearables and apps (2.2) 6) Feeling better physically and mentally when eating less (smaller quantities, fasting) (5.1) (5.6) 7) Effects of food on mental health and wellbeing (5.1)(5.6) 8) Awareness of what healthy foods are (5.1) 9) Not eating late at night (5.1) 10) Eating seasonal foods (4.1)(5.1) 11) Taking supplements supporting women through the menopause transition (5.1) 12) Ordering healthy takeaways (5.1)(4.1) 14) Reading food labels (5.1)	Feedback on behaviour (2.2) Information about health consequences (5.1) Information about emotional consequences (5.6) Instructions on how to perform the behaviour (4.1) Biofeedback (2.6) Behaviour substitution (8.2)

TDF domain: Memory, attention, and decision processes (MAD)

The three main themes discussed in this domain included: menopause symptoms affecting one's health and wellbeing, planning meals and exercise, and tracking and feedback from technology (**Table 11**). Planning exercise classes and meals for the week, and choosing physical activity based on sleep data were found to be useful. For example, planning meals and preparing meals ahead of time was identified as an enabler to save time and avoid unhealthy food choices. The enablers were annotated to two unique BCTs (i.e., problem solving, action planning).

Table 11: MAD TDF domain mapping

Themes	Reported barrier	Reported enabler	BCTs
1) Menopause symptoms affecting health and wellbeing. 2) Planning meals and exercise. 3) Tracking and feedback from technology.	1) Brain fog, poor memory (menopause symptoms). 2) Not remembering exercises/instructions in a group class. 3) Lack of time.	1) Planning exercise classes and meals for the week (1.4) 2) Choosing physical activity based on sleep data (1.2)	Problem solving (1.2) Action planning (1.4)

Additionally, using technology to track activities and receive feedback on progress was motivating to the participants to engage in more physical activity. Simplicity of technology, tracking, feedback, and support for all aspects of wellbeing tailored to midlife women was found to be desirable. Furthermore, using technology was perceived as an accessible way to educate oneself about menopause, to make informed decisions when seeing a GP, and to also help other midlife women to better understand the impact of menopause on their health and wellbeing. Furthermore, based on the pre-focus group survey (general use of technology), over 80% (24/30) used technology for lifestyle support, and over 60% (19/30) used a smartwatch. Over 46% (14/30) used technology to increase their physical activity, live a healthy lifestyle (37%; 11/30), eat a healthier diet (30%; 9/30), and for weight loss (27%; 8/30). Additionally, based on the TAM questionnaire (part of the survey), perceived usefulness of using wearables, using apps to track physical activity were high (over 76%; 23/30) and moderately high for using apps to track diet (over 60%; 18/30). Perceived ease of use of using wearables was also rated high (73%; 22/30), using apps to track physical activity was moderate (60%; 18/30), followed by apps to track diet (47%; 14/30). To strengthen the desired behaviours of healthy eating and regular physical activity, enablement was identified as the primary intervention function to improve mental strength.

TDF domain: Behavioural regulation

Behavioural regulation domain had the highest number of themes discussed in the focus groups (**Table 12**).

Table 12: Behavioural regulation TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Self-image and identity as a midlife woman 2) Menopause symptoms affecting health and wellbeing. 3) Planning meals and exercise. 4) Tracking and feedback from technology. 5) Setting and evaluating physical activity goals. 6) Prompts to support heating eating and physical activity. 7) Knowledge of the impact of diet and physical activity on health and wellbeing. 8) Awareness of	1) Giving up on exercise if unable to exercise at the usual time, place (unable to exercise later in the day). 2) The effects of menopausal symptoms (physical and psychological). 3) Calorie counting. 4) Eating the same meals (lack of variability). 5) Inability to maintain regular meals. 6) Lack of or insufficient sleep. 7) Weight gain. 8) Alcohol and caffeine overconsumption.	1) Walking to work instead of going to the gym (8.2) 2) Doing house work when unable to go for a walks (8.2) (8.6) 3) Having a daily-steps goal set (1.1)(2.3) 4) Exercising with family (became a routine) (8.3) 5) Planning or prepping (meals and exercise) for the week (1.4) 6) Doing mobility exercises even though these were less enjoyable before (8.2) 7) Keeping track of physical activity throughout the day (2.3) 8) Establishing routine (eating and exercise) (1.1) (2.3)(1.4) (8.3) 9) Eating variety of foods (1.1)(2.3)(1.4) 10) Tracking foods consumed, eating habits (2.3) 11) Eating differently due to menopause (1.1)(1.4) 12) Replacing driving with cycling (8.2) 13) Self-monitoring physical activity using wearables (2.3) 14) Prompts to help with exercising at home (7.1)	Goal setting (behaviour) (1.1) Self-monitoring behaviour (2.3) Information about health consequences (5.1) Behavioural substitution (8.2) Generalisation of target behaviour (8.6) Habit formation (8.3) Action planning (1.4) Prompts/cues (7.1)

own eating habits. 9) Awareness of physical activity habits.		15) Prompts to drink more water (7.1)	

The participants shared various tips on how they were able to improve their diet and physical activity. For example, walking to work instead of going to the gym in the morning, doing housework when unable to go for a walk, having a daily steps goal, exercising with family (became a routine), planning or prepping meals for the week, establishing a routine for eating exercise, tracking foods consumed and having awareness of own eating habits, were found to be helpful. For example, planning food shopping was discussed extensively in focus groups, and this behaviour was formed during the COVID-19 lockdown and persisted after lockdown. The enablers were annotated to eight BCTs (e.g., goal setting (behaviour), self-monitoring behaviour, information about health consequences, behavioural substitution, generalisation of target behaviour, habit formation, action planning, prompts/cues).

Awareness of own dietary patterns either through education or food tracking apps (e.g., Slimming World, MyFitnessPal) was found helpful in learning about portion sizes, types of healthy foods and quantities to be consumed. Additionally, based on the survey (using SFFFQ), most participants consumed vegetables (73%; 22/30) and fruit (70%; 21/30) on seven days per week with an average portion of 3.13 vegetables (range 1-5) and 3.63 of fruit (range 1-6) per day. Half of the participants consumed less than 14 units of alcohol per week, while 30% (9/30) rarely consumed alcohol at all, with 20% (6/30) consuming over 14 units per week. Based on the focus group discussions, alcohol overconsumption increased during COVID-19 lockdown and persisted post-lockdown. Similarly, caffeine consumption was higher during lockdown with increased sedentary behaviour. The reported eating behaviours (using AEBQ) revealed that most of the participants enjoyed food (93%; 28/30) and were interested in trying new foods (63%; 20/30) and new variety of foods (86%; 26/30). Using prompts to get up and move, or to drink more water (instead of coffee) was found to desirable in changing these behaviours. Additionally, based on the survey results (using BREQ-2), the majority of the participants felt they valued the benefits of exercise (80%; 24/30), it was important to them to both, exercise regularly (74%; 22/30) but also to make effort to exercise regularly (77%; 23/30). Most participants enjoyed exercise (56%; 17/30) and found pleasure and satisfaction from participating in exercise (76%; 23/30). To strengthen the desired behaviours of healthy eating and regular physical activity, enablement was identified as the primary intervention function to improve mental strength.

6.3.3.2.2 Motivation

TDF domain: Social / professional role / identity (SPI)

A substantial part of each focus group discussion was around the effects of the menopause on health and wellbeing. Societal norms around the menopause and midlife and the ability to speak about the menopause at workplace, with a GP, or with friends was perceived as important. This domain consisted of three themes (e.g., self-image and identification as a midlife woman, general attitude and beliefs about midlife, societal norms around menopause and midlife) (**Table 13**).

Table 13: SPI TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Self-image and identification as a midlife woman. 2) General attitudes and beliefs about midlife. 3) Societal norms around menopause and midlife.	1) Lack of communities (gyms) joined by midlife women. 2) People don't want to talk about the menopause. 3) Lack of information and support for midlife women. 4) Childcaring responsibilities 5) Wearables not designed for midlife women.	1) Feeling good about midlife and the changes associated with it and passionate about the menopause (13.4) 2) Having a hobby (e.g., learning a new language) (13.4) 3) Enjoying new types of exercises (13.5)	Valued self-identity (13.4) Identity associated with changed behaviour (13.5)

Some of the barriers discussed included lack of communities for midlife women, and lack of information and support for midlife women. The participants shared tips on how to stay motivated, for example, by feeling good about midlife and the changes associated with it, having a hobby (e.g., learning a new language), and enjoying new types of exercises, which were annotated to two unique BCTs (i.e., valued self-identity, and identity associated with changed behaviour). Additionally, survey findings (based on MENQOL) revealed that over 70% (22/30) of the participants experienced dissatisfaction with their personal life, feeling anxious or nervous, feeling tired or worn out, and lacking energy.

> *"I've noticed in the last couple of years my anxiety. I am a very conscientious person, but I've become much more anxious about things I would never have been anxious about. My energy levels are really low, and that impacts on my motivation to do any exercise."* (Age 48, FG4).

Furthermore, over 65% (22/30) also experienced night sweats, feeling depressed or down, having poor memory.

> *"The biggest thing in the past six months has been the brain fog and the inability to put together a cohesive sentence about things in my work, where I used to be so articulate."* (Age 58, FG6).

TDF domain: Beliefs about capabilities

Aligned to this domain, the group discussions focused on six themes, including self-efficacy and confidence to eat healthy and exercise, motivation associated with beliefs about capabilities, challenging existing exercises (with new types, higher intensity, or replacing for others), accountability, and social support (**Table 14**).

Table 14: Beliefs about capabilities TDF domain mapping

Themes	Reported barrier	Reported enabler	BCTs
1) Self-efficacy and confidence to eat healthy and exercise. 2) Motivation 3) Challenging existing physical activity with new, more intensive, or replacing physical activity. 4) Challenging existing dietary patterns with new or replacing unhealthy with healthy. 5) Accountability 6) Social support	1) Lack of self-efficacy. 2) Perceived lack of control (unable to exercise when wanting to). 3) Lack of self-esteem (not feeling good about oneself). 4) Lack of willpower. 5) Menopause symptoms	1) Feeling good after exercise (5.1)(15.2) 2) Performing any activity including cleaning the house if unable to go for a walk (just moving) (13.2) 3) Feeling motivated (15.3)(15.4)(13.2)(15.1) 4) Finding new ways to eat and exercise (13.2) 5) Self-efficacy (15.3)(15.4) 6) Increased accountability (13.2)(15.1)(15.2) 7) Exercising with a friend/relative, a personal trainer (3.1)	Social support (unspecified) (3.1) Focus on past success (15.3) Self-talk (15.4) Information about health consequences (5.1) Mental rehearsal of successful performance (15.2) Framing/reframing (13.2) Verbal persuasion about capabilities (15.1)

The participants shared tips on how to improve beliefs of their capabilities to engage in healthy lifestyle behaviours. For example, by feeling good after exercising, performing any physical activity including cleaning their house when unable to go for a walk, finding new ways to eat healthy and exercise more, and exercising with a friend. Additionally, beliefs about capabilities to follow recipes and exercise classes, were discussed in the focus groups and were found to be affected by menopause symptoms (e.g., brain fog and fatigue). The enablers were annotated to seven unique BCTs (i.e., social support (unspecified), focus on past success, self-talk, information about health consequences, mental rehearsal of successful performance, framing/reframing, verbal persuasion about capabilities). Persuasion was identified as the primary intervention function to strengthen beliefs about capabilities.

TDF domain: Optimism

The optimism domain discussions centred around two themes, specifically motivation, and self-efficacy and confidence to eat healthy and exercise regularly (**Table 15**).

Table 15: Optimism TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Motivation 2) Self-efficacy and confidence to eat healthy and exercise.	1) Feeling guilty 2) Lack of self-efficacy.	1) Self-talk and encouragement (praise oneself for good progress) (15.1) (15.4) 2) Setting small goals that are achievable (15.1) (15.4)	Verbal persuasion about capabilities (15.1) Self-talk (15.4)

The barriers to healthy lifestyle included feeling guilty about not eating healthily and not exercising, as well as perceived lack of self-efficacy. Helpful strategies included self-talk and encouragement (praising oneself for good progress) and setting small goals that are achievable. The participants discussed giving themselves a self-talk, in a form of a permission to take a break and engage in a physical activity. The enablers were annotated to two unique BCTs (e.g., verbal persuasion about capabilities, and self-talk). The primary intervention function identified was persuasion.

TDF domain: Beliefs about consequences

This domain consisted of three themes (e.g., beliefs about consequences of diet and physical activity on health and wellbeing, accountability, and establishing a routine in healthy eating and regular exercise) (**Table 16**). The discussions were mapped to three unique BCTs (e.g., information about health consequences, salience of consequences, information about emotional consequences).

Table 16: Beliefs about consequences TDF domain mapping

Themes	Reported barrier	Reported enabler	BCTs
1) Beliefs about consequences of diet and physical activity on health and wellbeing. 2) Accountability. 3) Establishing a routine to healthy eating and physical activity.	1) Lack of accountability. 2) Negative emotions (feeling bad when eating unhealthy foods). 3) Not moving enough throughout the day. 4) Eating carbohydrate-rich meals. 5) Not consuming enough protein and experiencing negative impact on one's health.	1) Performing the exercise / eating healthy (even when one feel like it to avoid gaining weight), accountability (5.2) (5.1) (5.6) 2) Disease or medication prevention as a motivator (5.1) 3) Healthy lifestyle to live a healthy long life (15.1) 4) Understanding the impact of a healthy diet on health (15.1) (15.2)	Information about health consequences (5.1) Salience of consequences (5.2) Information about emotional consequences (5.6)

Discussions on helpful strategies to healthy lifestyles included exercising and eating healthy even when one doesn't feel like it to avoid gaining weight, for disease or medication prevention as a motivator, and following a healthy lifestyle to live and healthy long life. Specific food groups were perceived negatively. For example, eating carbohydrate-rich meals was generally seen as having negative consequences on body weight, although in many cases, this realisation occurred as a result of own experience with food and not from education on healthy diet. Furthermore, based on the survey (MENQOL), half (50%; 15/30) of the participants experienced weight gain as one of their menopause symptoms. The primary intervention functions identified were persuasion, education, and modelling.

TDF domain: Intentions

Intentions to engage in healthy lifestyle behaviours included five themes (e.g., accountability, motivation, attitude towards healthy diet and exercise, self-efficacy and confidence to eat healthy, challenging existing exercise (with new, more intensive, or replacing it for other types) (**Table 17**).

Table 17: Intentions TDF domain mapping

Themes	Reported barrier	Reported enabler	BCTs
1) Accountability. 2) Motivation. 3) Attitude towards healthy diet and physical activity. 4) Self-efficacy and confidence to eat healthy and exercise. 5) Challenging existing physical activity with new, more intensive, or replacing physical activity.	1) Lack of accountability (taking oneself off camera during online exercise classes to do other things). 2) Lack of motivation. 3) Negative emotions. 4) Lack of planning (thinking about exercising but not planning it) 5) Lack of routine. 6) Not enjoying exercise. Menopause symptoms.	1) Do any exercise you can do (e.g., swimming) if injured and unable to walk/run (1.8)(1.9) 2) Being physically active throughout the day (8.2) 3) Engaging in challenges to increase physical activity (1.8)(1.9) 4) Being determined to not quit set exercise goals (1.8)(1.9)	Commitment (1.9) Behavioural contract (1.8) Behaviour substitution (8.2)

The participants found it helpful to do any exercise one can, being physical active throughout the day, engaging in exercise challenges to increase physical activity, and being determined to not quit after setting own exercise goals. The participants felt negative emotions when they didn't follow through their intentions to exercise. Additionally, finding time throughout the day to do short exercise sessions using apps or going for a walk was found to be an efficient way to get in more exercise, and improved with planning and commitment to achieve small goals.

> *"Even just going [for a walk] for 10 minutes at lunchtime. Just to give yourself that break from your environment as well. You'll probably find you're more productive afterwards. So, I think it's thinking just a little bit, a little something is better than doing nothing, and setting some really small goals."* (Age 46, FG7).

The enablers were annotated to three BCTs (i.e., commitment, behavioural contract, behaviour substitution). The primary intervention functions identified were persuasion and incentivisation.

TDF domain: Goals

Goals domain was discussed frequently across six themes, including planning meals and exercise, establishing a routine, self-efficacy and confidence to eat healthy and exercise, setting goals to eat healthy and exercise regularly (**Table 18**).

Table 18: Goals TDF domain mapping

Themes	Reported barrier	Reported enabler	BCTs
1) Planning meals and exercise. 2) Work/family/social pressure. 3) Time constraint. 4) Establishing a routine to healthy eating and physical activity. 5) Self-efficacy and confidence to eat healthy and exercise. 6) Setting and evaluating physical activity goals.	1) Giving up on exercise if unable to exercise at the usual time, place (unable to exercise later in the day). 2) Social or family pressure (Inability to choose own meals).	1) Planning exercise (booking a class in advance so that one has to go) (1.4) 2) Planning meals for the week (1.4) 3) Adding variety of foods with a delivery of a healthy foods box once per week (1.1) (1.4) 4) Maintaining optimal weight (by walking more) (1.1) (1.4) 5) Doing any exercise based on ability (1.4) (1.5)	Goal setting behaviour (1.1) Review behaviour goals (1.5) Action planning (1.4)

The participants found it helpful to plan their exercise (booking classes), planning meals for the week, adding variety of foods with a delivery of a healthy foods box one weekly, maintaining optimal weight, doing any exercise based on ability). Additionally, setting goals for physical activity, primarily when the goals are linked to greater cause (e.g., 'pink ribbon' breast cancer walk) or involve community, were found to be motivating in the focus groups. The enablers were annotated to six unique BCTs (e.g., goal setting (behaviour), review behaviour goals, action planning). The primary intervention function identified was enablement.

TDF domain: Reinforcement

Reinforcement domain included discussions across seven themes, including motivation, attitude towards healthy diet and exercise, incentives to maintain healthy habits, social support, cost associated with not completing set goals, repetition of learned exercises, and self-reward to engage in exercise and healthy eating (**Table 19**). The participants found it helpful to do housework if unable to exercise, making sure they were enjoying exercise (by listening to a favourite podcast), and repeating exercises learned in the gym. Financial impact included benefits or earning points for completing activity, but also attending booked classes to avoid no-show charges.

Table 19: Reinforcement TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Motivation. 2) Attitude towards healthy diet and physical activity. 3) Incentives to maintain healthy eating and physical activity goals. 4) Social support. 5) Cost associated with not completing set goals. 6) Repetition of learned exercises. 7) Self-reward to engage in exercise and healthy eating.	1) The pandemic (unable to meet with friends). 2) Unable to break habit. 3) Relapse after using diet or weight loss apps.	1) Doing house work (e.g., vacuuming) if unable to go for a walk/gym (8.2) 2) Enjoying exercise (listening to a favourite podcast when exercising alone) (10.9) 3) Financial benefit or earning points for completing activity (10.3) 4) Repeating exercises learned in the gym (online classes) when at home (8.6) 5) Attending booked class to avoid no show charges (14.1) 6) Social support - exercising with family (3.1) 7) Kudos (10.4)	Social support (unspecified) (3.1) Behaviour substitution (8.2) Social reward (10.4) Self-reward (10.9) Non-specific reward (10.3) Generalisation of target behaviour (8.6) Behaviour cost (14.1) Habit formation (8.3)

Furthermore, social support and kudos provided additional reinforcement. Some participants discussed how they intentionally seek credible sources of healthy lifestyle behaviours to reinforce feeling better about themselves.

> *"You have to be motivated; I think. You have to be in that right frame of mind, and you feel stronger and you feel happy and then you get the positive reinforcement of seeing yourself look better. I was watching lots of different YouTubers and trying to pick up all the positive stuff I could from all these various people."* (Age 63, FG5).

The enablers were annotated to eight unique BCTs (e.g., social support (unspecified, behaviour substitution, social reward, self-reward, non-specific reward, generalisation of target behaviour, behaviour cost, habit formation). The primary intervention functions identified were environmental restructuring and incentivisation.

TDF domain: Emotions

Emotions were discussed around five themes, including motivation, emotions, understanding benefits of healthy eating regular exercise on health and wellbeing, work/family/social influence, menopause symptoms (influencing emotions, attitudes and choices) (**Table 20**).

Table 20: Emotions TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Motivation 2) Emotions 3) Understanding benefits of healthy eating and physical activity on health and wellbeing. 4) Work/family/social influence 5) Menopause symptoms	1) Comfort eating. 2) Menopause symptoms (lack of sleep, feeling physical pain, low mood). 3) Stressful day. 4) Feeling	1) Feeling good after exercising (physically and emotionally)(5.1)(5.4)(5.6) 2) Knowing one will feel better after exercise (13.2)(11.2) 3) Encouragement and support from family, friends, workplace (3.3) 4) Going to the gym feels like having a break (5.6)	Information about health consequences (5.1) Monitoring of emotional consequences (5.4) Framing/reframing (13.2) Information about

influencing emotions, attitudes, and choices.	tired (eating more and exercising less) 5) Negative emotions.	(13.2) 5) Kudos on social media (Strava) (3.3) 6) Enjoying exercise (5.4) 7) Allowing oneself a treat (not being to self-critical) (11.2)	emotional consequences (5.6) Reduce negative emotions (11.2) Social support (emotional) (3.3)

Menopausal symptoms (lack of sleep, feeling physical pain, low mood), experiencing stressful day, feeling tired (eating more and exercising less, emotional eating), all played a role in decreased engagement in healthy lifestyle behaviours. Negative emotions were experienced when women did not have access to the right tools and information to support their healthy lifestyle behaviours. On the other hand, the participants found it helpful to focus on feeling good after exercising (physically and emotionally), knowing one will feel better after exercising, enjoying exercise, and going to the gym to feel like one is having a break from work. Additionally, receiving encouragement and support from family and friends, receiving kudos on social media, and allowing oneself a treat (not being self-critical). The enablers were annotated to six unique BCTs (e.g., information about health consequences, monitoring of emotional consequences, framing/reframing, information about emotional consequences, reduce negative emotions, social support (emotional)). The primary intervention functions identified were enablement, persuasion, coercion, incentivisation, and modelling.

6.3.3.2.3 Opportunity

TDF domain: Environmental context and resources (ECR)

The discussions centred around six themes in this domain, including time constraint, availability of resources, convenience (time, location, weather), tracking and feedback from technology, simplicity and ease of use of technology, and the COVID-19 pandemic reducing opportunities for engaging in healthy lifestyle behaviours (**Table 21**).

Table 21: ECR TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Time constraints 2) Availability of resources 3) Convenience (time, location, weather) 4) Tracking and feedback from technology 5) Simplicity and ease of use of technology 6) The pandemic causing loss of opportunities	1) Lack of time. 2) Stressful working conditions, loss of job (due to menopause). 3) The pandemic (inability to go outside for walks and to the gym, overconsumption of alcohol) 4) Weather conditions (rain, dark and cold during winter). 5) Sedentary job.	1) Gym in a convenient location (12.1) 2) Booking classes ahead (planning and time management, using apps) (1.2) (1.4) 3) Living near a park for walks (12.1) 4) Doing other types of physical activity if unable to go for walks/to go gym (exercising outside) (1.2) 5) Ordering from healthy take aways when unable to cook (12.1) (1.2) 6) Adding variety of foods with a delivery of a healthy foods box once per week (12.1) (1.2) 7) Access to supplements supporting women through the menopause transition (12.5) 8) Time of day to exercise (preferably mornings) (12.1) 9) Using weight loss apps (12.5) 10) Using technology that supports all aspects of health and wellbeing (12.5)	Problem solving (1.2) Action planning (1.4) Restructuring the physical environment (12.1) Adding objects to the environment (12.5)

The participants found it helpful to go to a gym in a convenient location, book classes ahead (e.g., for the week), living near a park for walks. With gym closures during COVID-19 lockdown, the participants engaged in more walking with their families when their environment supported these activities. The enablers were annotated to four unique BCTs (e.g., problem solving, action planning, restructuring the physical environment, and adding objects to the environment). The primary intervention functions identified were environmental restructuring and enablement.

TDF domain: Social influences

Social influences were one of the most frequently discussed domains in the focus groups. Discussed were five themes, including social support, the pandemic causing lack of opportunities to exercise, work/family/social influence on healthy behaviours, and social reward for engaging in physical activity (**Table 22**).

Table 22: Social influences TDF domain mapping

Themes	**Reported barrier**	**Reported enabler**	**BCTs**
1) Social support 2) The pandemic causing lack of opportunities 3) Work/family/social influence 4) Societal norms around menopause and midlife. 5) Social reward for engaging in physical activity.	1) Lack of accountability (in group classes). 2) Lack of support (from family, work, GP). 3) Childcaring responsibilities. 4) The pandemic (inability to meet with friends for social support). 5) Alcohol overconsumption. 6) Unable to make own decisions about meals due to family pressure.	1) Exercising with a friend, relative, personal trainer (3.1)(3.2)(3.3) 2) Kudos on social media (Strava) (3.1)(3.3) 3) Walking a dog (3.1) 4) Joining group exercise classes (3.2)(12.2) 5) Being in charge of own meals (1.2) (12.2) 6) Enjoying a nice meal with friends and family (3.1) 7) Enjoying a treat when eating out with friends (10.9) 8) Talking about the menopause (at workplace, friends, GP) (3.1)	Social support (unspecified) (3.1) Social support (practical) (3.2) Social support (emotional) (3.3) Problem solving (1.2) Restructuring the social environment (12.2) Self-reward (10.9)

The participants enjoyed exercising with others (a friend, relative, or personal trainer), kudos on social media (Strava), walking a dog, joining group exercise classes, and being in charge of own meals. For example, enjoying meals with friends and socialising was found to be rewarding and even more vital after the pandemic.

> *"For me it is about community. It is essential. I've done running on my own for years, I've done a bit of swimming on my own, a bit of cycling on my own, but it's purely about seeing other human beings now."* (Age 50, FG4)

In additional to an in-person social support, a vital contributor of social support also included platforms with virtual communities, including running apps to motivate one another, giving kudos to others for engaging in any exercise, and joining exercise challenges with others.

> *"There was a group of maybe eight of us, we joined a Strava group and so we could see what everybody was doing and give people kudos. That sense of being part of a group, that you joined a challenge, and you were all doing it together again, really, was a motivation."* (Age 52, FG4)

The enablers were annotated to six unique BCTs (e.g., social support (unspecified, practical, emotional), problem solving, restructuring the social environment, and self-reward). The primary intervention functions identified were environmental restructuring and enablement.

6.4 Discussion

This mixed-method study was guided by a theoretical framework to systematically categorise UK-residing midlife women's views and lived experiences with lifestyle health behaviours. The study identified behavioural components for a DHBCI that are personalised specifically to the population of midlife women, in the UK. It is therefore providing the next level of granularity in a subpopulation (group-level) for a DHBCI design, from the generic (population-level) set of BCTs identified in the previous chapter (Study 1). Overall, 39 BCTs were mapped to each TDF domain's enablers. Most of the behavioural determinants were targeting the COM-B model's Motivation component (31%; 52/100), followed by Capability (20%; 33/100), and lastly Opportunity (9%; 15/100), suggesting that more of the lifestyle support needs to emphasise motivation rather than increasing opportunities to engage in health-promoting behaviours. Other research shows that motivation to engage in health-promoting behaviours, such as physical activity, is substantially reduced during midlife and older age, and the preferred activity is executed at a slower pace than in young adulthood (Alley et al., 2018). Motivation was also highlighted as a barrier and facilitator in the adoption of a healthy diet in midlife adults, in the UK (Timlin, McCormack and Simpson, 2021). Furthermore, the TDF domains of social influences, behavioural regulation, reinforcement, and beliefs about capabilities had the highest number of BCTs, indicating that more emphasis for support may be needed in these domains. Examples of other research in the health-context involving inductive analysis of the themes and deductive mapping to the TDF included focus groups to identify facilitators to a healthy lifestyle, and the most prominent TDF domains included Social influences, and Environmental context and resources (Cardol et al., 2022). A study exploring TDF domains to capture eating and physical activity behaviours of nurses also included Social influences, Beliefs about capabilities, and Knowledge, as the key domains of focus (Lawton et al., 2016). Social connection, whether through group exercise classes or eating out with friends was one of the key themes that could potentially be facilitated by encouraging the participants to join group classes and by regular coaching interaction between the researcher and the participants.

The focus group discussions revealed multi-factorial influences on health behaviours. For example, setting smaller, feasible and achievable goals was identified to support sustainable behaviour change. Furthermore, having a big goal (e.g., running a marathon, radical weight loss) can feel frightening and discouraging, whereas putting in place small goals without focusing too much on the outcome, can help one get out running every day, join a running group, or just to keep moving. Goal setting and graded tasks were also identified in the systematic review (Study 1) as one of the most frequently used BCTs in DHIs for midlife women and one of the key self-regulation techniques in a meta-analysis of BCIs for healthy eating and physical activity (Michie, Abraham, et al., 2009a). Furthermore, the participants generally prioritised their health and fitness by committing to their new daily lifestyle behaviours (e.g., joining a group exercise class, walking to work, cooking based on healthy recipes), and therefore the BCT for commitment was used to support goal setting of target behaviours. Commitment was perceived to result in improved self-efficacy, enjoyment, and health outcomes (e.g., reduced menopause symptoms, weight loss) with a new 'habit formation' BCT annotation. Relapse generally occurred when more emphasis was placed on the outcome (i.e., the goal), which initially led to excitement but when the expected results were not reached it led to disappointment. Therefore, although goal setting is one of the most frequent BCTs, supporting goal setting by other techniques (e.g., commitment, graded tasks) may make goal setting more effective. Additional strategies for lack of progress towards goals may include engaging participant in problem-solving (Hilditch et al., 1996) and incorporating strategies to increase self-efficacy (Burke, Ewing, et al., 2015).

The COVID-19 pandemic had an impact on the participants' lifestyle habits (Taylor et al., 2022), which in some cases persisted shortly after the lockdown, when this research was conducted. Challenges with the sense of connection to others, experiences of anxiety and loneliness were reported in another qualitative study describing lived experiences of adults during the lockdown in the UK (Taylor et al., 2022). In this research, social connection was also considered more important than before lockdown. (Taylor et al., 2022) concluded that there is a need for interventions that promote wellbeing with focus on developing social networks and social support (e.g., mutual help groups). Moreover, alcohol overconsumption increased and persisted after lockdown, which was noted also in another focus group study with midlife women, in the UK (Davies et al., 2023). Encouraging behavioural substitution in unwanted behaviours (e.g., alcohol, caffeine, and unhealthy snacks consumption) was identified as an enabler in physical opportunity TDF domain and as a potential strategy for behaviour change (Davies et al., 2023a). Moreover, increasing knowledge alone may be insufficient for behaviour change (Davies et al., 2023a). A review of evidence for the effectiveness of BCTs to promote healthy behaviours recommended using social support, self-monitoring, and risk communication to complement the overreliance on providing knowledge, materials and facilitation (i.e., professional support) to patients (Van Achterberg et al., 2011). Therefore, incorporating social support (such as interaction with a coach, encouragement to join group classes or to go for a walk with a friend) may further support improvements in health-promoting behaviours. Furthermore, combining groups of techniques, such as knowledge and awareness, intention and facilitation, is also recommended (Van Achterberg et al., 2011).

Technology use and perception were very positive overall (both in the survey and focus group discussions), which might have been strengthened by the increased reliance on technology in daily chores (e.g., shopping, access to exercise classes, access to communities) during COVID-19 lockdown. Only a few studies have explored personalised and adaptive DHIs targeting midlife women, for example with focus on increasing physical activity (Arigo, Lobo, et al., 2022), although no other study identified BCTs to inform the design of such DHIs. This study achieved its aim to capture views and lived experienced of midlife women in the UK on healthy eating and regular physical activity. The identified BCTs and their corresponding mechanism of action systematically captured in the BCW/TDF/COM-B representation have the potential to be replicated and operationalised in other studies targeting lifestyle health behaviours and the population of midlife women, in the UK. Therefore, operationalising DHBCIs based on the results of this study has the potential to address the unique needs of this under-researched group of population through a group-level intervention personalisation.

6.4.1 Limitations

This study took place online shortly after COVID-19 lockdown restrictions were lifted in the UK, and a large part of each focus group discussion naturally reflected the experience of lifestyle changes during the lockdown and as a result of the lockdown. Therefore, as a result of this, the participant's lifestyle behaviours may have been different to how they were pre-lockdown (e.g., consuming more alcoholic beverages, engaging in more planning due to limited shopping opportunities, emphasising social connections), which was also acknowledged in other studies with UK populations (Davies et al., 2022; Solomon-Moore et al., 2022). An England-wide survey of around 6,000 midlife adults (aged 40-60 years) also found that almost half of the population (43%) felt more motivated to improve their lifestyle behaviours (e.g., increase physical activity, lose weight, eat healthier) due to COVID-19 (Public Health England, 2021). Additionally, the sample was recruited opportunistically and lacked diversity. Although the goal was to achieve a high level of heterogeneity within each focus groups (i.e., ethnicity, education, marital status, with/without children), the recruitment led to a very narrow diversity, with 92% of the participants being White British, higher educational (i.e., university or postgraduate degree), and higher household income (than the UK average) (Office for National Statistics, 2023). Societal norms and views on midlife and the menopause, lack of communities and information, self-identify and openness to engage in the topic have possibly impacted the recruitment process. It is important to note however, that this was a UK sample who would have experienced different local cultures (e.g., alcohol drinking) from women in other countries (Davies et al., 2022).

6.4.2 Conclusions

This study identified theory-based DHBCI components that are specific to the population of midlife women in the UK, providing intervention design personalisation at the group-level. The intervention components were based on focus group discussions that captured the target population's lived experiences with health-promoting behaviours. Applying the BCW framework allowed for systematically capturing barriers and enablers to healthy eating and regular physical activity and identifying the smallest components (i.e., BCTs) of the intervention that captured the needs of this population. Together, this study provides the next level of granularity for a DHBCI design personalisation (at the group-level), expanding on the generic global-population level intervention components captured in the systematic review (Study 1). The next chapter (**Chapter 7**) builds on the findings from this study (Study 2) and the review (Study 1) to complete the intervention design in a co-production approach involving a public/patient involvement (PPI) group of UK-residing midlife women. The PPI group's high level of diversity further allows for soliciting attitudes and experiences of women from different social groups and ethnicities so that a breath of experiences could be captured. Furthermore, in the next study (Study 3), the combined design is tested for feasibility and acceptability with a sample of UK-residing midlife women.

7. The Feasibility and Acceptability of Co-Produced Multimethod Digital Health Behaviour Change Intervention for Midlife Women in the UK

7.1 Introduction

Women in midlife experience myriad changes, including the onset of menopause and shifting social roles and responsibilities (Infurna, Gerstorf and Lachman, 2020; Arigo et al., 2023). With decreased physical activity alone, women in midlife are at higher risk of developing cardiovascular disease (Arigo et al., 2023) and gaining abdominal fat (Davidson, Tucker and Peterson, 2010; Fenton, 2021). Thus, midlife introduces unique physical and psychosocial stress for women, as well as opportunities to reflect on their values and priorities (Arigo et al., 2023). Consequently, there is a critical opportunity to develop innovative lifestyle health-promoting resources and interventions that can effectively address women's needs at midlife including healthy eating and physical activity (Arigo et al., 2023). However, interventions designed for midlife women often lack theoretical grounding and therefore provide limited knowledge about the factors that influence the success of these lifestyle improvements (Arigo, Romano, et al., 2022a; Sediva et al., 2022). This feasibility study is addressing this limitation by designing and evaluating the design of a theory informed and evidence-based multimethod intervention, targeting midlife women in the UK. Additionally, this study is addressing the need to establish a community partnership with midlife women in co-designing DHBCIs to improve healthy eating and regular physical activity behaviours. The systematic review (Study 1) revealed that designs of DHIs cannot be generalised across different contexts and populations and instead, require involvement of key stakeholders to meet the needs of the target population to be effective, also acknowledge in other studies (Craig et al., 2008; Wight et al., 2016). Therefore, the mixed-method study (Study 2) was undertaken to provide the next level of granularity, capturing group-level personalisation specific to the population of midlife women, in the UK through focus group discussions. However, to further strengthen inclusion and diversity in research (Atkin, Thomson and Wood, 2020) and to ensure the research is fit for purpose, it is relevant, acceptable, and appropriate for the needs of the target population (Greenhalgh et al., 2019; Oliver, Kothari and Mays, 2019), this feasibility study is also addressing this gap in literature by involving PPI to co-design and test the multimethod DHBCIs design. It is recommended that co-produced research is incorporated in health-related topics (Masterson et al., 2022), and it has become an expected feature of many health-related research grant applications and funding awards (Foley et al., 2023). Co-producing this research has the potential to generate value across three axes including: 1) building relationships with people (i.e., UK-residing midlife women) that live with the issue being researched, 2) developing more robust knowledge to inform interventions that will in turn be more effective and acceptable, and 3) upholding an ethical mandate to broaden research participation and knowledge development (Gradinger et al., 2015). Furthermore, interventions specifically using mHealth applications are providing new prospects for assessments and management of health-promoting behaviours, including greater scalability, intervention adherence, and at a minimum, short-term effects (Cavero-Redondo et al., 2020). Mobile technologies enable capturing of data and provide an opportunity to learn about people's disposition, behaviour, and environment (Spanakis et al., 2017). Within mHealth applications, just-in-time adaptive interventions (e.g., EMAs) offer one of the most used methods in smartphone-based monitoring (Porras-Segovia et al., 2020) by providing a continuous real-time assessment that takes place in the person's natural (ecological) environment with minimum interference (Stone and Shiffman, 2002). Therefore, such intensive repeated measure interventions have the potential to accurately assess momentary and variable experiences of the studied population at a micro timescale (over a few days) (Bamberger, 2016). Intensive repeated measure interventions use intensive longitudinal methods (ILMs), to conduct in situ assessments on participants repeatably in short intervals, often multiple times per day to capture momentary experiences or characteristics of the participants (Bamberger, 2016). As such, ILMs can support our understanding of how the intervention works for further investigation of within-person change processes (Bamberger, 2016).

To my knowledge there are no intensive assessment feasibility studies that explored improving healthy eating and physical activity behaviours in the population of UK-residing midlife women, and consequently, there is insufficient evidence to guide decisions about intensive assessments in this population. A limited number of previously published studies (Grossman, Arigo and Bachman, 2018; Arigo, Lobo, et al., 2022) used high frequency data collection assessments (using EMAs) in DHIs targeting US-residing midlife women. Moreover, the designs of these studies were not based on intervention components that were co-designed with the target population. Instead, the designs were adjusted based on the participants' feedback from usability tests assessing the participants' preferences on the content options and flow of the EMA survey. This feasibility study is advancing the current design approaches by incorporating a multimethod DHBCI design with the target population's inputs into the design's individual intervention components. Specifically, using the PBA approach alongside PPI has the potential to lead to optimally engaging interventions by incorporating a greater diversity of feedback (Muller et al., 2019).

Furthermore, feasibility studies are vital for the future evaluation of the intervention effectiveness and should be therefore conducted prior to an extended study (e.g., RCT) (Sekhon, Cartwright and Francis, 2017). While this research involves a single feasibility study to test the multimethod design (consisting of Study 1, Study 2, and co-production), following the PBA approach (Yardley et al., 2015) it is expected that additional feasibility studies may be required to achieve acceptable level of intervention optimisation (i.e., personalisation). For example, (Danielle Arigo et al., 2021) conducted a follow-up feasibility study by incorporating results from their initial 7-day EMA feasibility study with midlife women (N=13) that tested intervention design that was based on a literature review. Subsequently, qualitative interviews were conducted with another sample of midlife women (N=10) to elicit women's perceptions of revised items and to identify additional opportunities for refinement. The follow-up feasibility study with a third sample of midlife women (N=13) completed second 7-day EMA feasibility study to test the revised items and found meaningful group-level improvements in the target behaviours, including the participants' reporting of social comparison and intentions for social interactions. Although intermediate (rather than final) outcomes from single-arm feasibility studies are not designed to assess intervention effectiveness (Bowen et al., 2009), the preliminary outcomes from this DHBCI can help to further refine the intervention design in the subsequent feasibility studies.

The aim of this chapter is to complete a multimethod intervention design and to test the feasibility and acceptability of the design in a single-arm repeated measure longitudinal intervention with UK-residing midlife women. These aims are completed in four sequential steps:

1) Co-producing the intervention's key components with a PPI group and a group of health experts, providing key input into shaping this research.
2) Developing the intervention (in the EMA app used in the intervention) based on the multimethod intervention design by selecting and combining intervention components from three workstreams (Study 1, Study 2, co-production).
3) Evaluating the feasibility and acceptability of the three workstream design in a DHBCI.
4) Evaluating intermediate outcomes and group-level improvements in three target behaviours (e.g., steps count, consumption of vegetables, consumption of fruit).

*Note: Relevant supplementary materials for this study are presented in **Appendix C** of this thesis.*

7.2 Methods

7.2.1 Assessment of Feasibility and Acceptability

This single-arm repeated measure longitudinal feasibility study aims to evaluate the feasibility and acceptability of a DHBCI designed for midlife women, in the UK. The feasibility assessment consists of the following four measures:

1) Recruitment rate measures the proportion of enrolled participants with those potential participants who showed interest in the intervention.
2) Dropout rate measures the portion of participants who dropped out of the intervention from the total number of enrolled participants.
3) Response rate measures adherence to the intervention, including:
    a. Number of EMAs surveys answered using the intervention mEMA app from the total number of EMA surveys generated per participant and the group, for the intervention period (total answered / total generated)
    b. Education library content accessed on the intervention mEMA app, aggregated total number of times each day and for the intervention period
    c. Steps recorded each day using Garmin fitness tracker (aggregated daily per participant).
    d. Daily total sleep and deep sleep minutes recorded using Garmin fitness tracker (aggregated daily per participant)
4) Data collection tools and methods (feasibility of the procedures to extract data from mEMA and Garmin, and prepare the intervention dataset for statistical analysis)

Acceptability of the intervention is assessed post-intervention, based on the feedback from the intervention participants using the TFA questionnaire (Sekhon, Cartwright and Francis, 2022). The questionnaire is assessing eight areas of acceptability, including affective attitude, burden, ethicality, perceived effectiveness, intervention coherence, self-efficacy, opportunity cost, and general acceptability (see **Chapter 4** for details on this questionnaire). Additionally, acceptability of the intervention prototype is assessed based on the feedback from the PPI group (pre-intervention) (see **Section 7.2.5.1**).

7.2.2 Assessment of Intermediate Intervention Outcomes

Preliminary analysis of the effects of the intervention (e.g., design and delivery) were evaluated on group-level improvements in the target behaviours (identified in co-production). The preliminary analysis includes:

1) Descriptive statistics (e.g., number of participants engaged on each day of the intervention, average group-level change in each intervention outcome (on each intervention day)
2) Within- / between-person variability in the outcomes, and the effects of time on the intervention outcomes using multilevel modelling (MLM).
3) Correlation analysis of all intervention outcomes using weighted Spearman's Rank Correlation (r_s)

7.2.3 Intervention Setting and Participating Criteria

The study setting was in the participants' real-life environment (e.g., home, work) and required no visits to the university. Recruitment inclusion criteria included cisgender females, aged 40 – 65 years, and residing in the UK. The participants were required to not participate in any other lifestyle intervention concurrently and not travel during the intervention, potentially resulting in changes in their typical daily dietary, sleep, and physical activity behaviours. The participants were required to read and understand instructions in English and be able to engage in light physical activity, such as walking. Ethical approval (ETH2223-0933) was obtained by the University of Westminster Ethics Committee on 16/3/2023, prior to recruitment. The study protocol was registered with the ISRCTN (ISRCTN reference: 15365883).

7.2.4 Sample Size and Recruitment

For the purpose of the feasibility study, the aim was to recruit a minimum of 27 participants to generate useful data for statistical analysis. Additionally, it required a dataset that allowed for conducting a statistical analysis in a 2-level MLM. Anticipating mean completion rate of EMA surveys of 76% (Degroote et al., 2020) and a drop-out rate of 17% (de Vries, Baselmans and Bartels, 2021), the aim was to enrol 35 participants through purposive and snowball sampling. Following ethics application approval, the study recruitment flyer was posted on X (former Twitter), the researcher posted flyers at building of the university and shared the flyer with healthcare professionals specialising in menopause. During the recruitment process, the participants expressed learning about the study on various menopause-related support groups on Facebook, suggesting the flyer was reposted by others. To improve the diversity of the participants, the researcher attended several events to promote the study. This included two events organised by the black menopause community, a women's digital health (FemTech) event and presentations at two scientific meetings. The researcher followed up with each interested candidate by providing them with the study's Participant Information Sheet (PIS) and Informed Consent (IC), by email. Each participant attended a 15-minute introductory meeting on Microsoft Teams in which the researcher screened the participants for eligibility to join the study and further reviewed the PIS and IC forms. The participants had an opportunity to ask questions about the study and discuss any needs and constraints (e.g., planned travel, inability to wear fitness tracker continuously). After the introductory session, the participants were asked to sign the IC in Qualtrics software, under the University of Westminster license. Participants were offered the fitness trackers they used during the intervention for full participation in the research (e.g., no dropouts, wearing their fitness tracker daily for the duration of the study resulting in recorded daily steps and sleep data).

7.2.5 Intervention Design

7.2.5.1 Co-Production of the Intervention Design

Co-designing key intervention components (e.g., identification of target behaviours and intervention content) was completed with the involvement of a public/patient involvement (PPI) group and a health expert group, providing the final input for the multimethod intervention design. The intervention content provided to the participants digitally during the intervention was developed in collaboration with health experts, consisting of a nutritionist specialising in menopause, an NHS GP providing health and menopause-related content, and by an exercise physiologist (see **Contributors** section of the thesis). While additional experts (e.g., a professor of female endocrinology and exercise physiology, UK menopause-app charity, technology experts specialising in low-code apps) were invited to collaborate individually or in a group setting, they declined the invitation to contribute to this research.

7.2.5.1.1 PPI Group Characteristics

A total of seven midlife women (mean age 47 years, range 42 – 59) were recruited as members of the PPI. The sociodemographic diversity included ethnicity (e.g., Indian, Asian, Middle Eastern, White British, European White), number of children (e.g., 0 to 2), education (e.g., lower secondary to post-graduate), marital status, and income level, gender identity (one woman referred to herself as gay). Self-assessed menopause status indicated that three were pre-menopause, three perimenopause, and one post-menopause and two women were currently on HRT. The group members were compensated for their time participating in all activities according to the NIHR payment guidelines (NIHR, 2022), and funded by the University of Westminster Participatory Research Award.

7.2.5.1.2 Theoretical Frameworks and Approaches

The Person Based Approach (PBA) (Yardley et al., 2015), which typically combines stakeholders and PPI with in-depth qualitative and mixed methods research, was at the core of the co-production approach in this research. The PBA has a strong emphasis on person-centred planning, optimisation, and evaluation of DHBCIs. Additionally, in this research, the BCW guide (Michie S, Atkins L, 2014) supported all PBA Planning phase activities and combined the co-produced content (presented in this study) with in-depth primary mixed methods research (Study 2) and a synthesis of existing evidence (Study 1) (**Figure 11**). The co-design process in this research was guided by the BCW guide in defining target behaviours, COM-B components, TDF domain links, intervention functions, and BCTs (see **Chapter 3** for description of these theoretical constructs).

Furthermore, the three-workstream design (i.e., Study 1, Study 2, co-production) led to the development of the intervention prototype that was tested for usability by the PPI, in the PBA Optimisation phase (see **Figure 11**). The PPI suggested changes from their usability testing of the intervention prototype were captured in the PBA's Table of Changes template, in which the changes are prioritised using the MoSCoW technique (Bradbury et al., 2014) and identifies changes in four categories (e.g., 'Must have', 'Should have', 'Could have', or 'Won't have') (Ferrey et al., 2018) (see **Appendix C, Table 57**). Subsequently, the intervention design was adjusted based on the captured feedback, thus following an iterative process between Optimisation and Planning phases. Following the adjusted intervention design, testing the final multimethod design was done in the intervention, followed by an optimisation of predictors using ML, described in the next **Chapter 8** (Study 4). Additionally, while PBA also includes an Implementation and Evaluation phase, this phase is not included in this research. However, in the future, this phase can follow the final optimisation iteration of the intervention design completed in the PBA Optimisation phase (see **Figure 11**).

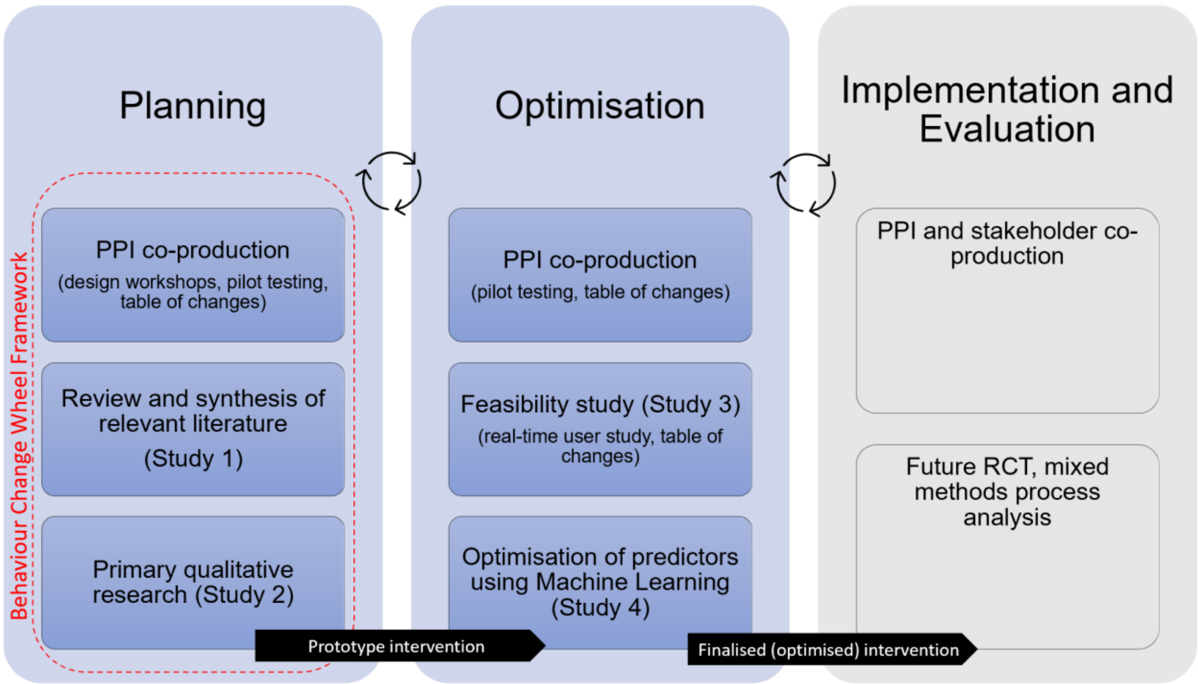


Figure 11: The person-based approach (PBA) adjusted for this research, adapted from (Yardley et al., 2015)

7.2.5.1.3 Co-Production Objectives and Activities

The co-production activities, guided by the BCW guide, included three group workshops, each preceded by an individual preparation (pre-workshop activity). The primary objective of the workshops was to identify key intervention components, including: 1) target behaviours for healthy eating and physical activity, 2) describing target behaviours using the COM-B model and TDF framework to identify a broad spectrum of theoretically derived influences on lifestyle behaviours, 3) identifying relevant educational content topics on diet and physical activity, and identifying the mode of delivery (MoD) and intervention functions (e.g., types and frequency of prompts) to best engage with the intervention participants (see **Figure 12**). In addition, two practical components were also included, 1) to experience the intervention technologies, and 2) to perform usability testing of the intervention prototype (see **Table 23** for details of each activity completed by the PPI). Participation in each activity was high, with 90% (6/7) of members on average participating in each activity. Concurrently to this design study, focus groups were conducted with midlife women (see previous **Chapter 6**). The PPI group reviewed focus group surveys and participated in a pilot focus group session to ensure the focus group topics were relevant, acceptable, and addressed the needs of this population (see **Appendix C, Table 56** for a summary all activities the PPI group was involved in, including in Study 2).

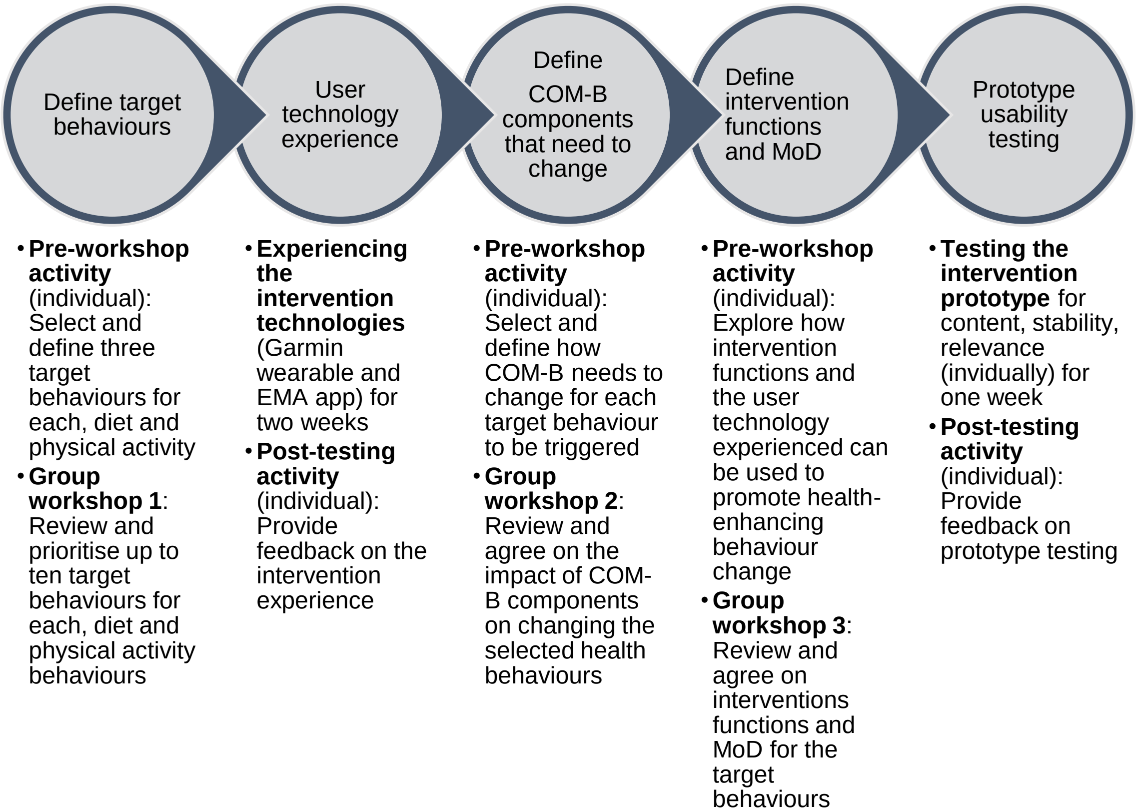


Figure 12: Intervention co-design process and activities following the BCW guide

Table 23: Co-production activities in intervention design

Workshop #	Title and summary of the activity	PPI group tasks (pre-workshop activity)	Supporting material	Links to BCW stages	Post-workshop activity (completed by the research team)	Methodology/ Framework applied
Workshop 1	Define the 'problem' in behavioural terms	Select and define 3 target behaviours for each, diet and physical activity	Presentation and audio recording explaining the topic and task. Link to an online form to complete the task.	*Stage 1: Understand the behaviour*: 1a) Define the problem in behavioural terms 1b) Select target behaviour	Consolidate PPI group discussion inputs. Identify target behaviours for healthy eating and for physical activity.	BCW guide worksheets: Who does what, when, where?
Testing	User technology experience	A two-week period of using the technology in daily life. The EMA app was programmed to interact 4 times daily.	Each participant received a Garmin device and EMA app instructions on downloading and setting up the app. A link to an online survey form (JISC) to provide feedback on the user technology experience.	N/A	PPI group provided feedback (e.g., frequency of interactions, types of input, what worked, what did not work well) on their user technology experience via online survey form.	COM-B

Workshop 2	Understand behaviour in the context and identify change barriers/enablers	Select and define how COM-B needs to change for each target behaviour to be triggered.	Presentation and audio recording explaining the topic and task. Link to an online form to complete the task.	*Stage 1: Understand the behaviour:* 1c) specify the target behaviour 1d) Identify what needs to change.	Consolidate input and identify COM-B mapping for eating and for physical activity.	TDF
Workshop 3	Define intervention functions and mode of delivery for each target behaviour	Exploring how intervention functions and the technology experienced can be used to promote healthy eating and regular physical activity.	Presentation and audio recording explaining the topic and task. Link to an online form to complete the task.	*Stage 2: Identify intervention options:* 2a) Intervention functions *Stage 3: Identify content and implementation options:* 3a) Behaviour Change Techniques (BCTs) 3b) Mode of delivery	Consolidate input and finalize the BCW mapping, by completing the TDF, intervention functions, and identify BCTs.	BCT taxonomy
Prototype Testing	Prototype usability testing	Testing of the content and usability of the intervention prototype	Each participant receives instructions on how to connect Garmin with EMA and instructions on how to test the prototype A link to an online survey	N/A	PPI group to provide individual feedback on the usability (number of interactions, length of instructions, clarity of messages) of	MOST, PBA

			form (JISC) to provide feedback on the prototype testing experience.		the prototype via online survey form.	

The content of the design workshops was guided by the BCW guide, which provided example worksheets for each workshop. The BCW guide describes three stages in the behaviour change intervention design process, which often require an iterative process (see **Chapter 3** for description of the guide). Each workshop was built on the completed activities and discussions in previous workshops, allowing for a more natural familiarisation and progression, starting with identifying target behaviours (Workshop 1), specifying what needs to change in the target behaviours (from Workshop 1 into Workshop 2), and identifying how the specified target behaviours (from Workshop 2) can be delivered in the intervention (Workshop 3) (see **Table 23**). Although the workshops followed the BCW guide in a sequential order, the discussions between each workshop were iterative, and occasionally as the discussions progressed, some topics previously discussed were further refined and adjusted in the subsequent workshops. For example, the initial definition of the target behaviour to 'replace coffee break with a short walk' (in Workshop 1) was further refined as the group felt that it is not always possible to go for a walk in the middle of the day. It was adjusted (in Workshop 3) to include getting up and moving throughout the day, creating a walking meeting initiative at work, having a cup of coffee while walking. Topics for the educational library content for the intervention's EMA app were collected throughout the workshops (as new topics naturally came up in the group discussions) and were grouped into topics on menopause, diet, and physical activity (see **Appendix C, Table 59** for education topics). The content for the topics was co-produced in collaboration with health experts (**Section 7.2.5.1**).

7.2.5.1.3.1 Workshop 1: Identifying Target Behaviours

In the first workshop, the group met for the first time and the first part of the session was dedicated to introductions, the role and responsibilities of the PPI group, the research project objectives, and overview of each activity. Prior to workshop 1, the group was provided with instructions on how to complete the pre-workshop activity and how to submit their individual input via JISC prior to the workshop. The first two-hour workshop was dedicated to identifying target behaviours for healthy diet. The richness of the discussion led to scheduling a one-hour follow-up meeting to identify target behaviours for physical activity. At the end of each workshop, the group prioritised the target behaviours, resulting in 13 healthy eating target behaviours (e.g., decrease consumption of caffeinated and alcoholic beverages, increase hydration (water intake), add healthy snacks, decrease consumption of unhealthy snacks, add fresh healthy meals, remove ultra-processed foods, increase healthy protein intake, decrease consumption of red meat, consume more fruit and vegetables, eat regular three meals per day, consume less food than stressed (bored or watching TV), reduce take-aways (cook more at home)) and 10 physical activity behaviours (e.g., increase walking with progression, replace driving or public transportation with walking, increase strength building exercises, join an exercise class or group exercise activity, reduce sedentary behaviour by replacing coffee break with a short walk, incorporate walk-to-run, incorporate mobility exercises, make a commitment to your exercise plan, change existing exercise routine to find new exercise options, try different strategies to exercise (different time of day or place)).

7.2.5.1.3.2 User Technology Experience

The user technology experience activity was originally not planned; however, it was introduced before Workshop 2 to improve the group's familiarity with the intervention technologies prior to discussing how such technologies can be used to improve healthy eating and physical activity. Prior to this workshop, only one group member used a fitness tracker, and no one was familiar with mobile applications that provide prompts and ask for user input. This activity was added to ensure the group was better prepared for the subsequent design workshops. In this two-week experience, each group member was provided with the intervention's planned technologies: a Garmin Vivosmart4 device (fitness tracker) and instructions on how to install Ilumivu EMA app (mEMA). All group members were able to setup the fitness tracker themselves. Two members reported difficulties with charging the device. All group members also installed the EMA app on their own mobile devices and the researcher programmed the mEMA app to provide a sample of varied types of interactions to experience. For example, the mEMA app displayed prompts in different duration, asked for user input in various formats (e.g., sliders, checkboxes, radio buttons), displayed reminders, and provided sample educational content. During the subsequent two weeks, the Garmin fitness tracker provided each member with information on their physical activity (through both the device and Garmin Connect app) and the EMA triggered four user interactions daily. The group reported challenges with the EMA app (e.g., messages not being triggered when traveling to a different time zone, skipped messages), which were logged and communicated to the Ilumivu support team. The group completed a survey at the end of the technology experience with their feedback. Tailored timing of messages, short length of messages, and tailored lifestyle options were found to be desirable.

7.2.5.1.3.3 Workshop 2: Identifying What Needs to Change (COM-B and TDF)

The pre-workshop activity was provided together with detailed audio/written instructions and examples of the COM-B model. As an extra challenge for those members wanting to explore each target behaviour in-depth, the TDF framework was introduced with examples on how it can be used. All members completed the COM-B exploration of each target behaviour (from Workshop 1), but only two members attempted to complete the TDF mapping. Overall, the group did not find the TDF framework easy to follow and therefore, the researcher adjusted the pre-workshop and workshop objectives to focus only on the COM-B model. An example of a completed pre-workshop activity by all members shows their input into 'what needs to change in a midlife woman's capability, opportunity, and motivation to eat healthier', with each target behaviour expanded into Capability, Opportunity, and Motivation. The same activity was completed also for physical activity target behaviours asking the question 'what needs to change in a midlife woman's capability, opportunity, and motivation to exercise regularly'. The consolidated pre-workshop activity was utilised in the two-hour group workshop. Overall, the group had most difficulties with exploring the COM-B model's 'opportunity' (e.g., time, money, resources), which might have been influenced by the higher socio-economic background of the group, and therefore by already having access to these resources.

7.2.5.1.3.4 Workshop 3: Identifying Intervention Functions and Mode of Delivery

The pre-workshop activity involved identifying intervention functions (e.g., how should the intervention help women achieve this), and mode of delivery (e.g., a description of when, how, how often to deliver the intervention component, using the intervention technology (Garmin or mEMA)). An example of the completed pre-workshop activity shows how this was addressed for 'swapping coffee break for a walk'. A two hour-workshop completed the group's intervention design input.

7.2.5.1.3.5 BCW Mapping and BCT Identification (by the researcher)

After the final workshop was completed, the researcher (HS) finalised the TDF mapping and identification of BCTs for the target behaviours (developed by the PPI group across the three workshops). On average, there were 30 BCTs (range 27 – 32) identified across seven use cases. The majority of the BCTs were mapped to the 'Social support', 'Self-belief', 'Repetition and substitution', 'Natural consequences', 'Antecedents', and 'Goals and Planning' BCT clusters (at 100%, 64%, 57%, 57%, 55%, and 54%, respectively). The use cases represented groupings of related components of the target behaviours into the BCW worksheets. For example: the ten physical activity target behaviours were grouped into four BCW specifications (i.e., 'reduce sedentary behaviour: increase walking'; 'incorporate cardio: power walking, running, cycling, swimming'; 'incorporate strength training: increase strength building exercises'; and 'incorporate mobility training: stretching, joint mobility, Pilates, yoga'). Additionally, 'increase walking' target behaviour included: 'increase walking with progression';

‘replace coffee break with a short walk’; and ‘replace driving or public transportation with walking’. Three exercise target behaviours to 1) ‘change your routine to find new exercise options - do any physical activity that you enjoy’; 2) ‘make a commitment to your exercise plan - set daily time to exercise for 1hr, exercise regularly, stay patient and consistent’; and 3) ‘try different strategies - try to exercise first thing in the morning, if it doesn't work, try in the afternoon’ were incorporated into all physical activity use cases. Similarly, healthy eating target behaviours were grouped into three BCW specifications representing three use cases: 1) ‘decrease consumption of caffeinated beverages’; 2) ‘decrease consumption of alcoholic beverages’; and 3) ‘consume healthy meals and snacks’. The target behaviour to ‘increase consumption of water’ was incorporated into use case 1 and 2, and all other diet target behaviours were incorporated into use case three. The final activity involving intervention prototype testing is described in **Section 7.2.6.2.5**, after describing development of the intervention.

7.2.5.1.4 Reflexivity

Reflexivity is central to not only qualitative research (Jamieson, Govaart and Pownall, 2023) and recommended in TA, but it has also been applied to co-production (Foley et al., 2023). Co-production research hold enormous value within the health science and with heavy focus on what research participants think, do, or know, it provides a missed opportunity to reach its potential (Foley et al., 2023). While PPI are ought to be equal participants in the research process, together with the researcher, reflexive awareness during co-production illuminates power dynamics within the co-production group. PPI groups with greater diversity and social hierarchies (Foley et al., 2023) also require awareness of the researcher. For example, some group members had access to more advanced technologies than the provided Garmin device and EMA app, while other group member have never owned such device. Reflexivity involved checking if the PPI group understood the topics of discussion. Although consensus for example in the prioritisation of target behaviours was important to achieve, the researcher was also aware of the power dynamics, as collaborative research relations often trigger tension among co-creators (Foley et al., 2023).

7.2.5.2 Combining Multimethod Intervention Design

The multimethod intervention BCTs from the systematic review (Study 1), focus groups (Study 2), and co-production (described in this chapter) were combined (**Appendix C, Table 60**). The combined intervention design consisted of a subset of 34 BCTs. Specifically, the majority of the BCTs (17%; 6/34) were selected from the Behaviour change category (BCC) of Goals and planning, while Regulation and Covert learning had no BCTs identified through any of the three studies (**Table 24**). The mechanism of action (MoA) (i.e., the processes through which a BCT affects behaviour) (Cane, O'Connor and Michie, 2012a) linked to BCTs were consolidated. Triangulation between the BCTs and MoA were reviewed using the Theory and Technique Tool (TaTT) (Bohlen et al., 2018; Michie, Carey, et al., 2018; Johnston et al., 2021; Michie et al., 2021). Mode of delivery (MoD), representing an attribute of the intervention delivery that is the information or physical medium through which the behaviour change is provided (Marques et al., 2020), was also combined when applicable. For example, informational MoD included how to deliver rewards (e.g., a badge and congratulation on the mEMA app on reaching goals, enabling feature on the fitness tracker to display when steps goals were reached), human interactional MoD (e.g., how the researcher will communicate with the intervention participants in real time).

Table 24: Combined intervention design BCTs

Behaviour Change Category (BCC)	**BCTs, n**	**Behaviour Change Techniques (BCTs)**
Goals and planning	6	Goal setting behaviour, Problem solving, Action planning, Behavioural contract, Commitment
Feedback and monitoring	3	Feedback on behaviour, Self-monitoring of behaviour, Biofeedback
Social support	3	Social support (unspecified, practical, emotional)
Shaping knowledge	2	Instruction on behaviour, Information about antecedents
Natural consequences	3	Information about health consequences, Salience of consequences, Information about emotional consequences
Comparison of behaviour	1	Demonstration of behaviour
Association	1	Prompts/cues
Repetition and substitution	5	Behavioural practice/rehearsal, Behavioural substitution, Habit formation, Habit reversal, Graded tasks
Comparison of outcomes	1	Credible sources
Reward and threat	2	Social reward, Self-reward
Regulation	0	

Antecedents	3	Restructuring the physical environment, Restructuring the social environment, Adding objects to the environment
Identity	1	Framing/reframing
Scheduled consequences	1	Rewarding completion
Self-belief	3	Verbal persuasion about capability, Focus on past success, Self-talk
Covert learning	0	N/A

7.2.6 Intervention Development

7.2.6.1 Intervention Technologies

To achieve the study objectives, including monitoring physical activity and providing behavioural content for improving diet and physical activity, the intervention technologies included in both, co-production activities and in the intervention with the participants, consisted of an a just-in-time adaptive intervention (JITAI) application, and a fitness tracker. The mobile application was based on an EMA type of application developed by Ilumivu under the name "mEMA" (Ilumivu.com, 2009), which provides a customisable platform for researchers to develop JITAI. In addition to the mEMA app, each participant was also provided with a Garmin Vivosmart4 fitness tracker (Garmin.com, 2020) to track their daily physical activity and sleep. This specific device was selected for the intervention for its existing built-in integration with the mEMA app. Therefore, with this integration, raw Garmin steps and sleep data collected from the participants were available for extraction on the Ilumivu data server. Garmin Connect application was also used to setup Garmin devices and for the researcher to review setups and verify data was being collected.

7.2.6.2 Operationalising Intervention Components

To assist in the development of the intervention on the mEMA platform, use cases (if-then scenarios) were designed for each of the five daily EMA surveys (e.g., morning, late morning, early afternoon, late afternoon, evening) and for each of the ten selected target. Each of the five use cases consisted of a pre-condition, review of tasks, assessment, counselling, assignment of tasks, and post-condition (**Appendix C, Figure 70**). For example, the morning EMA consisted of 13 BCTs, with most (9/13) BCTs invoked through the with basic flow (i.e., the 'happy path' that does not require counselling), and additional counselling with 4 BCTs that is invoked when the participant doesn't reach their goals (**Figure 13**). Late morning, early afternoon, late afternoon EMAs consisted of 12, 11, 6, 11, BCTs, respectively (see **Appendix C**, **Figures 71, 72, 73, 74**).

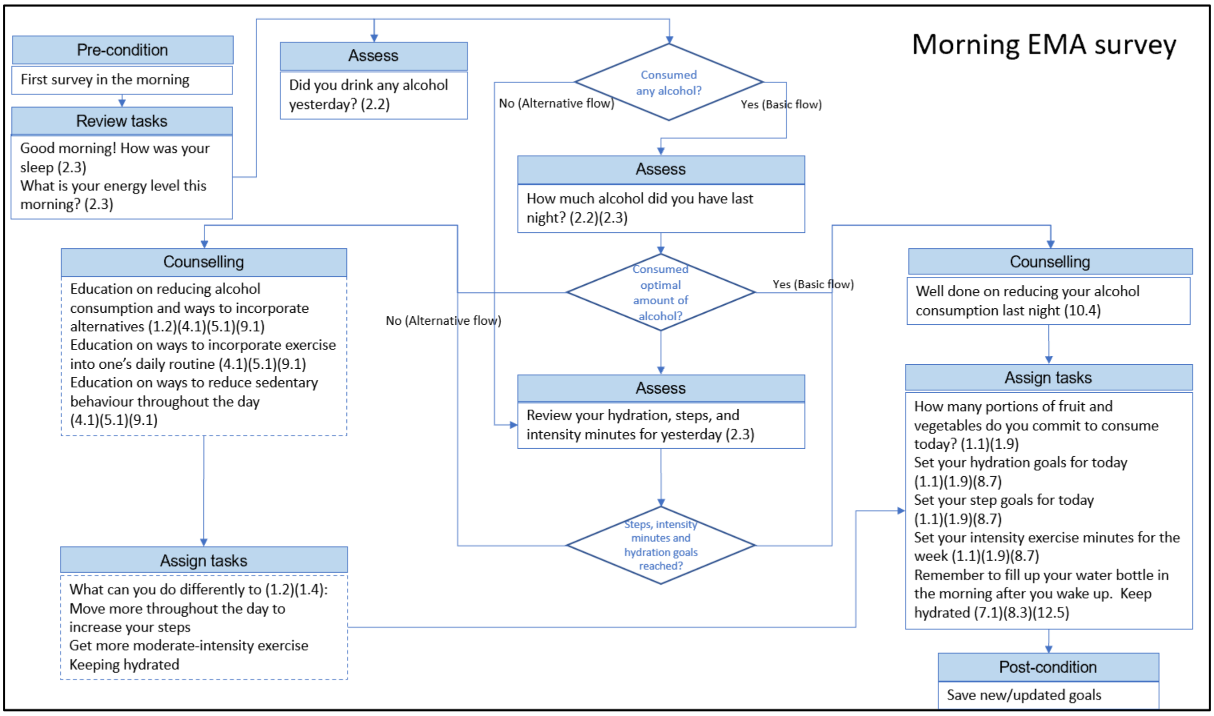


Figure 13: Morning EMA use case

Following the if-then scenarios, a detailed design was developed for each interaction between the participants with the intervention technologies (**Appendix C**, **Table 61**). This template was developed by the researcher and consisted of a description of the mode of delivery, type of interaction, the text displayed, user input options, and links to the pre-intervention survey questions to measure participant responses prior to the intervention and during the intervention using the same measures to evaluate changes over time. Each interaction was also linked to a group of at least one or more BCTs.

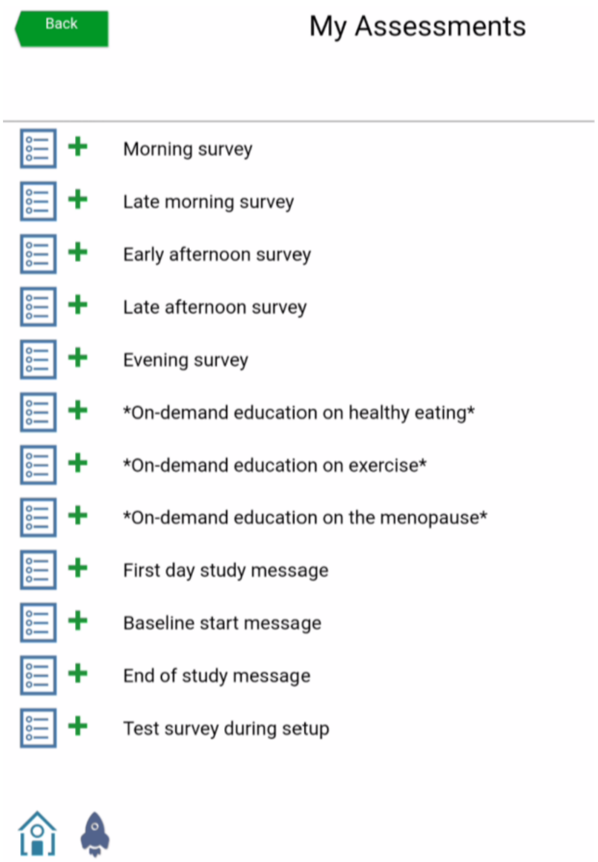
7.2.6.2.1 Primary Intervention Outcomes

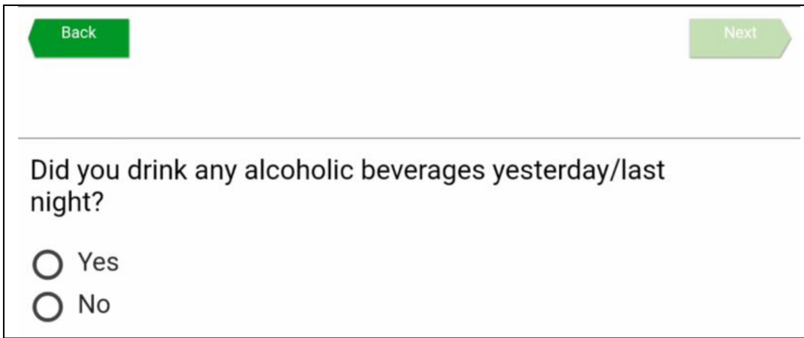
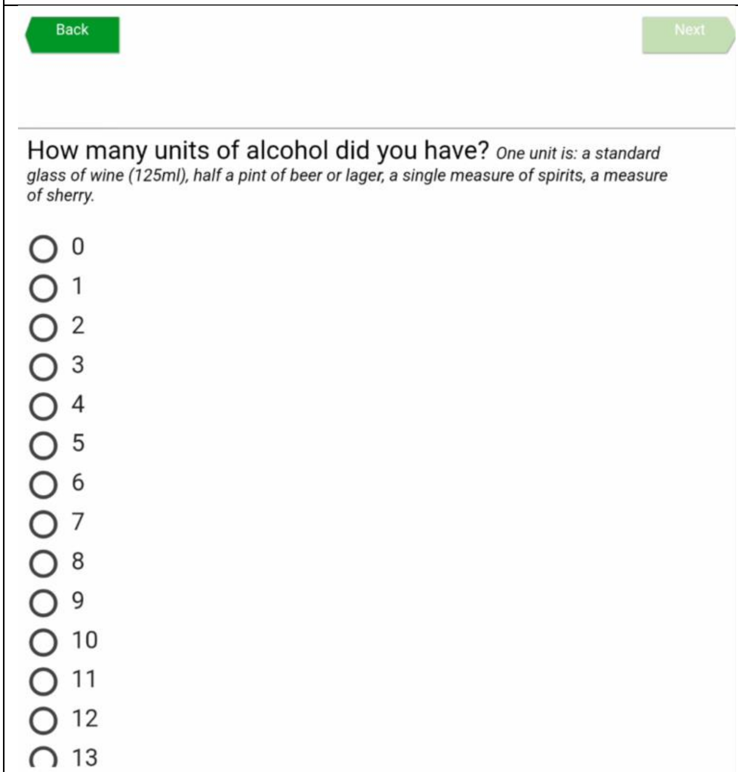
Most of the content in both education and EMA surveys focused primarily on improving steps count, consumption of vegetables, and consumption of fruit. Therefore, these three outcomes (i.e., steps count, consumption of vegetables, and consumption of fruit) are referred to as the primary intervention outcomes, while the rest of the other seven outcomes (i.e., water intake, caffeine intake, alcohol consumption, snacks consumption, and meal consumed, sleep quantity, and sleep quality) are referred to as the secondary intervention outcomes. Several studies encouraged adoption the MeDi diet (patterns) in midlife adults (Herber-Gast and Mishra, 2013; Sayón-Orea et al., 2015; Berti et al., 2018; McEvoy et al., 2018; Flor-Alemany et al., 2020; Recio-Rodriguez et al., 2022), which promotes higher consumption of fruit and vegetables. Additionally, promoting colourful meals has been shown to increase consumption of fruit and vegetables in other studies (König and Renner, 2019) and the education content developed in this study by Dr Wyness also emphasised consuming colourful foods. Additionally, the participants received daily EMA prompts (after breakfast, lunch and dinner) to rate how colourful their meals were, to increase their consumption of fruit and vegetables. Furthermore, to maximise accessibility, physical activity behaviour was defined as total steps per day. Steps are a commonly used metric to evaluate physical activity and are associated with improved health outcomes (Hajna, Ross and Dasgupta, 2018). Other studies promoting increasing physical activity in midlife adults focused on increasing walking (i.e., steps count) (Arigo and König, 2024), and ability to walk was also included in this study's participant inclusion criteria. Furthermore, the Garmin fitness tracker's functionality is best suited for steps count that is recorded automatically without the participants needing to start or stop the exercise activity, and it is therefore less disruptive.

7.2.6.2.2 mEMA App User Interface and Survey Screenshots

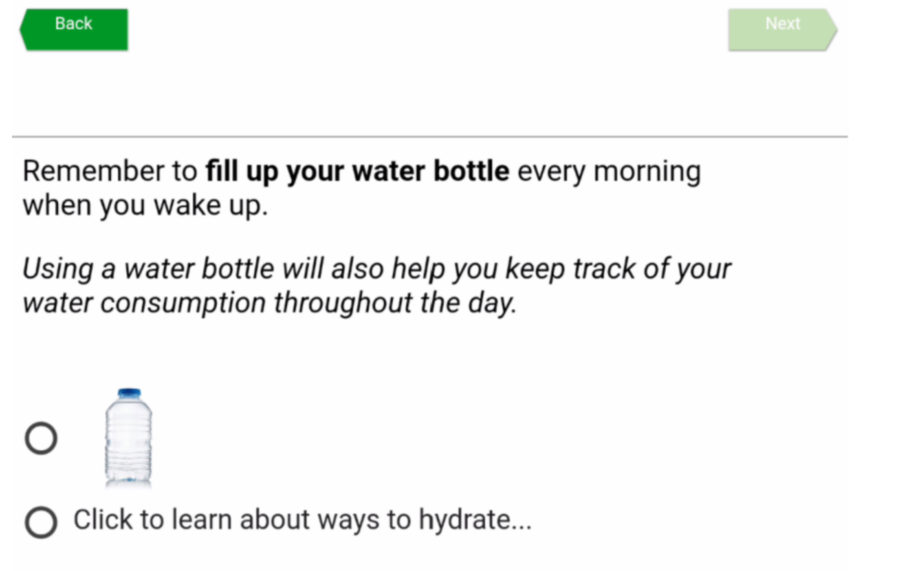
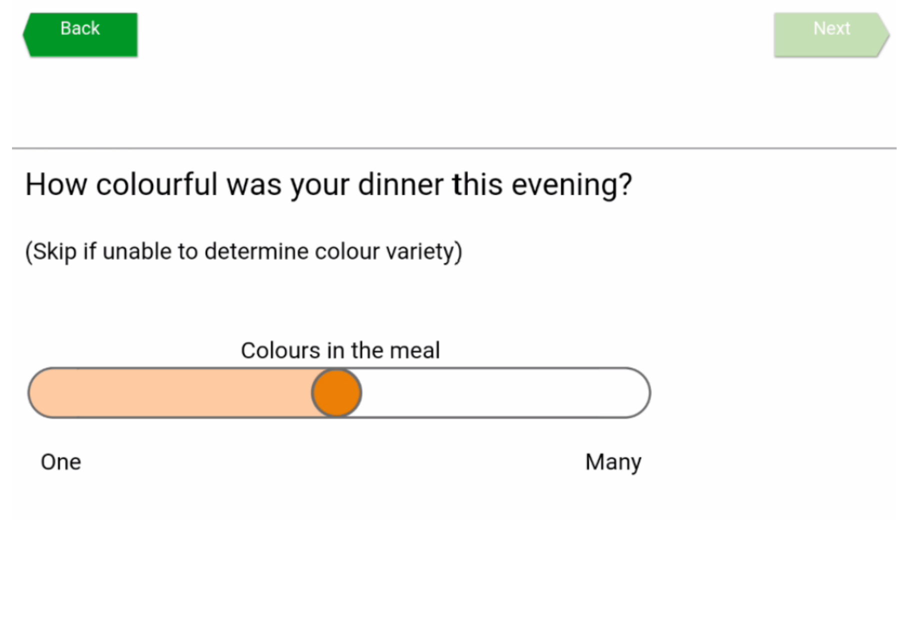
The researcher developed the intervention on the mEMA platform by following the intervention design process flows and the intervention template. A few examples of screens from the mEMA app are shown in **Table 25**, with examples of daily surveys and educational content. It is important to note that the mEMA platform had limitations to how each survey could be displayed, including unsupported change of font, colour, and weblinks, limited use of images, and navigation. There is no natural 'nesting' structure that would allow for easy navigation between different topics.

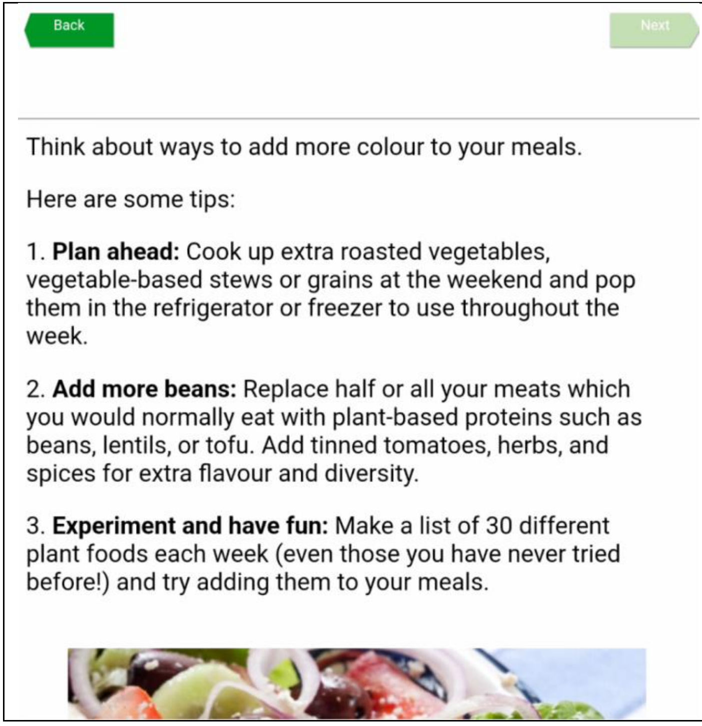
Table 25: Screenshots from the mEMA app

mEMA app screenshot	Purpose
	**Main menu:** Accessing daily surveys through 'My Assessments'
	**Accessing daily surveys:** Typically, the participants would see only the three sets of education with * around the title. All other surveys were triggered automatically and available to access during their scheduled time.

	**Collecting data:** alcoholic beverages consumption. This is an **outcome** data and needs to be provided for data analysis.
	**Collecting data:** alcoholic beverages consumption. This is an **outcome** data and needs to be provided for data analysis.

Back Next Did you know, there are some practical ways to reduce alcohol consumption, including: • **Set you own limits** – you could limit your drinking to a maximum of 1 or 2 alcoholic drinks at a time and to only drink at a weekend or any two days of the week. You could also set yourself a time limit where you completely stop drinking alcohol for a period 2 weeks or 4 weeks or perhaps longer? • **Drink mindfully** – when you do have a drink, really focus on the flavour and aroma and mouthfeel. This should help you be more aware of what you're drinking, rather than mindlessly drinking whilst distracted watching TV. • **Dilute the drink** – drink a glass of water along with an alcoholic drink, or make sure you have a non-alcoholic drink in between an alcohol drink. Diluting wine with plain water or soda water or drinking a gin and tonic in a tall glass can help the drink last longer and makes the alcohol less concentrated.	**Counselling:** Triggered by the participant's data input. Example when entering more than 14 units of alcoholic beverages consumed. Counselling targeting alcoholic beverages consumption **outcome** improvements.
Back Next How many portions of **fruit** do you **plan** to consume today? *A portion of fruit includes: a handful of berries (raspberries, blueberries, strawberries), or a piece of medium-sized fruit (apple, banana, pear, orange), a handful of larger fruit (mango, pineapple, melon), or a more than 2 pieces of small fruit (apricots, kiwi).* *Having about 3 portions of fruit a day, spaced out across the day may be a useful target to aim for.* 0 1 2 3 4 5 6 7 8 9	**Goal setting:** Portions of Fruit Used in data analysis to identify correlation between goal setting and fruit portions consumption. Both, whether the goal was set (if the survey was answered) and how many portions were entered were used in data analysis.

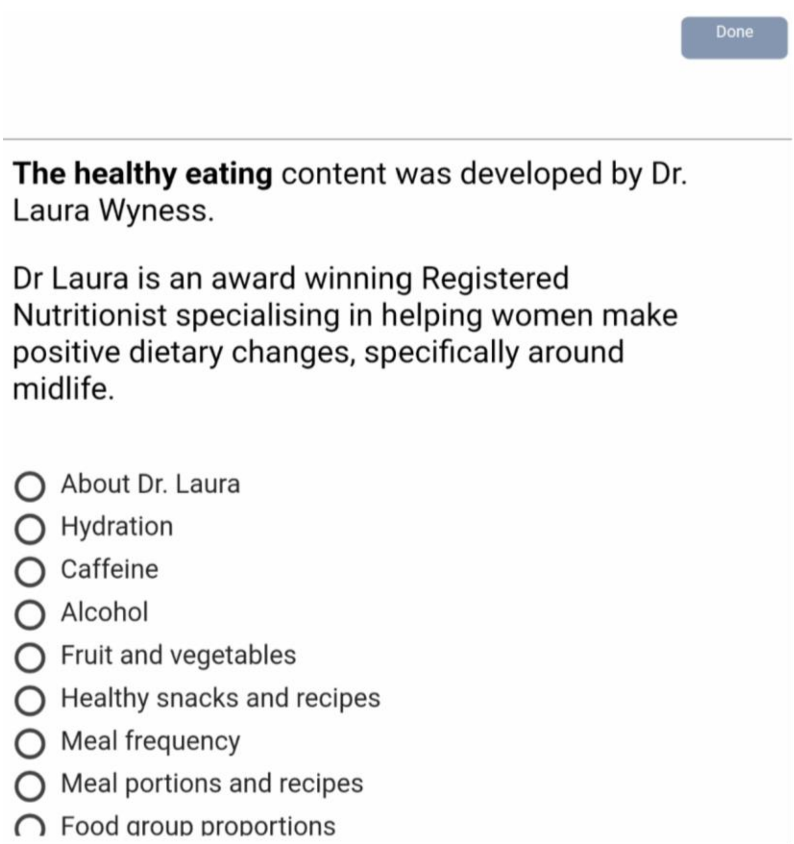
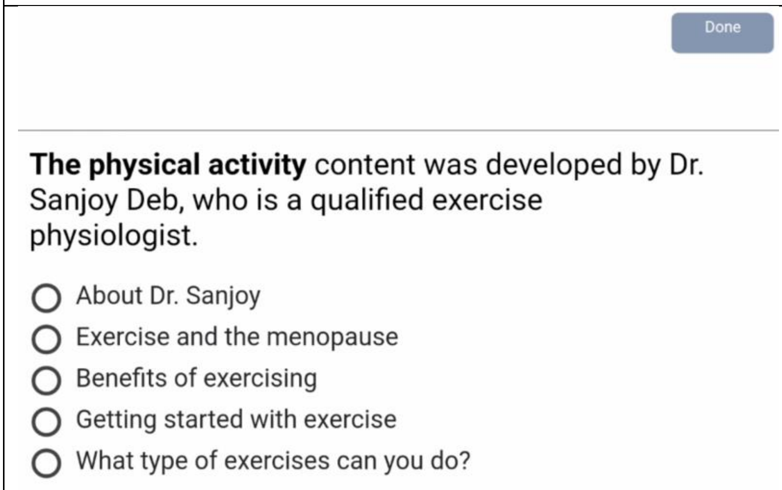
	**Counselling:** Daily morning survey reminder. (not triggered by user input). Counselling targeting water consumption **outcome** improvements.
	**Collecting data/counselling:** Colourful meal rating (same question in the late morning, early afternoon, and evening survey) This data is used in data analysis to determine correlation between meal colourfulness rating and portions of fruit and vegetables consumed at each meal/

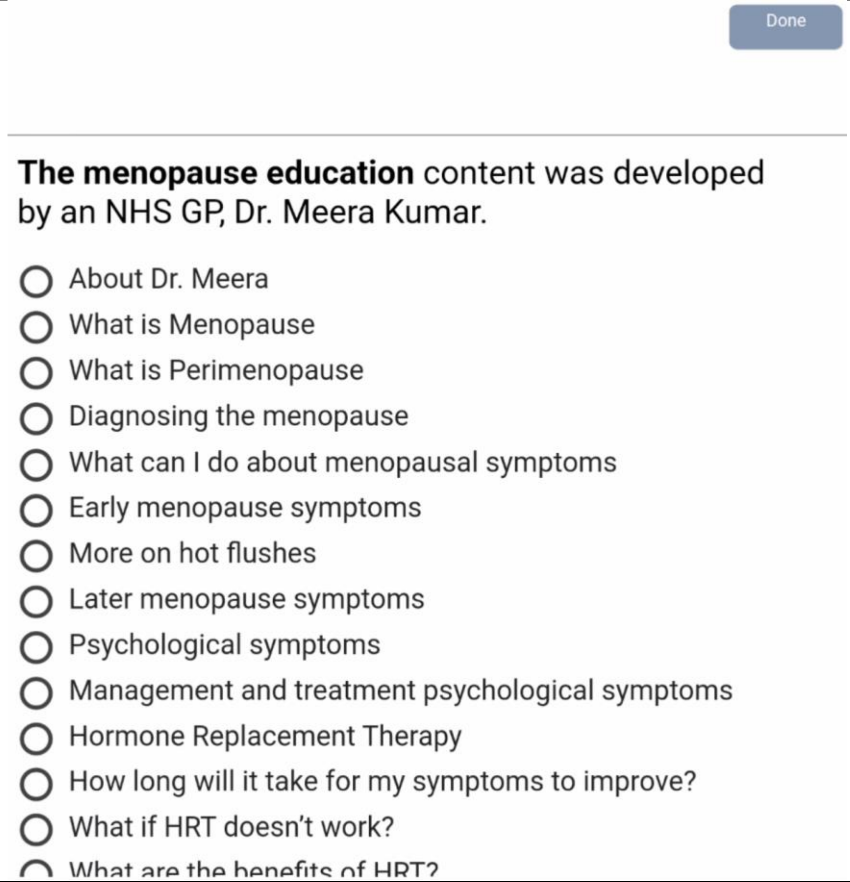
	**Counselling:** Shown based on the previous entry by the participant. If colourful rating is low, counselling on how to improve colourfulness is shown at each meal rating data collection. This content is also available in the on-demand educational library.

7.2.6.2.3 Educational Library on Diet, Sleep, Physical Activity, and Menopause

The mEMA app also included an 'educational library' content on healthy eating, physical activity, and menopause, specifically tailored to midlife women. The topics for this content were identified in co-production with the PPI group (**Appendix C, Table 60**) and written in collaboration with health experts (i.e., a qualified PhD nutritionist, an exercise physiologist, and an NHS GP), to provide the required level of credible sources (BCT 9.1 Credible Sources was also included in the intervention design). Once written, the researcher implemented the content in the mEMA app. This educational content was available to the participants on the mEMA app at all times, during the 14-day programme. Each main topic had subtopics that were accessible through the menu on the mEMA app. For example, main topics included diet (e.g., hydration, caffeine, alcohol, fruit and vegetables, healthy snacks and recipes, meal frequency, meal portions and recipes, food group proportions, supplements, sleep), physical activity (e.g., exercise and the menopause, benefits of exercising, getting started with exercise, what type of exercises can you do), and menopause (e.g., what is menopause, what is perimenopause, diagnosing the menopause, what can I do about menopausal symptoms, early menopause symptoms, more on hot flushes, later menopause symptoms, psychological symptoms, management and treatment of psychological symptoms, hormone replacement therapy, how long will it take for my symptoms to improve, what if HRT doesn't work, what are the benefits of HRT, what are the risks of HRT, HRT and breast cancer risk, HRT and clotting problems, HRT and cardiovascular disease risk) (see **Table 26** for examples of how education was displayed in the mEMA app).

Table 26: Education content screenshots from mEMA

Educational content menu screenshot	**Purpose**
	**On-demand education:** Healthy eating content menu. Access to this content is used in correlation with improving all diet-related outcomes. Both, accessing the content but also how much content was accessed is used in the data analysis.
	**On-demand education:** Physical activity content menu. Access to this content is used in correlation with improving all physical activity (steps)-related outcomes. Both, accessing the content but also how much content was accessed is used in the data analysis.

	**On-demand education:** Menopause content menu. Access to this content is used in correlation with improving all outcomes. Both, accessing the content but also how much content was accessed is used in the data analysis.

7.2.6.2.4 Garmin Fitness Tracker Design

All participants had the same setups during different phases of the intervention that were completed in their Garmin Connect app (**Figure 14**). For example, all alerts and viewing steps on their fitness trackers were disabled during baseline but enabled during the intervention phase. The fitness tracker was used for self-monitoring steps and the Garmin Connect app was used to set daily steps goals. Asking the participants to set their daily steps in Garmin Connect and re-entering the steps in mEMA was a workaround that was also discussed with the mEMA technical support team. The mEMA app does not provide the functionality to change and track daily steps goals. To ensure the participants received accurate updates from their fitness tracker, the steps goal was entered in Garmin Connect. However, to collect the steps goal data, required re-entry in the mEMA app. This workaround functionality was tested by the PPI group, and it was found acceptable.

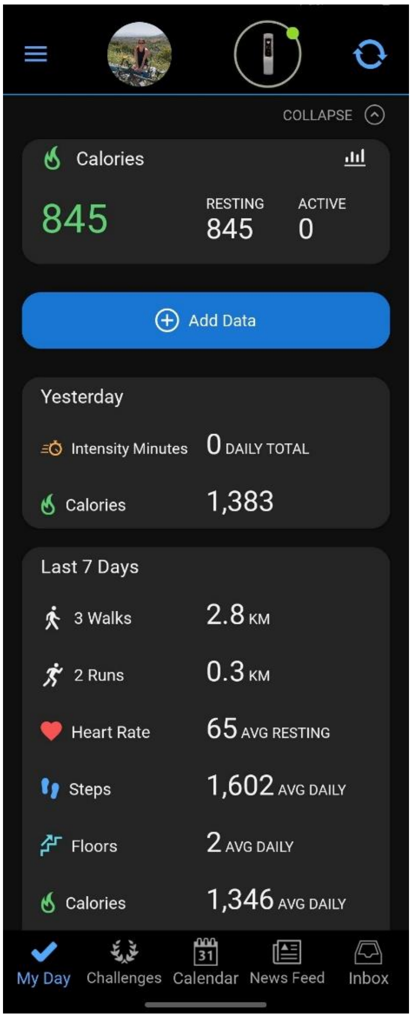


Figure 14: Fitness tracker setup and activity view in Garmin Connect app

7.2.6.2.5 Intervention Prototype Testing by the PPI Group

Once the researcher developed the combined and co-designed three-workstream intervention design in the mEMA app, the PPI group was invited to contribute to the intervention prototype testing. The objective of the prototype testing was to evaluate user-friendliness, technology stability, content appropriateness and relevance, and to identify opportunities for improvements prior to initiating the DHBCI with the intervention participants. Usability prototype testing feedback was recorded in Qualtrics using a questionnaire and reviewed by the researcher. This involved collecting views on each intervention element or feature, extracting all negative and positive comments and logging them in the appropriate columns of the PBA's Table of Changes template (Yardley et al., 2015). Positive comments typically do not need to be acted on but were also recorded for completeness. For negative comments, solutions were suggested in the 'Possible Change' column. The 'Reason for change' column was used to record why this change should be made (Yardley et al., 2015). Testing of the baseline survey included four changes, two of which were implemented to improve data entry. Requests to changes to standardized scale of questionnaires were not implemented. EMA changes included nine requests, seven of which were implemented (e.g., improving data entry, adding visuals, updating training documentation with troubleshooting tips). The remaining two positive comments did not require updates. The group found received five-time daily EMA surveys acceptable with a 90-minute response window and adjustable/personalised time of each survey prompt. The feasibility of including these ten behaviours in a short two-week intervention without overwhelming the participants with too many prompts was also considered. This feasibility was identified through the researcher's own testing of the mEMA app and from the PPI prototype testing feedback indicating that the number and length of prompts should not be increased.

7.2.6.3 Personalisation

Personalisation of the intervention included primarily group-level factors (BCTs) and minor individual-level personalisation of the intervention content, content order, level of guidance, communication with users (**Table 27**). Although additional types of personalisation were discussed in focus groups and with PPI, due to the limitations of the Ilumivu EMA software, it was not possible to personalise further. For example, ideally, each participant should be able to select what behaviours they want to focus on each day and receive personalised educational content accordingly. The app should also provide personalised greetings, including the participants' name. Therefore, to add additional level of personalisation, the researcher used the individual's first name in every communication during the intervention.

Table 27: Personalisation level, dimension, and mechanism applied in this thesis

Level	Dimension	Mechanism	Description
Individual	Content	User choice	Tailoring the time of the day of five daily EMA surveys based on each individual's preferences.
Individual	Guidance	Rule-based	The researcher contacting the participants individually when noticing issues with capturing data from mEMA and Garmin.
Individual	Guidance	Provider choice	The researcher pausing and restarting the intervention if a participant is engaged in the intervention but missed a few days due to illness.

Group	Communication	Rule-based	Reminder from mEMA app to complete surveys, and from Garmin when detecting physical inactivity.
Group	Content	User choice	Skipping questions that did not apply to the individual (e.g., questions about alcohol consumption for individuals who are abstinent).
Group	Content	Order	The participants were able to select the order of the content in the education library accessed in the mEMA app.
Group	Content	Rule-based	The mEMA app was developed using if-then scenarios, in which different content was shown based on the previous answer (e.g., if no alcohol was consumed, the question on how many units were consumed was skipped)

7.2.7 Conducting the Intervention: Schedule and Data Collection Procedures

The intervention involved a 21-day dietary and physical activity programme, with a limited emphasis on sleep behaviour (that was tracked passively by Garmin fitness tracker). The intervention schedule consisted of training and setup, in which extensive training was provided for the group and individually. Each participant was assigned to a group for the consecutive three weeks, starting with a 7-day baseline phase, in which baseline for steps and sleeps was obtained as a 7-day average from the Garmin-recorded data. Baseline survey was also completed in this phase. The baseline phase was followed by 14 days of intervention, in which the participants received surveys on the mEMA app five times daily (at the same time), accessed the on-demand education on the EMA app (at any time), and passively recorded their steps and sleep using their Garmin fitness tracker. The post-intervention phase included completing post-intervention survey and acceptability questionnaire, within seven days of completing the interventions (see **Figure 15** outlining this process).

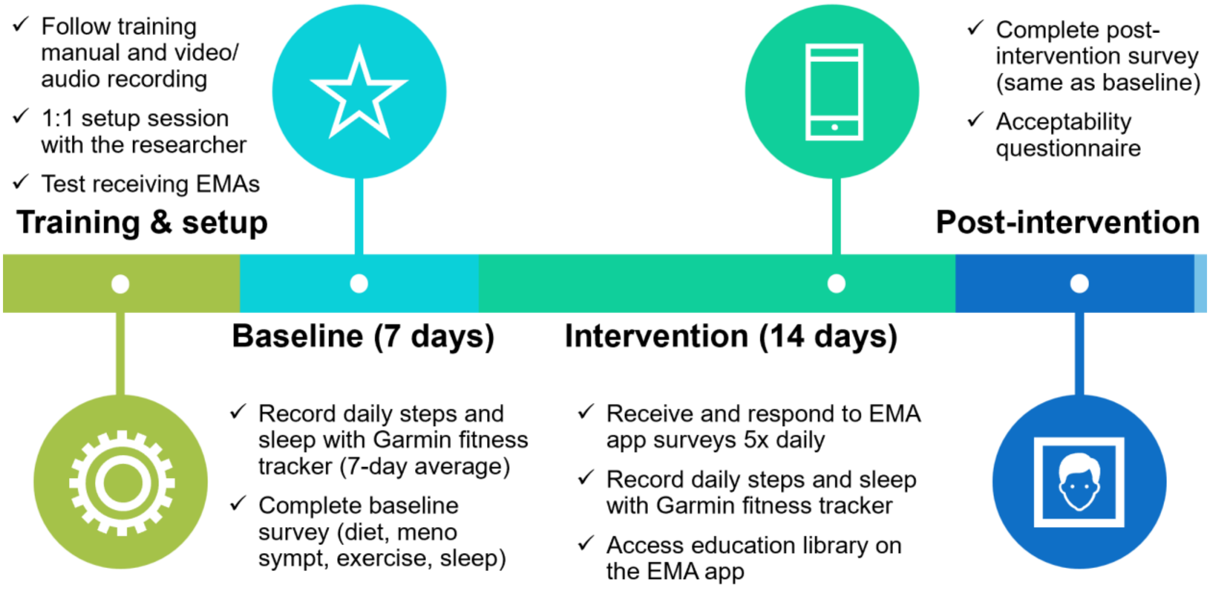


Figure 15: Intervention process and data collection components

7.2.7.1 Setup and Training Phase

Once the participants provided their shipping address, their fitness tracker was shipped. The participants were issued a unique Participant ID (generated by the mEMA app) to access the mEMA app and to identify themselves in all surveys. The researcher also created unique logins for the Garmin Connect app for each participant for the duration of the intervention. The participants were provided with set-up instructions, both written and audio/video recorded, to complete setups of their Garmin fitness tracker, Garmin Connect app, and mEMA app. The researcher set up individual Teams sessions to validate the participants' settings and connectivity of the study technologies and to further train the participants by guiding them through completing a test survey in the mEMA app. The participants were assigned to groups based on their preferred start date for baseline and the intervention phase. The start dates of each group were staggered, and each group size was expected to not exceed 10 participants to ensure the researcher had the capacity to support each participant through each phase of the intervention. The group assignments were not known to the participants, although to strengthen social support, email communication during the programme was addressed to the group, with only the first names of the group members being revealed.

7.2.7.2 Baseline Phase

During the 7-day baseline phase, the study participants were asked to 1) complete a baseline survey and 2) wear the provided fitness tracker at all times (i.e., minimum 8 hrs/day, ideally

24 hrs/day) to record their daily physical activity and sleep. The eight-part baseline survey was used to capture the participants' typical lifestyle behaviours prior to the intervention (see **Chapter 4** for description of each questionnaire). Additionally, the participants were further trained by receiving two scheduled mEMA survey messages (i.e., the day before baseline, and the day before the intervention phase) to ensure they received and experienced triggered surveys, prior to the start of the intervention. The training messages were informational, notifying the participants of the activities in the upcoming intervention phase. No other content was available on the mEMA app during baseline. To allow for passive monitoring without any interruptions (to avoid potential alternations to typical lifestyle behaviours), the researcher supported the participants in disabling all alerts on their fitness trackers (through Garmin Connect app).

7.2.7.3 Intervention Phase

Following the baseline phase, the participants commenced their 14-day intervention phase, typically on a Monday of each participant's chosen week. Mondays, and not weekends were chosen to strengthen engagement in the intervention, as suggested in in a recent review of factors influencing adherence to DHIs (Jakob et al., 2022). During the intervention phase, the participants were asked to complete the following three tasks, including wearing Garmin fitness tracker at all times, respond to surveys on the mEMA app, and access education content on the mEMA app (**Table 28**).

Table 28: Intervention phase tasks for the participants to complete

Task	Description
1	Wear the provided Garmin fitness tracker at all times to record their physical activity and sleep.
2	Answer five EMA surveys daily triggered on the mEMA app. The timings for the daily surveys could be customised for each participant, and generally were offered at the following times, within a 90-minute availability and two reminders every 30 minutes: 1) Morning: 7:30am until 9:00am 2) Late morning: 11:00am until 12:30pm 3) Early afternoon: 1:30pm until 3:00pm 4) Late afternoon: 3:30pm until 5:00pm 5) Evening: 7:30pm until 9:00pm

3	Review education content on healthy eating, physical activity, and menopause, available in the EMA app on-demand, at all times. The participants were asked to review this content at their leisure.

7.2.7.3.1 Daily Assessments and Sources of Data Collection

In total ten outcomes (target behaviours) were assessed daily. All target behaviours were assessed at baseline (using either a survey, or Garmin data) and on each day during the intervention using the mEMA app input and Garmin data. See **Table 29** for mapping of intervention outcomes to sources of data at baseline and during the intervention. The baseline Garmin data for steps and sleep were averaged to provide one figure representing baseline (i.e., day 0).

Table 29: Intervention outcomes and sources of data

Behaviour type	Target behaviours	Baseline data collection source	Intervention data collection source
Diet	Fruit portions	Baseline survey	EMA (late morning, afternoon, evening)
Diet	Vegetables portions	Baseline survey	EMA (late morning, afternoon, evening)
Diet	Water glasses	Baseline survey	EMA (evening)
Diet	Caffeine cups	Baseline survey	EMA (evening)
Diet	Alcohol units	Baseline survey (calculated amount based in two fields: times per week and units consumed on one of those days)	EMA (morning, asking for the day prior)
Diet	Snacks portions	Baseline survey	EMA (evening)
Diet	Meals number	Baseline survey	EMA (calculated field, based on whether the participants selected having breakfast, lunch, and dinner)
Physical activity	Steps number	Garmin, 7-day baseline average	Garmin, daily recorded steps, aggregate
Sleep	Sleep total mins	Baseline survey, and also Garmin, 7-day baseline average. (When Garmin data was unavailable, survey data was used for data analysis)	Garmin, daily recorded total sleep minutes
Sleep	Sleep deep mins	Baseline survey, and also Garmin, 7-day baseline average. (When Garmin data was unavailable, survey data was used for data analysis)	Garmin, daily recorded total sleep minutes

7.2.7.4 Post-Intervention Phase

The day after completing the intervention phase (this was typically a Monday, Day 22), each participants received their final EMA message congratulating them on completing the study. The researcher also sent an email to each group to remind them to complete the post-intervention tasks (**Table 30**) (see **Chapter 4** for details on surveys and questionnaire).

Table 30: Post-intervention phase tasks for the participants to complete

Task	Description
1	Complete post-intervention survey (same as pre-intervention baseline survey, excluding PARQ).
2	Complete Acceptability questionnaire
3	Uninstall the mEMA app on their phone
4	Disconnect their Garmin fitness tracker from their study provided Garmin Connect account. The participants were advised to create their own Garmin Connect account to continue using their Garmin fitness tracker.

7.2.7.4.1 Data Preparation for Statistical Analysis

In longitudinal studies where observations are measured repeatedly, missing observations can frequently occur particularly whenever human subjects are enrolled (Scott, Simonoff and Marx, 2013). There can be many possible causes to missing data, and it was hypothesized that the intervention participants may miss surveys if they are unavailable to answer each survey in its allocated 90-minute availability to answer. Steps and sleep may also not be recorded if the participant forgets to charge their device, forgets to wear the device or finds it inconvenient to wear, the device or data transfer malfunctions, or for similar reasons. Datasets containing missing data, inconsistent data, or mixed data (i.e., containing inconsistent missing numerical and categorical data) contribute to data inconsistencies and a higher probability of misprediction and misled results (Ahsan et al., 2021). Therefore, data preprocessing steps, such as feature selection (reduction), data conversion, and data scaling were performed to form a standard dataset that leads to reduction in inaccuracy in final predictions (Ahsan et al., 2021). According to (Zhu, 2014), the complete cases (CC) or Multiple Imputations (MI) method was found the be the most appropriate method used under Missing Completely at Random (MCAR) (Zhu, 2014). Although all missing data methods suffer from severe drawbacks, for example, there may be a substantial loss of information (Scott, Simonoff and Marx, 2013), complete dataset is required in this intervention to determine if a predictor has an effect on the outcome. Therefore, the CC method was incorporated, and incomplete data sets were removed. Each daily record was considered complete if it included all data required for data analysis were present (i.e., data entered through four of the five daily EMAs and Garmin steps and sleep data) (**Appendix C, Table 62**). Additionally, for regression analysis, a minimum of two observations (days) were required from each participant to compare each variable (e.g., setting a steps goal) over time (Cernat, 2023). These two observations represented a baseline data point (wave 0) and one intervention data point (any data point in waves 1 to 14).

7.3 Results

7.3.1 Participant Characteristics

The recruited participants (N=37) were all female cisgender with an average age of 48.3 years (range 40 - 65 years), 19% (7/37) were of non-White ethnicity, and 46% (17/37) were non-native British. A subset of 65% (24/37) of the participants were included in the statistical data analysis with an average age of 47.13 years (range 40 – 58 years), 25% were of non-White ethnicity, and 50% (12/24) were non-native British (**Table 31**). (See additional baseline data, including general health, menopause symptoms and lifestyle in **Appendix C, Tables 63 - 67**).

Table 31: Participants characteristics

Variable	**All participants**		**Participants included in data analysis**	
Demographics	**N**	**(%)**	**N**	**(%)**
Gender: Female	37	(100)	24	(65)
	Mean	**(SD)**	**Mean**	**(SD)**
Age	48.30	(4.99)	47.13	(3.99)
Weight, kg	70.41	(13.94)	73.10	(14.69)
Height, cm	165.69	(6.61)	164.77	(6.32)
	N	**(%)**	**N**	**(%)**
Ethnicity:				
Black African	2	(5.41)	2	(8.33)
Chinese	1	(2.70)	1	(4.17)
Indian	1	(2.70)	1	(4.17)
Latin American	1	(2.70)	1	(4.17)
Other White background	9	(24.32)	6	(25.00)
White and Black Caribbean	2	(5.41)	1	(4.17)
White British	19	(51.35)	11	(45.83)
White Irish	2	(5.41)	1	(4.17)

Marital status:				
Divorced, separated, widowed	5	(13.51)	3	(12.50)
Married, living as married	25	(67.57)	15	(62.50)
Never married	6	(16.22)	4	(16.67)
Prefer not to say	1	(2.70)	1	(4.17)
Number of children:				
0	9	(24.32)	7	(29.17)
1-2	22	(59.46)	13	(54.17)
3 or more	6	(16.22)	3	(12.50)
Generation British:				
First generation	10	(27.01)	7	(29.17)
Second generation	3	(8.11)	2	(8.33)
Third generation or more	4	(10.81)	3	(12.50)
Native	20	(54.05)	12	(50.00)
Qualification:				
College or university	12	(32.43)	8	(33.33)
Lower secondary	1	(2.70)	1	(4.17)
Postgraduate degree	24	(64.86)	15	(62.50)
Employment:				
Full-time	18	(48.65)	13	(54.17)
Not working	3	(8.11)	2	(8.33)
Part-time	16	(43.24)	9	(37.50)
Annual household income:				
< £18,000	1	(2.70)	0	(0.00)
£18,00 to £30,999	4	(10.81)	4	(16.67)
£31,000 to £51,999	5	(13.51)	3	(12.50)
£52,000 to £100,000	17	(45.95)	12	(50.00)
> £100,000	6	(16.22)	3	(12.50)
Prefer not to say	4	(10.81)	2	(8.33)

7.3.2 Feasibility Results

7.3.2.1 Recruitment Rate

Overall, 38 women expressed interest to join the study by contacting the researcher by email that was provided in the recruitment flyer. From the interested group, one potential participant dropped out prior to being recruited (i.e., prior to their individual session with the researcher to learn more about the study). The IC form was signed by 37 participants, resulting in a recruitment rate of 97% (37/38). Five groups were formed with average of 7 participants (range 2-15). For the majority of the participants, each phase followed seamlessly from one to the next. In a few cases, where the participants (N=4) reported being ill, the intervention was paused for no longer than 7 days. The first group began on May 22nd and the last participant completed the intervention on July 26th (**Table 32**). Five participants joined the study with a friend or someone they knew.

Table 32: Intervention schedule

Group	Participants, n	Baseline start	Intervention end
1	8	May 22, 2023	June 12, 2023
2	15	May 29, 2023	June 18, 2023
3	5	June 5, 2023	June 25, 2023
4	7	June 12, 2023	July 2, 2023
5	2	July 3, 2023	July 25, 2023

7.3.2.2 Dropout Rate

No dropouts were reported, and data was collected from all (N=37) intervention participants.

7.3.2.3 Feasibility of Data Collection Tools and Methods

7.3.2.3.1 Data Extraction Procedure Feasibility

Survey data was extracted from Qualtrics, resulting in three Excel files (i.e., baseline survey, post-study survey, acceptability survey). Raw data consisting of 44 csv files were extracted from the Ilumivu servers after the last participant completed the intervention. The data was organised in individual steps data and combined files for all other outcomes (**Table 33**).

Table 33: Intervention data files from Ilumivu/Garmin software

File	Purpose
Garmin steps	35 files (1 file per participant with available steps data). 2 participants had a missing file.
Garmin sleep	1 file containing all sleep data (for participants who recorded at least one day of sleep data)
EMA morning survey	1 file containing all morning surveys data
EMA late morning survey	1 file containing all late morning surveys data
EMA afternoon survey	1 file containing all afternoon surveys data
EMA late afternoon survey	1 file containing all late afternoon surveys data
EMA evening survey	1 file containing all evening surveys data
EMA diet education	1 file containing all diet education data
EMA exercise education	1 file containing all exercise education data
EMA menopause education	1 file containing all menopause education data

The full dataset consisted of 587 records, representing 16 days of data captured (i.e., baseline surveys and Garmin steps and sleep (Day 0), intervention phase (Day 1-14), and post-study surveys (Day 15)). The dataset therefore represented 99% (587/592) of all possible data records that could be captured. All 47 files were loaded to R studio statistical software. The files were merged into a long format where each row represented one day of observations for an individual. Therefore, data for each individual consisted of a maximum of 15 rows (baseline row and 14 rows of intervention data). Overall, the data extraction procedure was feasible.

7.3.2.3.2 Data Cleansing Procedure Feasibility

Data cleansing consisted of seven steps to prepare the dataset for analysis. All steps were completed programmatically in R studio with no manual file manipulation.

Step 1: Removing Post-Intervention Data

For statistical analysis of daily outcomes, the first waves 0 – 14 were included in the analysis. Post-intervention exit questionnaire data was analysed for all participants who completed the survey, and therefore this data was initially removed from the dataset. After merging 47 raw data files, the final dataset consisted of 551 records from 37 participants. The dataset therefore represented 99% (551/555) of the total possible records (37 participants * 15 waves) that could be recorded.

Step 2: Removing Records with Missing Steps or Sleep Data

After removing records where Garmin did not record steps or sleep, the file included 62% (343/551) initial records from 89% (33/37) participants. There were several reasons for not having this data recorded, including:

- Technical issues with the Ilumivu connectivity where data was not being transferred from Garmin Connect to Ilumivu server. Two participants had no physical activity records transferred although all participants had their sleep transferred.
- Garmin fitness tracker not being charged. The participants reported having difficulties charging the device or forgetting to charge it. Without being charged, the device would not record steps or sleep.
- Possibly, not wearing the device, which is difficult to determine given the participants were in their natural environment without supervision.

Additionally, steps data files for two participants were unavailable on the Ilumivu server. The Ilumivu technical support team implemented changes to the platform during the intervention, which changed the original Garmin integration user interface on the mEMA app. The researcher reported unexpected changes to the recorded data dates, which showed dates recorded in the future. This was fixed by the technical support team, but it is unclear whether any data issues affected the intervention outcomes. The participants reported difficulties charging their Garmin fitness tracker and, in some cases, broke their charger. The participants also reported the fitness tracker not recording steps at all times.

Step 3: Removing Records with Unanswered or Partially Answered EMAs

Each answered EMA survey was stamped by the mEMA app as being answered. Answered EMA surveys could have been however opened (clicked on) but not necessarily completed. Although five EMAs were triggered daily, input from the participants was required in four EMAs daily (i.e., morning, late morning, afternoon, evening) with the fifth EMA providing counselling messages only. Removed were 142 records that did not have EMAs stamped as answered in waves 1 – 14. After removing this data, the file included 36% (201/551) initial records from 86% (32/37) participants. Furthermore, the participants had an option to skip entering fruit and vegetables portions in the daily surveys, if they did not have breakfast, lunch, or dinner. There were two options to treat such data: i) Exclude this data because this would result in zero amounts despite goal setting, ii) Include the data because the participants had the option to skip a meal and still participate in the intervention. Therefore, if the participants reported not having breakfast, lunch or dinner, their fruit and vegetables portions were set to zero for that meal and this data was included in the dataset. Additional 19 records were removed due to being identified as answered but being only partially completed. This removal resulted in 33% (182/551) of initial records and 86% (32/37) participants.

Step 4: Removing Records with Only Baseline or Only Intervention Data

Additional eight records were removed from the dataset with missing baseline or intervention days data. Two records with no baseline and 6 records with only baseline data and not a single full day of intervention data were removed. The final dataset used for data analysis consisted of 31% (171/551) of initial records and 65% (24/37) participants. It is important to note that this dataset includes only those observations that had a complete diet, steps, and sleep data for the same day. The excluded records did not have a complete recoding of diet, steps, and sleep data for the same day to be included. Therefore, the final dataset consisted of full-day responses from 24 participants with a baseline record (wave 0) and a minimum of 1 intervention data record (wave 1 – 14). The final dataset contains on average 7 days of data per participant (range 3 – 13 days). Each wave contained data from 11 participants on average (range 6 – 24 participant records) (**Figure 16**). Data analysis relevealed that across all intervention days (days 0-14), no-missing data records (i.e., containing data on steps, sleep, daily answered EMAs) were recorded primarily in the early days of the intervention with an average of 46% (11/24) of participants having complete data each day (i.e., wave) of the intervention (median=10; mode=17; range 6-24).

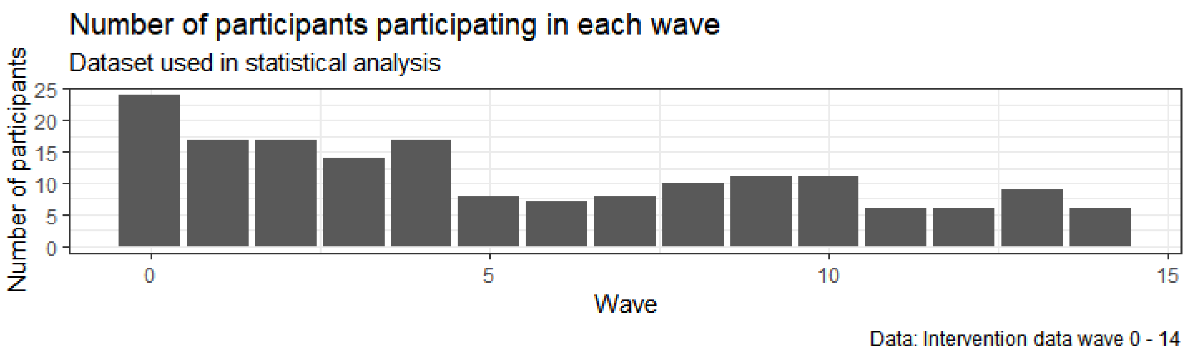


Figure 16: Final dataset used in statistical analysis, number of participants in each wave (wave 0 - 14)

Step 5: Data Scaling

Data scaling was performed for steps, total sleep, and deep sleep outcomes to bring the data to similar units of tens, as all other outcomes (e.g., glasses of water, cups of coffee, portions of vegetables), instead of hundreds (sleep minutes) and thousands (daily steps). For example, 8,000 steps were scaled to 8 steps. Sleep minutes were scaled from for example 400 minutes to 4 minutes.

Step 6: Data Weighting

To minimise bias and to increase results reliability and validity, weights were implemented to bring the intervention data to a similar scale. Weighting compensates for differences in the respondents' selection probability and non-response rates.

Step 7: Test for Normality in Data Distribution

Shapiro-wilk normality test shows that all outcome variables are not normally distributed ($p < 0.05$). All statistical tests therefore applied non-parametric tests, such as Spearman correlation (using weighted formula in R).

Overall, the data cleansing procedure was feasible and resulted in a dataset consisting of 171 records that was used in the data analysis (i.e., descriptive statistics, MLM, Spearman rank correlation). The feasibility of this procedure was also required prior to conducting the exploratory study (Study 4) in which the predictors are further optimised.

7.3.2.4 Response Rate

Adherence to the intervention consisted of completing three surveys (i.e., baseline survey, post-study survey, acceptability/exit questionnaire), capturing steps and sleep data using wrist-worn fitness tracker, answering EMAs, and accessing EMA education content. All 100% (37/37) participants completed the baseline survey during their baseline week, 97% (36/37) completed post-intervention survey, and 95% (35/37) completed the exit questionnaire. Garmin steps data was recorded on 81% (450/555; 37 participants *15 days, including baseline) of intervention days for all participants. Garmin sleep data was recorded on 85% (471/555) of intervention days for all participants. A total of 77% (1999/2590) EMAs were answered and at least one EMA was answered by the participants on 98% of the intervention days (510 records/518 possible records; 37 participants * 14 days). Over 62% (23/37) of the participants accessed the EMA education content. Education on diet was accessed the most at 53% (161/304 records) of all education accessed, followed by menopause content at 35% (105/305), and lastly exercise content at 13% (38/304). Education was accessed more on the 1st, 7th, and 14th day of the intervention (**Table 34**).

Table 34: Intervention feasibility results

Feasibility measure	Response rate
Baseline survey	100% (37/37) participants
Post-intervention survey	97% (36/37) participants
Exit questionnaire	95% (35/37) participants
Garmin steps data	81% (450/555) records

Garmin sleep data	85% (471/555) records
EMAs	77% (1999/2590) records
EMA education content	62% (23/37) participants

Note on missing data: One participant completed EMAs up to Day 14, just not the Post/exit surveys). Another participant was unavailable to participate on day 13 and 14 although they completed both post/exit questionnaires. The same two participants skipped both post-intervention survey and exit questionnaire).

7.3.2.5 Acceptability Results

The intervention acceptability was assessed using adapted form of the Theoretical Framework of Acceptability (TFA) (Sekhon, Cartwright and Francis, 2017, 2022). The questionnaire assessed eight areas of acceptability, including affectivie attitutude, burden, ethicality, perceived effectiveness, intervention coherence, self-efficacy, opportunity cost, and general acceptability (see **Chapter 4** for more details).

General Acceptability

The questionnaire was completed by 95% (35/37) of the participants and overall, general acceptability of the intervention was rated high. Over 97% (34/35) of the participants felt the intervention was acceptable or completely acceptable. (Note: One participant who rated the intervention unnacceptable might have misunderstood the question with all other written comments provided by this participant being positive). The participants also had an opportunity to provide their feedback in open ended questions. For example, the participants shared that they enjoyed the educational content and found the intervention motivating. For many the intervention resulted in more energy to exercise and engage in more physical activity.

> *"I enjoyed taking part in this study. The provided educational information was really useful. I made more of conscious efforts about moving, hydration and food choices." (age: 46 years)*
>
> *"The study has been a great motivation to improve physical activity, diet and mental health." (age: 42 years)*
>
> *"I feel fitter after two weeks and have more energy - the main changes have been that even though walking has been my main form of exercise, I now walking much faster. Also, I am drinking much more water which has made me feel so much better." (age: 44 years)*

Affective Attitude, Ethicality

Responses to “affective attitude” questions suggest that the majority 80% (28/35) liked self-monitoring their physical activity using the fitness tracker, 63% (22/35) liked self-monitoring their diet using the EMA app, and 77% (27/35) liked using Garmin Connect platform to join group challenges. Futher, 74% (26/35) liked the educational content on diet, and 86% (30/35) felt comfortable wearing the fitness tracker for three weeks. Over 82% (29/35) felt that entering steps goals was not burdensome and self-monitoring steps goals required little effort or no effort at all. Over 85% (30/35) of the participants felt that answering any of the 5 EMAs required a little effort or no effort at all. Only 8% (3/35) felt that reviewing educational content requird a lot of effort or huge effort and 11% (4/35) felt that answering pre-study survey required a lot of effort or huge effort. Setting everything up for the study resulted in primarily neutral feedback from 57% (20/35) of the participants. “Ethicality” (i.e., the extend which the intervention was a good fit with an individual’s value system) rating suggests that most (88%; 31/35) participants felt it was fair to use digital health technology to support midlife women in improving their physical activity and diet.

Intervention Coherence

“Intervention coherence” (i.e., understanding of how the intervention works) suggests that over 88% (31/35) and 74% (24/35) of the participants agreed that making small dietary changes (e.g., adding colourful vegetables, filling up a water bottle in the morning) and having an understanding of a nutritionist-recommendated diet for midlife women, respectively, can help them improve healthy eating. Futhermore, 94% (33/35) and 89% (31/35) of the participants understood that setting goals to move more and being aware of their sedentary time, respectively, is intended to improve their physical activity. Some participants shared that they liked the reminders to eat healthier and to self-monitor their steps and sleep.

> *“It was interesting to be reminded about my diet and the amount of sleep or steps I take daily, a very important reminder of how my everyday choices impact my overall health and well-being.” (age: 51 years)*

Perceived Effectiveness

Responses to “perceived effectiveness” suggest that 69% (24/35) of the participants felt the study improved their physical activity. Although 60% (21/35) of the participants disagreed that suggestions to join walking groups or to exercise with a friend was helpful, 14% (5/35) of the participants joined the study with a friend. Some participants shared that they enjoyed short bursts of exercise, which was provided in the educational content on the EMA app. Although the participants wanted more reminders for other exercises, which they were encouraged to do (in the exercise education), the focus of the intervention was on increasing steps count.

> *"I would have liked some motivation to do more exercising at home e.g., yoga or Pilates online classes." (age: 45 years)*

Furthermore, 69% (24/35) felt that the intervention improved their diet, and specifically consumption of fruit and vegetables. Over 51% (18/35) felt diet improvements were impacted by learning new healthy eating information on the app. Over 74% (26/35) improved their water consumption, although 44% (15/35) and 37% (13/35) felt they did not decrease their consumptoin of coffee or alcoholic beverages, respectively. Many participants shared that they increased their hydration and consumed less caffeine.

> *"It did make me consider caffeine and water intake more, and I started eating fruit with my breakfast initially, so I hope to keep that going." (age: 53 years)*

Over 80% (28/35) felt the study helped them to be motivated to improve their diet and physical activity (at 86%; 31/35). Over 80% (25/35) felt participating in the study was enjoyable. The majority (60%; 21/35) of the participants felt motivated by being awarded monetary incentives (i.e., being provided a Garmin fitness tracker). Receiving positive messages when completing goals was liked by 57% (20/35) of the participants. Over 60% (21/35) were motivated by prompts from their fitness tracker to get up and move and over 68% (24/35) were motivated by receiving positive notification (e.g., badges) displayed on their fitness tracker when reaching goals. The participants shared they found the the focus on colourful meals, to increase their consumption of fruit and vegetables, useful.

> *"I found that the prompts had a big impact on the food I bought in our big weekly shop and I made sure I had enough vegetables, which I put entirely down to the accountability in this programme, so that was incredibly useful." (age: 43 years)*

Self-Efficacy

Self-efficacy rating suggests that over 83% (29/35) of the participants felt confident in rating meals and 60% (21/35) were confident in setting goals in daily surveys. Over 65% (24/35) of participant were confident in applying new knowledge about healthy eating in their daily routine. Over 65% (23/35) of the participants felt confident that they could achieve their daily goals, although a few participants shared feeling frustrated when they were not reaching their goals:

> *"I just didn't have the time to do the exercise however and felt guilty a lot that I wasn't reaching the goals." (age 53 years).*

Furthermore, participants who followed the exercise education recommendation on including exercise bursts reported positive feedback:

> *"I did more short bursts of exercises rather than thinking I had to include an hour in my day which I don't have time for when I am working." (age: 47 years)*

Opportunity Cost

Opportunity cost rating suggests that 22% (8/35) of the participants felt that entering surveys interfered with their other priorities. Receiving prompts or alerts from the EMA app or the fitness tracker interfering with other priorities was rated at 14% (5/35) and 9% (3/35), respectively. Over 54% (19/35) agreed that 5 daily prompts were too many and too frequent, although only 6% (2/35) felt that the EMA app prompts took too long to answer. Comments from the participants indicate that they would have preferred to have the surveys available for more than 90 minutes although longer time periods would defeat the purpose of just-in-time assessments. Suggestions for improvements included having a chat function (social support), improved personalisation, and more statistics.

> *"One thing about the programme was that I started the day with very good intentions but somehow life got in the way. I wonder if there was an element of tracking yourself against other participants that would spur you on? Perhaps a chat function?" (age: 49 years)*

> *"I would have been more engaged with more detail, stats and personalisation." (age: 46 years)*

Finally, the use of technology was perceived positively for self-monitoring heart rate, stress level, steps, and sleep. Participants new to digital health felt confident using the technology.

> *"I've always avoided digital technology to track my fitness/wellbeing. However, the study has given me the confidence to see the benefits of such use." (age: 46 years)*

7.3.3 Changes in Target Behaviours

Three primary intervention outcomes of steps count, vegetables consumption, and fruit consumption are provided in this section. Descriptive statistics for the remaining seven outcomes (i.e., hydration, caffeine intake, alcohol consumption, meals consumed, snacks consumed, total sleep minutes, deep sleep minutes) are available in **Appendix C, Tables 68 - 74**. Overall, as shown in **Figure 17**, improvements occurred in all ten behaviours, with large variability across the intervention days, primarily in steps count. An increase in vegetables consumption, fruit consumption, water intake are shown. A decrease in the consumption of coffee is desirable. (Note: Figure 17 was produced in Excel using a feature that automatically generates figures from raw data).

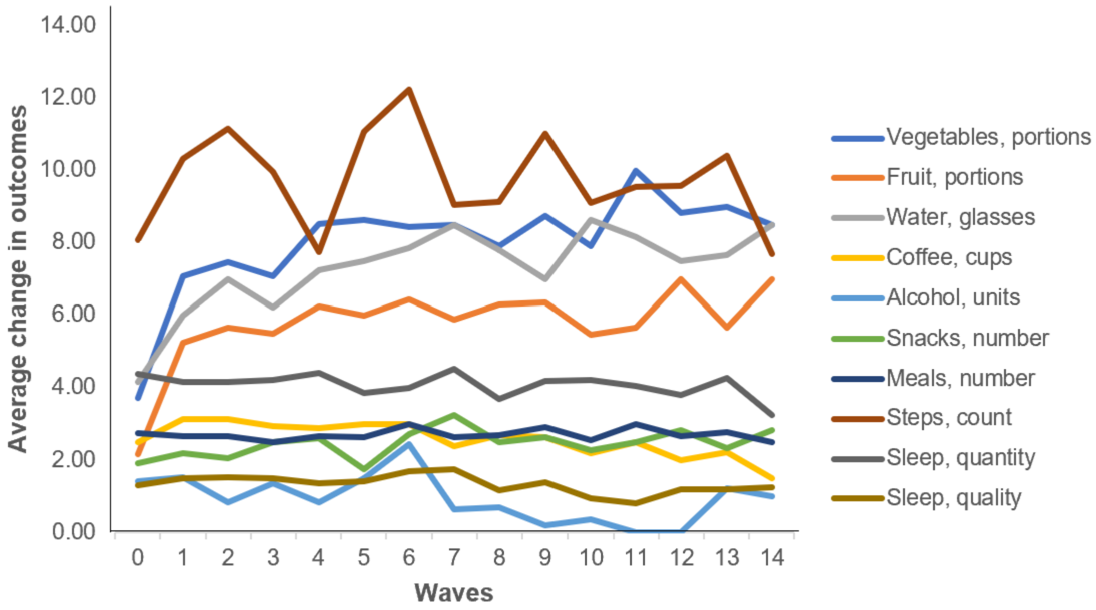


Figure 17: Average group-level (N=24) change in the target behaviours (wave 0 -14)

The following data analysis for each intervention outcome consists of two parts. This includes: i) descriptive statistics describing changes in the outcomes in time, and ii) multilevel models describing the within- and between-person variability in the outcomes and the effects of time. Finally, associations among target behaviours are explored using weighted Spearman correlation analysis.

7.3.3.1 Physical Activity (Daily Steps Count) Results

7.3.3.1.1 Descriptive statistics: Daily steps count

The baseline (wave 0) steps value for each participant consisted of an average of their daily steps count during their 7-day baseline phase. Steps count data were recorded on average on 5 days during the 7-day baseline (median = 5; range 1 – 7 days) and 37.5% (9/24) of the participants recorded their steps on 7 days in the baseline phase. Daily steps at baseline (wave 0) were on average 8,071.95 (SD 3,722.31) for the group of participants (N=24). This increased in the intervention period (wave 1 – 14) to an average of 9,862.00 steps (SD 4,869.08). A breakdown of daily steps at each wave of the intervention shows a maximum increase halfway through the intervention (wave 6), with 12,246.90 steps (SD 5,266.45) (**Table 35**).

Table 35: Descriptive statistics for daily step count

Wave	Count	Mean	VAR	SD	Median	IQR
0	24	8071.95	13855594.00	3722.31	8305.67	6091.93
1	17	10335.59	23005354.00	4796.39	9981.00	3891.00
2	17	11147.65	24839766.00	4983.95	12310.00	6959.00
3	14	9954.71	23743102.00	4872.69	8281.50	4365.75
4	17	7732.12	19113310.00	4371.88	7536.00	6953.00
5	8	11078.62	56424608.00	7511.63	8569.00	6191.50
6	7	12246.86	27735480.00	5266.45	11701.00	8358.00
7	8	9043.75	12397066.00	3520.95	9643.50	4285.25
8	10	9128.30	18614365.00	4314.44	9083.50	4254.00
9	11	11012.09	30351265.00	5509.20	9006.00	7154.00
10	11	9089.91	17276700.00	4156.53	8336.00	3695.00
11	6	9552.67	15365690.00	3919.91	8762.00	6447.00
12	6	9583.17	15381448.00	3921.92	10268.00	4566.75
13	9	10402.11	41339023.00	6429.54	7541.00	3359.00
14	6	7679.33	16008195.00	4001.02	7472.00	5278.50

Graphically, individual steps data trajectories varied based on the available data included in the data analysis (**Figure 18**).

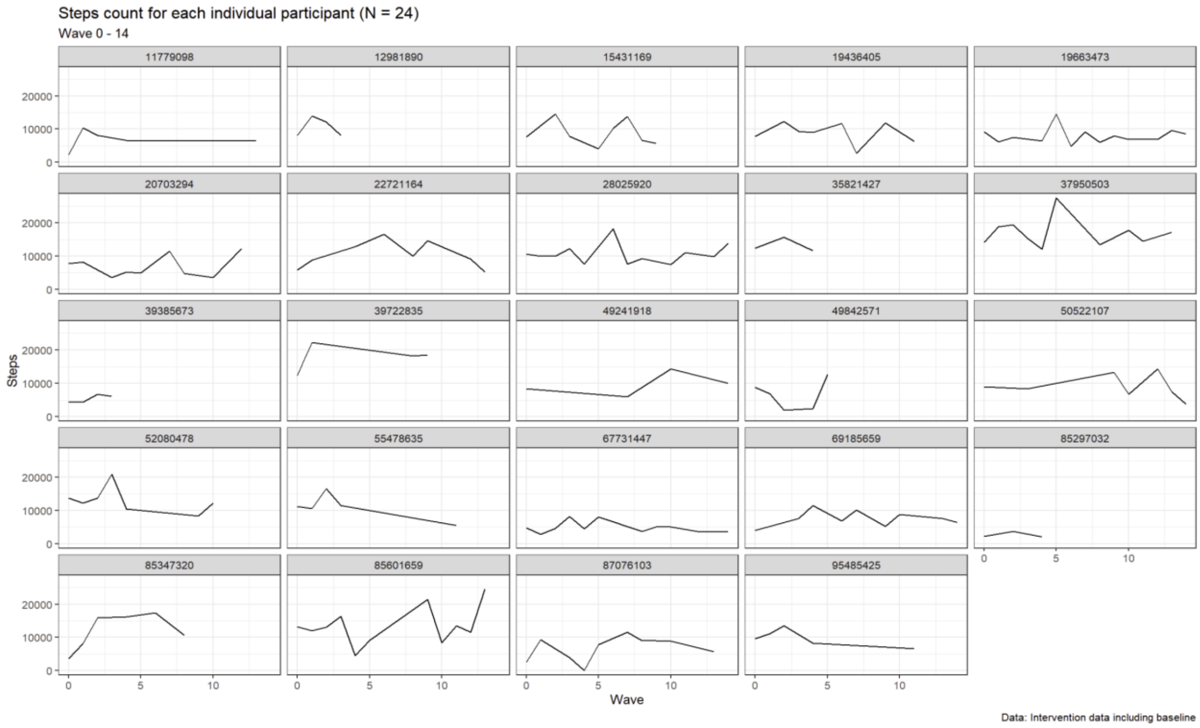


Figure 18: Individual daily steps for all (N = 24) participants (wave 0 - 14)

7.3.3.1.2 The Unconditional Means Model for Steps

The unconditional change model was used to estimate the amount of variation at both, within and between person levels. The fixed effects intercept (i.e., the grand mean) indicates that over all the time points (i.e., days in the intervention) and all individuals the average step count was 9,626.3 steps. The between-people variation (indicating how different the participants are from each other) was 11,176,036 steps. The residual coefficient indicating how much each individual varied around their average was 5,590,559 steps. Therefore, the proportion of variation between individuals, represented by the interclass correlation coefficient (ICC) is 0.67 (11,176,036/ (11,176,036 + 5,590,559)). This means that around 67% of the variation in steps is due to differences between people while the remaining variation of 33% (100% - 67%) is due to the within person fluctuations. Therefore, the differences between individuals are greater (and more pronounced) than the differences within individuals in explaining the change in the step count.

7.3.3.1.3 The Unconditional Change Model for Steps

In the unconditional change model, time (i.e., wave) is added as a predictor to provide the amount of variation in time. The between-people variation at the starting point of the intervention (Wave 0) was 11,650,000.00 steps, while the coefficient for “wave” representing between variation in the rate of change of 260.10 steps. This means that the intervention participants had a different step count at the start of the study but also different rate of change in their step count during the intervention. The within-person variation (indicating how much each individual varies around their average) was 5,629,000 steps at the start of the intervention. The model estimates an expected step count of 9,585.456 steps and a rate of change of 8.641 steps in the next wave (time goes up by 1 day). Based on this model, the step count is therefore expected to slowly increase in time.

7.3.3.2 Vegetables Consumption Results

7.3.3.2.1 Descriptive Statistics: Vegetables Consumption

The average portions of vegetables per day at baseline (wave 0) was 3.71 (SD 2.14). This increased in the intervention period (wave 1 – 14), with an average of 8.12 (SD 3.33) portions. A breakdown of vegetables portions intake at each wave of the intervention shows maximum increase in the later phase of the intervention (wave 11), with 10 portions (SD 3.35) (**Table 36**).

Table 36: Descriptive statistics for portions of vegetables per wave

Wave	Count	Mean	Var	SD	Median	IQR
0	24	3.71	4.56	2.14	3.50	3.00
1	17	7.06	3.68	1.92	7.00	3.00
2	17	7.47	3.51	1.87	7.00	3.00
3	14	7.07	11.15	3.34	7.00	5.25
4	17	8.53	14.39	3.79	8.00	5.00
5	8	8.62	19.12	4.37	7.00	8.00
6	7	8.43	10.29	3.21	8.00	4.00
7	8	8.50	19.71	4.44	8.00	8.00
8	10	7.90	12.32	3.51	6.50	3.75
9	11	8.73	9.42	3.07	9.00	3.50
10	11	7.91	15.09	3.88	8.00	7.00
11	6	10.00	11.20	3.35	11.00	5.00
12	6	8.83	25.37	5.04	11.00	6.75
13	9	9.00	11.75	3.43	8.00	5.00
14	6	8.50	15.50	3.94	8.00	5.75

7.3.3.2.2 The Unconditional Means Model for Vegetables Consumption

The fixed effects intercept indicates that over all the time points and all individuals the average portions of vegetables consumed was 7.08 portions. The between-people variation was 4.26 portions. The residual coefficient was 3.23 portions, and the ICC was 0.57 (4.26/ (4.26 +

3.23)). This means that around 57% of the variation in portions of vegetables consumed is due to differences between people while the remaining variation of 33% (100% - 57%) is due to the within person fluctuations. Therefore, the differences between individuals are greater (and more pronounced) than the differences within individuals in explaining the change in the portions of vegetables consumed.

7.3.3.2.3 The Unconditional Change Model for Vegetables Consumption

The between-people variation at the starting point of the intervention (Wave 0) is 2.66 portions, while between variation in the rate of change is 0.006 portions. This means that the intervention participants have a different portions of vegetables consumption at the start of the study and no difference (i.e., 0.006) in the rate of change in their portions of vegetables consumed. The within-person variation is 2.87 portions at the start of the intervention. The model estimates an expected portions of vegetables of 5.91 and a rate of change of 0.23 portions in the next wave. Based on this model, the portions of vegetables consumed are therefore expected to increase in time.

7.3.3.3 Fruit Consumption

7.3.3.3.1 Descriptive Statistics: Fruit Consumption

The average portions of fruit per day at baseline (wave 0) was 2.17 (SD 1.43). This increased in the intervention period (wave 1 – 14), with an average of 5.91 (SD 2.25). A breakdown of fruit portions intake at each wave of the intervention shows maximum increase in the later phase of the intervention (wave 14), with 7 portions (SD 2.76) (**Table 37**).

Table 37: Descriptive statistics for portions of fruit per wave

Wave	Count	Mean	VAR	SD	median	IQR
0	24	2.17	2.06	1.43	2.00	2.25
1	17	5.24	4.94	2.22	5.00	3.00
2	17	5.65	2.99	1.73	6.00	2.00
3	14	5.50	6.73	2.59	5.00	2.75
4	17	6.24	6.44	2.54	6.00	2.00
5	8	6.00	4.57	2.14	6.00	2.25
6	7	6.43	11.95	3.46	5.00	1.00
7	8	5.88	2.70	1.64	5.50	2.50
8	10	6.30	4.01	2.00	6.00	3.25
9	11	6.36	4.45	2.11	6.00	1.50
10	11	5.45	4.67	2.16	5.00	3.00
11	6	5.67	5.87	2.42	5.50	1.75

12	6	7.00	3.60	1.90	7.00	3.50
13	9	5.67	6.25	2.50	6.00	3.00
14	6	7.00	7.60	2.76	6.50	3.75

7.3.3.3.2 The Unconditional Means Model for Fruit Consumption

The fixed effects intercept indicates that over all the time points and all individuals the average portions of fruit consumed was 5.253 portions. The between-people variation (indicating how different the participants are from each other) was 1.572. The residual coefficient is 2.297, and ICC is 0.41 (1.572*/ (*1.572 + 2.297*)).* This means that around 41% of the variation in portions of fruit consumed is due to differences between people while the remaining variation of 59% (100% - 41%) is due to the within person fluctuations. Therefore, the differences between individuals are smaller (and less pronounced) than the differences within individuals in explaining the change in the portions of fruit consumed.

7.3.3.3.3 The Unconditional Change Model for Fruit Consumption

The between-people variation at the starting point of the intervention (Wave 0) is 2.45, while between variation in the rate of change is 0.04. This means that the intervention participants have a different fruit portions consumption at the start of the study and almost no difference (i.e., 0.04) in the rate of change in their portions of fruit consumed. The within-person variation is 1.64 at the start of the intervention. The model estimates an expected portions of fruit consumption of 1.14 portions and a rate of change of 0.25 in the next wave. Based on this model, the portions of fruit consumed are therefore expected to increase in time.

7.3.3.4 Correlation Between Target Outcomes

Weighted Spearman correlation coefficient (r_s) was used to measures the strength and direction of association between target outcome behaviours. Of the 45 correlations with 10 target behaviours (i.e., outcomes), 21 correlations were found to be statistically significant ($p<0.05$) (**Table 38**).

Table 38: Correlation between intervention outcomes

Target behaviour	Correlation outcomes
Fruit consumption	Fruit consumption had a significant strong positive correlation with vegetables consumption (r_s=0.927, p< 0.001) and with number of daily meals (r_s=0.685, p=0.029). On the other hand, fruit consumption had a significant strong negative correlation with cups of coffee consumption (r_s=-0.830, p=0.003), with total sleep minutes (r_s=-0.952, p<0.001), and with deep sleep minutes (r_s=-0.867, p=0.001).
Vegetables consumption	Vegetables consumption has a significant strong positive correlation with number of daily meals (r_s=0.879, p=0.001), and a significant strong negative correlation with cups of coffee consumption (r_s= -0.855, p=0.002), with total sleep minutes (r_s=-0.903, p<0.001) and deep sleep minutes (r_s=-0.758, p=0.011).
Hydration	Hydration (glasses of water consumption) had a significant strong positive correlation with daily steps count (r_s=0.661, p=0.038), with fruit consumption (r_s=0.842, p=0.002) and with vegetables consumption (r_s=0.733, p=0.016). Hydration had a strong significant negative correlation with consumption of alcoholic beverages (r_s=-0.636, p=0.048).
Caffeine consumption	Caffeine consumption had a significant strong positive correlation with total sleep minutes (ρ=0.855, p=0.002) and deep sleep minutes (r_s=0.745, p=0.013). It has a significant strong negative correlation with number of daily meals (r_s=-0.709, p=0.022).
Alcohol consumption	Alcohol consumption had a significant strong negative correlation with water consumption (r_s=-0.64, p=0.048).
Steps count	Step count had a significant strong positive correlation with water intake (r_s=0.66, p=0.0037).
Daily total meals	Daily total meals had a significant strong negative correlation with total sleep minutes (r_s=-0.636, p=0.048).
Total sleep minutes	Total sleep minutes had a significant strong positive correlation with deep sleep minutes (r_s=0.952, p<0.001)

7.4 Discussion

This chapter presented a novel experimental study that evaluated a multi-behavioural DHBCI specifically designed for UK-residing women in midlife, aimed to improve their diet and increase physical activity. The intervention is grounded on a behaviour change theory (i.e., the BCW framework), integrating BCTs in a multi-study multimethod design (Study 1, Study 2, co-production). Although the acceptability of the intervention (assessed using the TFA questionnaire (Sekhon, Cartwright and Francis, 2017, 2022)) was high and completely acceptable by 97% (34/35) of the intervention participants, it is vital to note that EMAs can be burdensome to participants and the benefits from using EMA in behavioural interventions depends upon the participant's engagement in the intervention (Ono et al., 2019). In this intervention, the participants responded to 77% of all triggered EMA prompts. This response rate is in line with other studies assessing physical activity and/or sedentary behaviour where the mean completion rate was 76% (Degroote et al., 2020). Furthermore, in this study, the researcher was extensively involved in training the participants, providing individual support, reviewing data collection throughout the intervention and communicating with the participants when EMA or Garmin data was not being captured. In some cases, the researcher discovered that a participant was ill, forgot to charge their fitness tracker, or was unclear on what to do with the EMA surveys. The participants were therefore aware that they were being continuously monitored, which might have impacted the high level of retention and compliance with intervention tasks. Additionally, the researcher also sent a message through the EMA app at the beginning of each phase (i.e., wave 1, 6, and 14) with motivational content and encouragement. Data analysis revealed that this motivational coaching communication sent to the participants by the researcher (primarily at the beginning of each phase) coincided with increased group-level access to the on-demand educational content on the EMA app, and therefore the role of a human-coach may be that of a mediator to achieve behaviour change. Another eight-week DHBCI with midlife adults (n=40; 89.2% female) demonstrated that health coaching support improved retention (McGuire et al., 2022). Using digital person-to-person intervention component (compared to face-to-face) can provide the needed human support while diminishing the barriers of in-person meetings (Santarossa et al., 2018). Human support has also been suggested as being the most important differentiating component in the effectiveness and adherence of BCIs (Mohr, Cuijpers and Lehman, 2011; Santarossa et al., 2018; Ryan et al., 2020). Digital person-to-person support is rooted in social and behavioural theories (e.g., Theory of reasoned action, Social cognitive theory), and further justified by the human support constructs of the supportive accountability model, and therefore, it requires that it creates accountability, generates opportunities for personalised feedback, and creates social support to successfully create health behaviour change (Santarossa et al., 2018). Given the benefits identified in the inclusion of human-supported interventions in this feasibility study, and also in other contexts, including mental health (Werntz et al., 2023), there may be a potential benefit in the future to equip clinicians and health coaches with digital health programmes that can support their patients/clients in the prevention and treatment conditions that may require improvements in health behaviours.

This intervention targeted multiple behaviours, including diet, physical activity, and to some extent also sleep. Other (longer term) interventions that included multiple lifestyle factors, such as diet (e.g., higher consumption of fruit and vegetables, increased hydration, moderate alcohol consumption, regular meals, non-smoking) and physical activity (e.g., moderate and vigorous physical activity minutes) were found to be positively associated with healthy ageing (Sabia et al., 2012; Sowa et al., 2016) and although individual healthy behaviours are moderately associated with health ageing, their combined impact is substantial (Sabia et al., 2012). Therefore, interventions addressing multiple lifestyle behaviours are needed both as a preventative treatment but also as a first-line option in the treatment of midlife women's bodily changes (e.g., reduced metabolism, onset of bone loss, loss of muscle mass and gaining of fat) and increasing risk of developing non-communicable diseases (e.g., type 2 diabetes, cardiovascular disease, osteoporosis, dementia) (Khandelwal, 2020). Moreover, multi-behavioural interventions are thought to share a reciprocal relationship. For example, greater physical activity levels are thought to improve sleep quality, and better sleep quality can contribute to increased levels of physical activity (Duncan et al., 2016). Similarly, in this multi-behavioural intervention, improvements were attained for all intervention outcomes, for example, average daily steps count increased by 22%, glasses of water consumed increased by 77%, and portions of vegetables consumed increased by 119%.

Additionally, based on the unconditional means MLM model analysis, most of the changes in the intervention outcomes occurred between individuals and slightly less within individuals. For example, 66% of the variability in the steps count occurred between persons and the remaining 34% within person. Another digital health intervention (Arigo, Hevel, et al., 2022) with midlife women (N=76) (mean age 51.61 years) found that moderate within-person variability of intended and observed moderate-to-vigorous intensity physical activity (MVPA) was moderated by positive affect (e.g., contentment) and body satisfaction. This finding may indicate that future interventions should interfere (i.e., activate behaviour change) when such within-person states are observed (Arigo, Hevel, et al., 2022). Another physical activity intervention (Barreira et al., 2016) with midlife women (N=68) (mean age 52.4 years) revealed great intra-individual variability in objectively determined daily sitting time and that on one day of the week an individual could be classified in the high sitter quartile (>11hr/day) and on another day within the same week, the same individual could be classified in the low sitter quartile (<7 hr/day) regardless of how much the individuals sat over the whole week or spent time in the recommended MVPA. The study also determined that four days of data collection (with actiPal accelerometer) was sufficient to achieve a desirable level of reliability (Barreira et al., 2016). These findings may indicate that individual tailoring and personalisation of the intervention is needed to account for individual trajectories in health-promoting behaviour change. Improvements in the target behaviours showed maximum increase in the middle or at the later stages of the intervention. For daily steps, the maximum average increase occurred halfway through the intervention (wave 6), with 12,246.90 steps (SD 5,266.45). A breakdown of vegetables and fruit portions intake at each wave of the intervention shows maximum increase in the later phase of the intervention (wave 11), with 10 portions (SD 3.35) and (wave 14), with 7 portions (SD 2.76), respectively. In another 8-week (non-digital) feasibility study with a group of midlife women (N=21) residing in New Zealand, intake of fruit and vegetables increased from 5 portions to 9 portions (while the portions of bread/cereals decreased) (Gunn et al., 2013b), indicating that midlife women in other (developed) countries respond positively to such interventions. Interventions, digital or not, have shown to be more feasible and acceptable if adapted to the specific needs of the target population group (Syundyukov et al., 2021). A culturally tailored 4-month theory-based digital physical activity intervention with a group of African American midlife women (N=20) was found to be feasible and acceptable and resulted in a group-level improvements in physical activity (Joseph et al., 2021). Therefore, considering multiple factors (including demographics, preferences, contextual) are needed to develop personalised and dynamic DHBCIs that have the potential to be more effective.

Understanding mechanisms by which interventions facilitate behaviour change is crucial in developing effective interventions (Borek et al., 2019). For example, a lifestyle intervention with Australian midlife adults revealed that motivation to change health behaviours (i.e., consumption of fruit and vegetables and physical activity) are strongly influenced by the participant's belief in their ability to achieve healthy behaviour change (i.e., action self-efficacy), revealing significant positive direct effects (Parkinson et al., 2023). In this feasibility study, self-efficacy (linked to TDF domain of Beliefs about Capabilities, Optimism, Intentions, and Goals) was activated using BCTs of Self-talk, Focus on past success, Verbal persuasion about capabilities, and Action planning. Additionally, based on the acceptability questionnaire (TFA), self-efficacy rating suggests that over 83% (29/35) of the participants felt confident in rating meals and 60% (21/35) were confident in setting goals in daily surveys. Over 65% (24/35) of participant were confident in applying new knowledge about healthy eating in their daily routine. Over 65% (23/35) of the participants felt confident that they could achieve their daily goals, although a few participants shared feeling frustrated when they were not reaching their goals. In the (Parkinson et al., 2023) study, individuals who held strong beliefs in their ability (self-efficacy) to modify their health behaviours and changes in their beliefs predicted increased planning to cope with potential setbacks or adversities. In this intervention, the participants were provided with numerous counselling EMA messages to support their self-efficacy, for example, they were congratulated on achieving their planned goals and activities or asked to think of ways to achieve their goals next time to help them with managing setback. Action planning was identified to play an important role in post-program behaviours (i.e., maintenance phase) in other studies (Kwasnicka et al., 2013; Parkinson et al., 2023). Planning activities plays a role in regulating behaviours over time, and aids in the automatization of behaviours through habit formation (Parkinson et al., 2023). In this intervention, education content around increasing physical activity included planning to walk by taking the stairs instead of the elevator, parking further away from the supermarket entrance, or taking a walk during lunch break. The participants were encouraged to make it fun by exploring new areas, and by enjoying the outdoors or joining a local walking group. Another multi-behavioural intervention aimed to improve diet and physical activity found that helping participants define a goal (e.g., eating five fruit and vegetables portions per day, monitor behaviour) were independently associated with better intervention effects (Samdal et al., 2017). In this intervention goal setting was incorporated primarily into daily morning EMAs (e.g., set goals for portions of fruit, vegetables, steps).

Furthermore, replicating and comparing evaluated interventions is vital to advance behavioural science in a cumulative approach (Borek et al., 2015). Although the study's design can be adapted to other interventions targeting other group-level populations of midlife women (e.g., other countries, communities) and different health behaviours and contexts (e.g., weight loss, smoking), replicating the intervention design may be possible to some extent. For example, the group of 32 BCTs were selected through a rigorous multi-study design and are specific to the context of healthy eating and regular physical activity in the population of midlife women who reside in the UK, and therefore who have similar cultural references and healthcare provided to them. Although the same group of BCTs can be selected and replicated in other studies, the exact application design may be more challenging to replicate due to the specific context, setting, and technology capabilities of the digital media used in the intervention. In this respect, attempts have been made to develop a checklist for reporting of group-based behaviour-change interventions (GB-BCIs) that are defined as behavioural interventions delivered by at least one facilitator to a group of (i.e., at least three) participants (Borek et al., 2015). Current reporting of GB-BCIs in scientific reports often prohibits accurate replication of interventions and identification of their components (e.g., BCTs) (Borek et al., 2015). Clearly, standardisation of reporting of GB-BCIs is needed to enhance the ability of a behavioural scientist for replication and implementation in the healthcare context (Borek et al., 2015). For this reason, the HBCP has also been established to provide specifications for how to make BCIs replicable (Michie, Thomas, et al., 2017a; West et al., 2023) (see **Appendix E** for more details). Finally, future phases of this DHBCI may include an iterative process of Planning and Optimisation by adjusting the design by transforming the BCT taxonomy (Michie et al., 2013) to the BCT ontology (Marques et al., 2023), including additional design workstreams (e.g., public advisory group), refining the set of intervention components based on the previous feasibility testing results, and conducting additional feasibility pilots in the Optimisation phase.

7.4.1 Strengths and Limitations

The multimethod intervention design provides a novel approach to designing lifestyle interventions. The design components (e.g., BCTs, mode of delivery, intervention content) are not only derived from literature (evidence-based), but they also represent voices and experiences of midlife women who co-designed the intervention with the researcher and participated in group discussions where women shared their experiences on menopause and effects of menopause on healthy eating and regular physical activity. The intervention itself resulted in high engagement and acceptability by the participants. This study is original in having a detailed view of every component implemented in the intervention and therefore provides for an opportunity for other researchers to replicate and extend the design to other contexts and populations. Additionally, although guided by the BCW guide, the researcher developed bespoke materials for workshop activities that should prove useful to other researchers and practitioners involved in intervention development for midlife women.

One of the main limitations is that the study was conducted as a single-arm feasibility study and therefore no conclusions can be made on the effectiveness of the intervention to achieve improvements in the target behaviours and on the effectiveness of the BCTs. The small sample size also reflects the study design and limited availability of fitness trackers that were provided to each participant. It is important to note that the intervention did not focus on including policy categories. For example, getting the participants to walk or cycle to work instead of driving or taking public transport was addressed by motivating them to try to convince them of the benefits (Persuasion). However, the behaviour change guide for local governments developed by Public Health England also suggests other intervention types, such as making it more expensive to park (Coercion), restricting the opportunity by removing parking spaces (Environmental Restructuring), increasing the opportunity to cycle by a cycle loan scheme (Enablement) (Public Health England, 2019). Future feasibility studies should explore other available intervention functions to achieve behaviour change.

7.4.2 Conclusions

The findings from this study confirmed that combining intervention components (including behaviour change techniques, mechanism of action, intervention content) from multiple methods is feasible and allows for implementation of these components in a digital health-promoting lifestyle intervention targeting midlife women. The high intervention acceptability confirmed the assumption that involving the public as equal decision-making contributors improves research quality, relevance, and acceptability. With all intervention components being reviewed in co-production with the PPI group led to an intervention that the intervention participants found to be enjoyable, the training material clear, and the intervention content relevant. Improved personalisation of the intervention was suggested as an improvement (in the acceptability survey). Thus, this study also revealed that having an understanding of the intervention components sets the foundation for improving personalisation of interventions to individuals or groups of individuals (e.g., UK-residing midlife women). Greater between- and within-person variability in the target behaviours indicate that there is an opportunity to address inter- and intra-individual fluctuations through improved individualisation of the intervention components. These assumptions set up the research objectives for the next study (**Chapter 8)**, utilising ML to identify groups of predictors with the greatest influence on predicting intervention outcomes (i.e., target behaviours). There is a lot of interest in the scientific community in utilising ML to assist in delivering adaptive, personalised and dynamic interventions to achieve greater effectiveness, engagement and responsiveness whilst minimising dropouts.

8. Predicting Health Behaviours in UK-Residing Midlife Women Using ML with EMA and Fitness Tracker Data: An Exploratory Study

8.1 Introduction

With increasing life expectancy globally, it is a pivotal public health concern to identify individual and contextual factors (Sadana et al., 2016) influencing the quality of ageing (Atallah et al., 2018) and to promote healthy populations as an important prerequisite for societal progress and prosperity (Kristiansen et al., 2016). Lifestyle factors (e.g., diet, physical activity, sleep, alcohol consumption, smoking) play a critical role in promoting good health and healthy ageing (e.g., good cognitive, physical, cardiovascular and respiratory functioning, and absence of disability, mental health problems and chronic diseases) at midlife (Sabia et al., 2012; Atallah et al., 2018). Furthermore, supporting lifestyle behaviours can benefit from effective mobile health applications, which utilise behaviour change theories and data science techniques to achieve individual states of a person status (e.g., activity, emotions, location) and assess their impact on undesirable health behaviours (e.g., unhealthy diet, sedentary behaviour) (Spanakis et al., 2017). To achieve this, the personalisation of treatments requires an understanding of the components (i.e., active ingredients) of an intervention that are effective for each individual in attaining lifestyle improvements (Greaves et al., 2011).

However, although BCTs, such as goal setting and self-monitoring, show positive effects on adoption and maintenance of health behaviours (e.g., physical activity) (Munson and Consolvo, 2012), these techniques are not widely effective among women in midlife (Murray et al., 2017). Several systematic and scoping review studies have attempted to identify intervention components through BCTs that are present in lifestyle improvements of midlife women (AlSwayied et al., 2022; Arigo, Romano, et al., 2022b; Sediva et al., 2022) and adults (Dombrowski et al., 2012; Van Rhoon et al., 2020; Carraça et al., 2021). However, it remains a challenge to isolate effective BCTs from a group of both effective and ineffective BCTs that are included in intervention designs (Michie, West, et al., 2018a) as well as to identify effective BCTs in real-time, "on the fly", to achieve adaptive intervention adjustments and personalisation (Nandola and Rivera, 2013; Moller et al., 2017). Some of these challenges stem from the current understanding of human behaviour being largely based on static "snapshots" of behaviour (Spring et al., 2013), rather than ongoing, dynamic feedback loops of behaviour in response to ever-changing personal, biological, environmental and social states (Spruijt-Metz, Wen, et al., 2015). Common personalisation strategies that have been used in DHBCIs include individualised feedback (e.g., customising messages to the user based on their previous physical activity data), and adaptation of the content based on user demographics (e.g., gender, BMI) (Monteiro-Guerra et al., 2020). However, such personalisation is insufficient, as it is based on the user's past behaviour (Zhu et al., 2021), without considering user's needs in the moment and adapting the intervention to immediate context (Monteiro-Guerra et al., 2020). A recent study (Arigo, Lobo, et al., 2022) explored population-level personalisation of a DHBCI's content that was aligned with individual characteristics of midlife women. However, the personalisation was limited to adjusting the web app's content based on user's preferences and together with its low-intensity (frequency) sampling of the participants' behaviour, it is unlikely to be widely effective as a stand-alone intervention for improving physical activity among midlife women (Arigo, Lobo, et al., 2022). Furthermore, although a group of five BCTs (e.g., goal setting, self-monitoring, social support, social comparison, and planning or intention formation) was included in the intervention design (Arigo, Lobo, et al., 2022), the relevance of individual techniques (and their combination) on behaviour change was not explored. As monitoring health and wellness using digital health technologies (e.g., mobile sensors, smartphones, cloud computing) is becoming more sophisticated and accurate (providing high-frequency sampling), increasing the level of real-time personalisation has the potential to improve effectiveness of DHBCIs (Monteiro-Guerra et al., 2020). Furthermore, utilising these digital health technologies has the potential to enable the development of new, dynamic models of human behaviour that could facilitate just-in-time adaptative and scalable DHBCIs (Spruijt-Metz, Wen, et al., 2015).

Moreover, incorporating ML, representing computational algorithms that provide insights into data by learning from past information to make accurate predictions (Bi et al., 2019)) has been found useful (Triantafyllidis and Tsanas, 2019) in facilitating effective personalisation of DHIs (Ghanvatkar, Kankanhalli and Rajan, 2019). However, a review of personalisation in the DMHIs (Hornstein et al., 2023) concluded that personalisation in interventions delivered with ML is still rare and that future interventions could provide even more personalised experience and especially benefit from using ML models (Hornstein et al., 2023). A review of personalisation in real-time physical activity coaching interventions using mobile apps (Monteiro-Guerra et al., 2020) revealed that personalisation based self-learning, context awareness and adaptation were used the least. Moreover, to provide personalisation that is based on prediction of activities for each individual, it is vital to understand the components and features of interventions (Hwang and Jiang, 2023). In this research, the intervention study

(Study 3) demonstrated that an intervention design that is based on systematically identified components and features of the intervention, and that is personalised at a group-level (by capturing the needs of the target population), can be successfully operationalised (actioned) in a DHBCI. However, using data-driven prediction techniques, such as ML, has the potential to further improve personalisation by optimisation of the intervention features (Hornstein et al., 2023). Therefore, this study explores a novel approach of using supervised ML with a sample of intervention features that are theoretically linked to groups of BCTs. The objective is to identify intervention components (i.e., predictors and BCTs) that are the most relevant in predicting health behaviours, using the longitudinal intervention dataset created in the previous chapter (**Chapter 7**). The aim of this chapter is to explore the feasibility of applying supervised ML Feature Selection models to identify groups of predictors for each intervention target behaviour. The feasibility will be evaluated using two methods, specifically feature ranking algorithm and recursive feature elimination algorithm (described in **Chapter 4, Section 4.3.4**). The aims will be performed in two steps:

1) Evaluate feasibility of identifying best-performing, statistically significant ($p<0.05$), time-varying predictors for each intervention outcome (i.e., target behaviour) using feature ranking algorithm (i.e., Correlation Matrix).
2) Evaluate feasibility of identifying the best-performing (lowest RMSE) groups of time-varying and time-constant predictors for each intervention outcome using recursive feature elimination (RFE). Two algorithms will be used and compared, specifically Random Forest and Gradient Boosting Regressor. Furthermore, following the feasibility of RFE to identify groups of predictors, additional two steps will be performed:

    a. Evaluate acceptability of the prediction accuracy (Normalised RMSE ≤ 0.30, corresponding to accuracy of over 70%) (Agrawal, Jain and Joshi, 2022) and power (R-squared ≥ 0.10) (Ozili, 2023) of the feature selection algorithm.

    b. Identify groups of BCTs theoretically linked to the identified groups of predictors that are the most relevant in predicting each intervention outcome.

Note: Relevant supplementary materials for this study are presented in ***Appendix D*** *of this thesis. Source code and the dataset are available in open access in* ***Zenodo*** (Sediva, 2024) *(see List of Presentations and Publications)*

8.2 Methods

8.2.1 Measures and Procedures

The high-level process flow to identify the best-performing groups of features predicting each intervention outcome begins with loading and preprocessing the intervention data described in Study 3. This is followed by applying ML algorithms that identify the best-performing ML Model for each target behaviour. The performance of the ML models is evaluated for accuracy and predictive power. The best-performing ML models identifies a subset of predictors (using feature selection) that are the most relevant in predicting each target behaviour (see **Figure 19**). A similar conceptual framework was described in a study that used ML models for detection of diabetes and prediction of glucose levels (Agrawal, Jain and Joshi, 2022). The following section describes each step of this process flow in detail.

Figure 19: Conceptual process to identify predictors

8.2.2 Data Acquisition and Preprocessing

8.2.2.1 Data Sources

The dataset used in the ML model prediction consists of a longitudinal dataset collected in the intervention and described in the previous chapter (**Chapter 7**). The dataset selected for data analysis consists of 171 complete observations (i.e., daily records) with no missing data, captured by (N=24) intervention participants. Completeness of each intervention day required steps count data, sleep data, and 4 EMAs answered, as well as baseline survey and baaseline steps count data (see **Chapter 7, Section 7.3.2.3** for details on record completeness requirements).

8.2.2.2 Data preprocessing

The data preprocessing involved transforming raw data into suitable format and combining data from multiple sources (e.g., EMA, fitness tracker, and baseline survey) for the ML model processing. Data preprocessing also included data cleansing, augmentation (e.g., generating new data that were imputed from existing data), encoding (e.g., converting categorical data into numerical or factor representations), removing missing values, and correcting inconsistent data (described in **Chapter 7, Section 7.3.2.3**).

8.2.3 Applying ML Algorithms

8.2.3.1 Process Flow to Identify Groups of Predictors and BCTs

The process of identifying groups of predictors and BCTs that are the most relevant in predicting intervention outcomes is divided into two main activities of 1) setting up the procedure and 2) applying ML algorithms. Setting up the procedure consists of selecting a sample of features (i.e., variables in the dataset) and developing regression-based ML algorithms with the identified groups of time-varying features (i.e., data that is dynamic, such as steps count, portion of fruit) and time-constant features (i.e., data that is constant, such as demographics). Applying (executing) ML RFE feature selection algorithms results in ML models with sub-groups of features. The RFE algorithm identifies groups of features that lead to the smallest RMSE, representing the optimal set of features to predict each intervention outcome (see **Chapter 3** for details on these methods). The acceptability of predictive accuracy and power of the RFE selected predictors is evaluated and the BCTs that are theoretically linked to RFE selected groups of predictors are identified (see **Figure 20**). The BCTs were identified in the intervention design and linked to each intervention feature (see **Chapter 7**). Feature ranking is also performed using Weighted Spearman Correlation Matrix to identify predictors with statistically significant strong correlation with each intervention outcome.

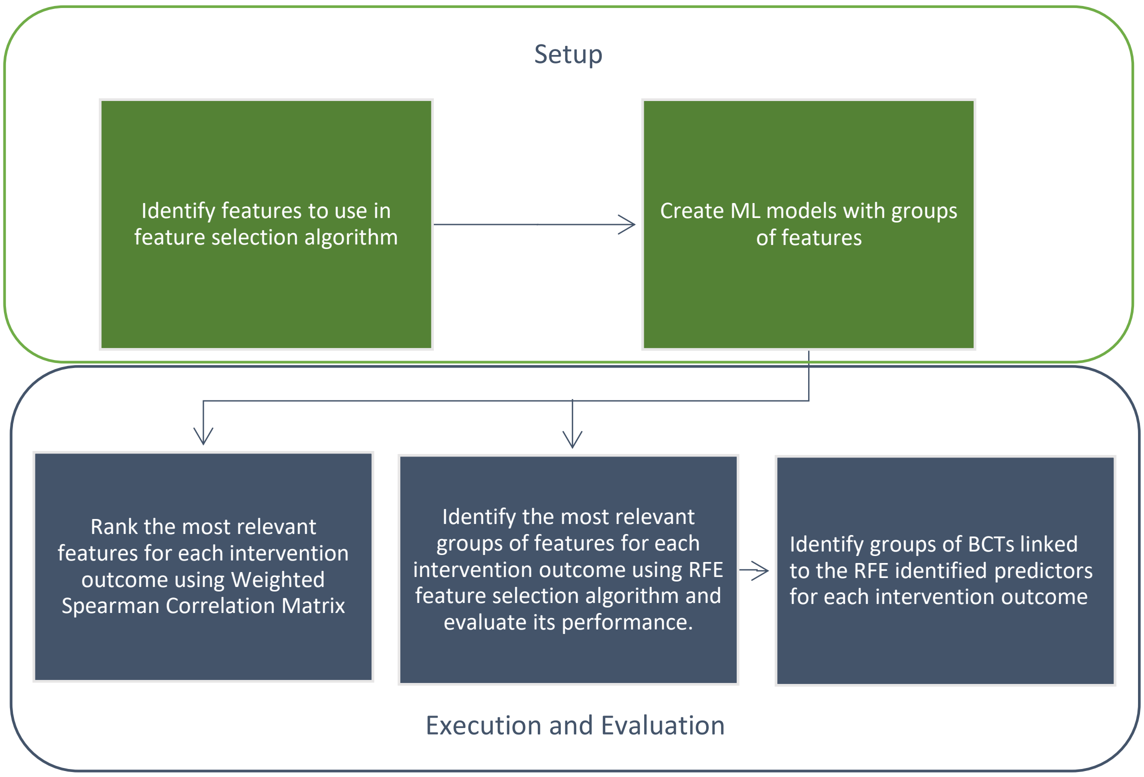


Figure 20: Process of identifying groups of relevant predictors for each intervention outcome

8.2.3.2 Outcome (Target Behaviours) Variables

Ten intervention outcome variables are included in the intervention dataset (Study 3) in the ML models. All outcomes were collected at baseline and during the 14-days of intervention. The outcomes include physical activity (e.g., steps count), diet (e.g., portions of vegetables, portions of fruit, glasses of water, cups of coffee, units of alcohol, number of snacks and number of meals) and sleep (e.g., total sleep minutes, deep sleep minutes).

The following section describes how features are selected and what features are included in two groups of time-varying features and time-constant groups of features.

8.2.3.3 Explanatory Features

8.2.3.3.1 Feature Construction to Identify Predictors

While features are variables in the dataset and not all features become predictors if they do not predict an outcome. Although deciding on what features to use and how to combine them in describing behaviour are two important tasks in feature selection at a conceptual level (Bluma and Langley, 1997), this study is not exploring what/how features should be constructed (crafted). Instead, the set of features (variables in the dataset) constructed in this study represents a broad range of features that were selected to demonstrate the process of applying supervised FS method in a behavioural health intervention. These features represent time-varying (i.e., dynamic and expected to change throughout the intervention, such as steps count each day) and time-constant (i.e., static and not expected to change, such as demographics) variables. These features are used in ML models to identify groups of time-varying and time-constant predictors that are the most relevant in predicting the outcome, with irrelevant features being removed by the algorithm and therefore excluded from the groups of relevant predictors. Consequently, removing irrelevant features increases performance of the ML model (Alshurafa et al., 2014).

8.2.3.3.2 Time-Varying Features

For testing purposes, the broadly selected 22 time-varying features (e.g., step goal set, vegetables portions goal set, meal rating, participated in a group exercise, accessed education content, number of counselling messages received), represent variables in the intervention dataset that were expected to change throughout the intervention (see **Figure 21** for R-code to create a model consisting of these variables). These 22 variables are theoretically linked to groups of 24 unique BCTs, from a total set of 34 BCTs that were used in the intervention design (described in **Chapter 7, Table 24**) that were used in the DHBCI to improve healthy eating and regular physical activity (**Table 39**).

```
dfStudy4_final_intervention <- subset(dfStudy4_final, wave >= 1 & wave <= 14)
dfPredictors <- subset(dfStudy4_final_intervention, select = c(
#time-varying predictors:
"ema_daily_total_surveys_answered",
"ema_daily_total_education_shown",
"ema_daily_total_education_read",
"ema_daily_education_library_accessed_binary",
"ema_veg_portions_goal",
"ema_fruit_portions_goal",
"ema_breakfast_colourful_rating_no_NA",
"ema_breakfast_colourful_rating_binary",
"ema_lunch_colourful_rating_no_NA",
"ema_lunch_colourful_rating_binary",
"ema_dinner_colourful_rating_no_NA",
"ema_dinner_colourful_rating_binary",
"ema_had_alcohol_last_night",
"ema_achieved_planned_exercise_binary",
"ema_group_exercise_participation_binary",
"ema_morning_exercise_plan_binary",
"ema_afternoon_exercise_plan_binary",
"ema_evening_exercise_plan_binary",
"ema_steps_goal_binary",
"ema_steps_goal_number_no_NA",
"ema_human_coach_interaction",
"ema_sleep_quality_transformed_scale",


#Outcome:
"daily_total_steps_scaled",
"daily_total_sleep_scaled",
"daily_deep_sleep_scaled",
"daily_total_veg",
"daily_total_fruit",
"daily_total_water",
"daily_total_caffeine",
"daily_total_alcohol",
"daily_total_snacks",
"daily_total_meals"

))
```

Figure 21: R-code to build a model with 22 time-varying predictors and 10 outcomes

Table 39: Mapping of BCTs to time-varying features for best-fit model identification

Features	**BCTs**
Step goal set (number)	1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks
Vegetables portions goal set (number)	1.1 Goal setting, 1.9 Commitment
Morning exercise planning goal	1.4 Action Planning, 2.3 Self-monitoring of behaviour
Number of counselling messages	1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment
Rating breakfast meals (more colourful = more fruit and vegetables)	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
Rating lunch meals (more colourful = more fruit and vegetables)	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
Evening exercise planning goal	1.4 Action Planning, 2.3 Self-monitoring of behaviour
Fruit portions goal set (number)	1.1 Goal setting, 1.9 Commitment
Participating in a group challenge exercise	3.3 Social support (emotional), 2.3 Self-monitoring
Rating lunch meals (yes/no)	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
Self-reported alcoholic beverages consumption previous day	2.3 Self-monitoring
Step goal set (yes/no)	1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring of behaviour, 8.7 Graded tasks
Accessing educational library (amount of content read)	4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 9.1 Credible sources, 12.1 Restructuring the physical environment
Accessing educational library (yes/no, regardless of the amount read)	5.1 Information about health consequences

Engagement level (number of EMA surveys answered)	2.2 Feedback on behaviour, 2.3 Self-monitoring of behaviour, 8.3 Habit formation
Rating dinner meals (more colourful = more fruit and vegetables)	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
Rating dinner meals (yes/no)	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
Self-reported achievement of planned exercise	1.6 Discrepancy between current behaviour and goal, 2.3 Self-monitoring, 15.1 Verbal persuasion about capabilities, 15.3 Focus on past success
Afternoon exercise planning goal	1.4 Action Planning, 2.3 Self-monitoring of behaviour
Rating breakfast meals (yes/no)	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
Rating sleep quality (scale)	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
Coaching (once weekly communication from the researcher, prior to the start of each phase)	2.2 Feedback on behaviour, 3.2 Social support (practical), 3.3 Social Support(emotional), 15.1 Verbal persuasion about capability, 15.3 Focus on past success

8.2.3.3.3 Time-Constant Features

Additionally, 20 time-constant features were randomly selected, representing variables that were not expected to change throughout the intervention (e.g., ethnicity, age group, generation British, county of residence, menopause stage, HRT use, knowledge about menopause, perspective on the menopause) (see **Appendix D, Table 75**). (For code to create a model using these variables, see **Figure 22**). These variables were selected to represent a subset of characteristics (e.g., demographics) that were captured only in the intervention's baseline survey. As these variables were not modifiable and not operationalised (actioned on) throughout the intervention, they are not theoretically linked to BCTs. It is assumed that these predictors could address the following research question: "What group-level characteristics of participating midlife women were the most relevant in explaining the intervention outcomes aimed to improve healthy eating and regular physical activity in UK-residing midlife women".

```
#constant predictors:
dfPredictors_constant <- subset(dfStudy4_final, select = c(
"survey_pre_age_group_fct",
"survey_pre_location_fct",
"survey_pre_tech_user_fct", #binary, asked at baseline
"survey_pre_health_status_fct", #scale, asked at baseline
"survey_pre_HRT_fct", #binary, never took or currently/in the past
"survey_pre_antidepressants_fct",
"survey_pre_CBT_fct",
"survey_pre_smoking_fct",
"survey_pre_generation_british_fct",
"ema_group_exercise_participation_fct",
"survey_pre_marital_status_fct",
"survey_pre_num_children_fct",
"survey_pre_children_home_fct",
"survey_pre_ethnicity_fct",
"survey_pre_qualification_fct",
"survey_pre_employment_fct",
"survey_pre_income_fct",
"survey_pre_meno_stage_fct",
"survey_pre_meno_perspective_fct",
"survey_pre_meno_knowledge_fct",


#Outcome:
"daily_total_steps_scaled",
"daily_total_sleep_scaled",
"daily_deep_sleep_scaled",
"daily_total_veg",
"daily_total_fruit",
"daily_total_water",
"daily_total_caffeine",
"daily_total_alcohol",
"daily_total_snacks",
"daily_total_meals"

))
```

Figure 22: R-code to build a model with 20 time-constant predictors and 10 outcomes

8.2.4 Performance Evaluation and Prediction

8.2.4.1 Procedure to Identify Predictors and BCTs for RFE FS

As outlined in **Figure 23**, the longitudinal intervention dataset (consisting of data captured through Garmin accelerometer, daily EMAs, and survey data) consists of daily data records with fields that represent variables. Conceptually, the variables represent features (and can also be combined into features), which themselves are conceptually linked to multiple BCTs (**Table 39**). The RFE feature selection algorithm generates groups of predictors that are most relevant in predicting each outcome variable. The RFE FS selected groups of predictors can therefore theoretically consist of up to all features used by the algorithm (i.e., 22 time-varying features) and combine both statistically significant and not significant predictors. However, in performance accuracy, models with many predictors are penalised and therefore using fewer predictors to predict an outcome leads to better model and better performance.

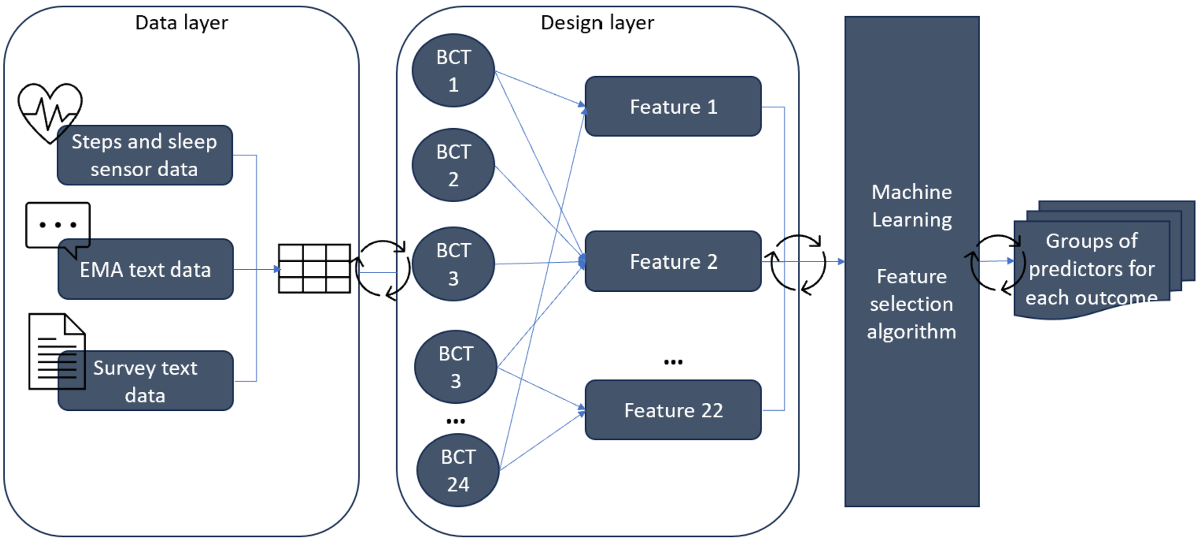


Figure 23: Visual representation of the prediction process in this study

While starting with feature ranking models (e.g., Correlation Matrix) is recommended for reducing the number of features, the second objective of eliminating redundancy can be addressed with forward selection or backward elimination models (Fogelman-Soulié, 2008). This study therefore explores feasibility of both, 1) feature ranking model using Correlation Matrix (CM) and 2) selecting a subset of features using RFE feature selection (FS) method. For comparison and to validate feasibility, two models are used with the RFE feature selection in predicting outcomes, including: 1) Random Forest (RF) algorithm (with predictions built in R), and 2) Gradient Boosting Regressor (GB) algorithm (with predictions built in Python). These models were selected based on their performance in predicting steps count target behaviour, in a test ML model.

The task of the ML algorithm is to learn how to most effectively make predictions, using features that characterise an event (i.e., 22 predictors selected in this study) along with specific instances of that event (Ignatow and Mihalcea, 2018b), represented by the longitudinal intervention dataset. Not every feature will have an impact on the outcome (i.e., output variable) and ML models that contain irrelevant features perform worse than models containing only relevant features (Bolón-Canedo, Sánchez-Maroño and Alonso-Betanzos, 2013). The main goal of the FS algorithms is to find the smallest subset of features that provides the maximum amount of beneficial information for prediction by eliminating redundant or irrelevant features in the intervention dataset (Alshurafa et al., 2014). The RFE algorithm starts with all features and removes features with lowest scores at each iteration (Khaire and Dhanalakshmi, 2022). The model trains with increasingly smaller sebset of features and finds the best group of features. This is done by recursively eliminating the weakest features until the specified number of features is left (Khaire and Dhanalakshmi, 2022). As a result, the output of RFE is the best-subset of predictors, in addition to predictor ranking.

8.2.4.2 Procedure to Assess Best-Fit Model for Each Intervention Outcome

This study uses key measures for model performance and the selection of the best model, including root mean squared error (RMSE), normalised RMSE (NRMSE), the mean squared error (MSE), R-squared (R^2), adjusted R-squared (adj R^2), Akaike's information criterion (AIC), and Bayesian Information Criterion (BIC) (Pham, 2019). These metrics were also used in other supervised ML dietary intervention studies in predicting short-term body weight prediction (Babajide et al., 2020) (see **Chapter 4, Section 4.3.4.3** for details on these metrics). Furthermore, these metrics assess how well the models fit to the same data that was used to build the regression model. The best-fit model identified by the RFE FS algorithm consists of a group of predictors with the lowest RMSE value. In this study, an NRMSE value resulting in accuracy of ≥ 70% (0 ≥ NRMSE ≤ 0.30) are acceptable.

The best groups of predictors are therefore the groups of predictors that were identified in the best-fit model with the lowest RMSE value. However, is important to note that with a small dataset, the ML models tend to overfit the model to the data (see **Limitations, Section 8.4.1**). Given the potential overfitting, it is expected that the model's performance (based on the mentioned metrics) will be favourable on test (seen) data, but the model will not perform well on unseen (validation) data. Therefore, in most cases, predictions that are based on training data are of less interest than prediction built on previously unseen data (test data). To address this limitation, cross-validation is typically performed, and it includes a set of methods for measuring the performance of a predictive model on a new, previously unseen, test dataset. For illustration purposes, this study describes assessing performance of only steps count ML model on unseen data using three most-commonly used cross-validation methods (e.g., leave one out cross validation, k-fold cross validation, and repeated k-fold cross validation), including 10-fold cross-validation (see **Section 8.3.1.4**).

The feasibility is assessed by the ability of the RFE FS algorithm to produce two sets of group-level predictive models: 1) Time-varying predictors linked to BCTs that are the most relevant in predicting the target behaviours, and 2) Time-constant predictors representing sociodemographic characteristics that are the most relevant in influencing the target behaviours. By identifying the most relevant time-varying predictors for each of the ten target behaviours, it is assumed that the groups of BCTs can also be identified (see **Table 39** for mapping of BCTs to features). The feasibility of identifying the BCTs based on the predictors selected by RFE FS will be evaluated. Acceptability constitutes the ML algorithm selecting a model with acceptable accuracy (NRMSE ≤ 0.3) and power (R-squared ≥ 0.10) that is acceptable in behavioural science to predict human behaviour (see **Chapter 3** for more details on metrics used in evaluations of ML models).

8.3 Results

8.3.1 Identifying Predictors for Each Outcome Using Correlation Matrix

Weighted Spearman correlation coefficient (r_s) is used to measures the strength and direction of association between ranked time-varying predictors. Of the 232 correlations among 22 time-varying predictors, 44 correlations were statistically significant ($p<0.05$) (see **Figure 24** for code and **Zenodo** for data). The correlation analysis used weighted Spearman's rank correlation coefficient measuring monotonic relationship between each two variables (see **Figure 25** and **Figure 26** for R-code to create the correlation matrix with time-varying predictors, and **Figure 27** for output).

```
w = dfStudy4_final_intervention$response_weight

matStudy4 <- as.matrix(dfPredictors)

weighted_corr <- cov.wt(matStudy4, wt = w, cor = TRUE)
corr_matrix <- weighted_corr$cor

write.csv(corr_matrix,
          file = "C:/R_code/study4/weighted_spearman_cor_matrix.csv",
          row.names = FALSE)
```

Figure 24: Weighted Spearman correlation matrix code in R, written to a csv file

```r
library("Hmisc")
flattenCorrMatrix <- function(cormat, pmat) {
  ut <- upper.tri(cormat)
  data.frame(
    row = rownames(cormat)[row(cormat)[ut]],
    column = rownames(cormat)[col(cormat)[ut]],
    cor  =(cormat)[ut],
    p = pmat[ut]
    )
}


res2<-rcorr(as.matrix(corr_matrix), type = "spearman")
mt_cor_matrix <- flattenCorrMatrix(res2$r, res2$P)
corr_matrix <- res2$r
ggcorrplot(corr_matrix, title = "Weighted correlation matrix with time-varying predictors
and outcomes outcomes")
```

Figure 25: Weighted correlation matrix code in R to graphically display time-varying predictors

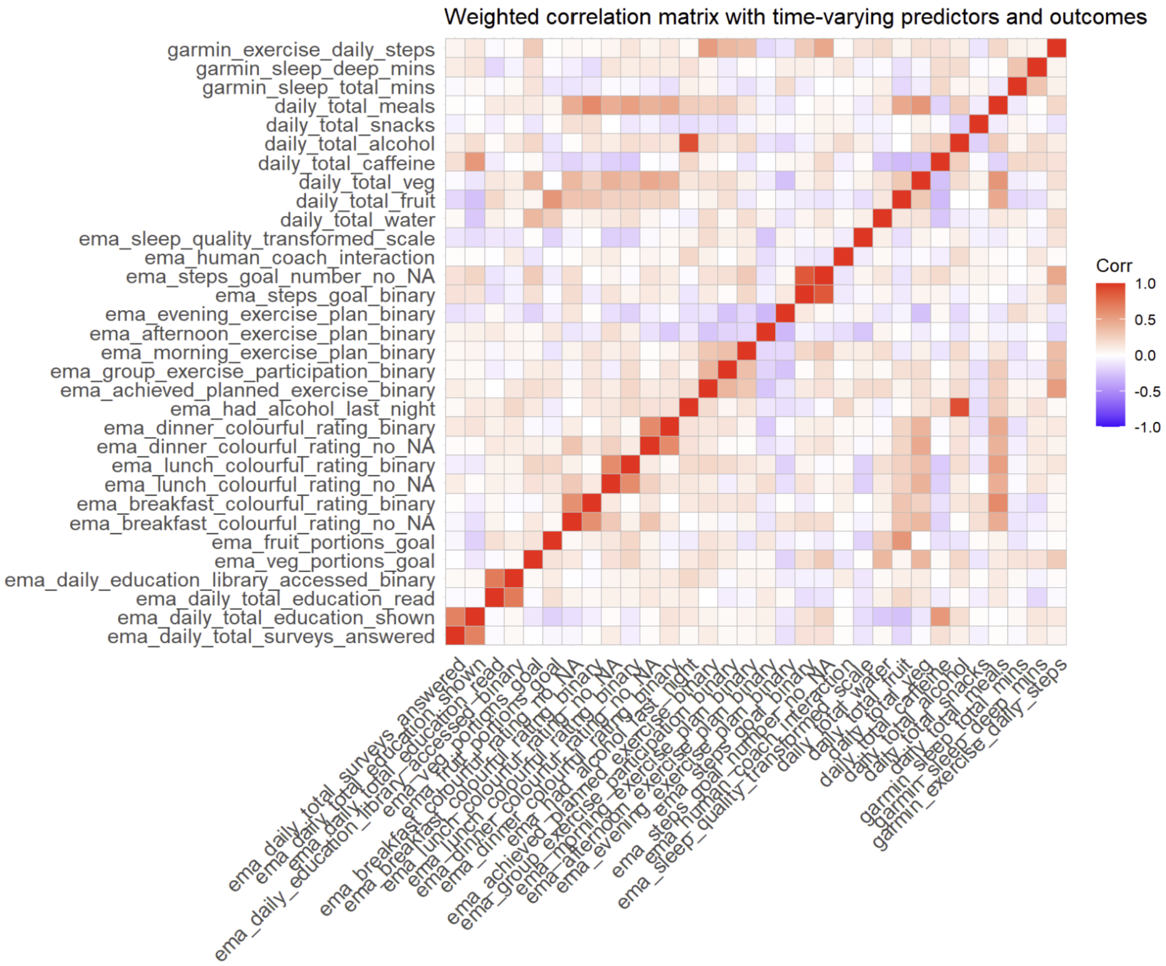


Figure 26: Correlation matrix between time-varying predictors and outcomes

The outcomes in the following sections are presented for daily steps count, portions of vegetables, and portions of fruit. The remaining outcomes are presented in **Appendix D, Tables 76 - 89)** and code with output screenshots are available in external storage (**Zenodo**). This section is followed by a summary on feasibility of predicting target behaviours and acceptability of the predictive power.

8.3.2 Daily Steps Count

8.3.2.1 Time-Varying Predictors for Steps Count With RFE

The best-fit RFE model ranked and selected six (27%; 6/22) time-varying predictors (e.g., achieving planned exercise, setting goal for a number of steps, setting goal for portions of vegetables, participating in group exercise, setting exercise plan to exercise in the morning, and setting a steps goal) (see **Figure 27** for code). This group of predictors resulted in the lowest RMSE (3.600) and MAE (2.818) and the RMSE result indicates that the average difference between the model's prediction and the actual steps count of 3,600 steps (see **Figure 28** for RFE results of iterating through different sets of predictors to select the best model, see and **Figure 29** for results of the RFE selected predictors). The NRMSE (0.1313; 3.600/27.411) (calculated as (RMSE/(y_{max} – y_{min}))) represents a low average error rate of 13.13%, and therefore a high prediction accuracy of 86.87%. This indicates that the RFE model (with a Random Forest estimator in R) fits the dataset well and produces acceptable predictions for steps count.

```
set.seed(7)
# load the library
library(mlbench)
library(caret)

# define the control using a random forest selection function
control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the RFE algorithm
results <- rfe(dfPredictors[, 1:22], dfPredictors[[23]], sizes=c(1:22), rfeControl=control)
# summarize the results
print(results)
# list the chosen features
predictors(results)
```

Figure 27: R-code to create a model with 22 time-varying predictors for predicting steps count outcome

	Variables <S3: AsIs>	RMSE <S3: AsIs>	Rsquared <S3: AsIs>	MAE <S3: AsIs>	RMSESD <S3: AsIs>	RsquaredSD <S3: AsIs>	MAESD <S3: AsIs>	Selected <S3: AsIs>
1	1	4.323	0.2330	3.522	0.8122	0.1929	0.6399	
2	2	3.630	0.4729	2.763	0.7385	0.1935	0.4252	
3	3	3.626	0.4807	2.834	0.6976	0.1967	0.4812	
4	4	3.679	0.4634	2.905	0.7517	0.2134	0.4842	
5	5	3.776	0.4535	2.953	0.7848	0.2071	0.5164	
6	6	3.600	0.4847	2.818	0.7747	0.2120	0.5831	*
7	7	3.628	0.4801	2.825	0.7550	0.2128	0.5550	
8	8	3.709	0.4562	2.866	0.7742	0.2140	0.5314	
9	9	3.715	0.4522	2.879	0.8004	0.2255	0.5676	
10	10	3.723	0.4543	2.897	0.7799	0.2183	0.5441	
11	11	3.739	0.4524	2.898	0.7867	0.2192	0.5354	
12	12	3.749	0.4471	2.910	0.8187	0.2157	0.5828	
13	13	3.765	0.4440	2.914	0.8209	0.2249	0.5828	
14	14	3.702	0.4658	2.866	0.8363	0.2265	0.5995	
15	15	3.694	0.4756	2.851	0.7922	0.2193	0.5670	
16	16	3.710	0.4755	2.840	0.7797	0.2209	0.5228	
17	17	3.759	0.4597	2.902	0.7932	0.2205	0.5327	
18	18	3.723	0.4674	2.896	0.7758	0.2173	0.5099	
19	19	3.719	0.4724	2.872	0.8072	0.2272	0.5423	
20	20	3.725	0.4677	2.865	0.7935	0.2255	0.5152	
21	21	3.756	0.4643	2.891	0.8002	0.2278	0.5396	
22	22	3.724	0.4767	2.902	0.7990	0.2289	0.5375	

22 rows

Figure 28: RFE results for selecting the best performing model with time-varying predictors for steps count

```
Recursive feature selection

Outer resampling method: Cross-Validated (10 fold)

Resampling performance over subset size:


The top 5 variables (out of 6):
   ema_achieved_planned_exercise_binary, ema_steps_goal_number_no_NA,
ema_veg_portions_goal, ema_group_exercise_participation_binary,
ema_morning_exercise_plan_binary

[1] "ema_achieved_planned_exercise_binary"
[2] "ema_steps_goal_number_no_NA"
[3] "ema_veg_portions_goal"
[4] "ema_group_exercise_participation_binary"
[5] "ema_morning_exercise_plan_binary"
[6] "ema_steps_goal_binary"
```

Figure 29: RFE results for selecting and ranking a subset of relevant time-varying predictors for steps count

For comparison, RFE with Gradient Boosting regressor in Python selected six predictors with half of the predictors (e.g., achieving planned exercise, setting goal for a number of steps, setting goal for a number of vegetables portions) being the same as RFE in R (see **Figure 30** for Python code and **Figure 31** for output).

```
#using RFE feature selection for steps
import warnings
warnings.filterwarnings("ignore")
from sklearn.feature_selection import RFECV
from sklearn.model_selection import RepeatedKFold
from sklearn.ensemble import GradientBoostingRegressor
import matplotlib.pyplot as plt
import pandas as pd
import random

random.seed(123)


data = pd.read_csv("C:/R_code/study4/dfPredictors.csv")
X = data.iloc[:,0:22]  #independent columns
y = data.iloc[:,-1]    #target column Garmin steps

rfecv = RFECV(estimator=GradientBoostingRegressor(),
              step=1,
              cv=RepeatedKFold(n_splits=10, n_repeats=3, random_state=1),
              scoring='neg_root_mean_squared_error')
rfecv.fit(X, y)
print("Optimum number of features: %d" % rfecv.n_features_)
print("Selected feature names:",rfecv.get_feature_names_out())

plt.figure( figsize=(16, 6))
plt.title('Total features selected for steps count versus RMSE')
plt.xlabel('Total features selected')
plt.ylabel('Model accuracy using neg RMSE')
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()


rfecv_df = pd.DataFrame(rfecv.ranking_,index=X.columns,columns=['Rank']).sort_values(by='Rank',ascending=True)
rfecv_df.head(22)
```

Figure 30: Python-code to create a model with 22 time-varying predictors for predicting steps count outcome

```
Optimum number of features: 6
Selected feature names: ['ema_veg_portions_goal' 'ema_breakfast_colourful_rating_no_NA'
 'ema_lunch_colourful_rating_no_NA' 'ema_dinner_colourful_rating_no_NA'
 'ema_achieved_planned_exercise_binary' 'ema_steps_goal_number_no_NA']
```

Figure 31: RFE results (in Python) for selecting and ranking a subset of relevant time-varying predictors for steps count

To obtain a list of statistically significant predictors, a linear model function is used. Using a linear model function, R-squared (0.5257) indicates that the model explains 53% of the variability in the outcome (i.e., steps count) and adjusted R-squared (0.5051) indicates 51% in variability with added penalty for the number of predictors (see **Figure 32** for code and **Figure 33** for output in R using linear model function). The RFE best-fit model (**Figure 28**) included half (3/6) of predictors that were statistically significant (e.g., achieving planned exercise, setting steps goal, setting a number of steps), indicating that these predictors had the greatest impact on physical activity, specifically steps count (**Figure 33**).

```
dfPredictors_0 <- data.frame(dfPredictors[c(1:22,23)])
dfPredictors_1 <- select(dfPredictors_0, daily_total_steps_scaled,
                         ema_achieved_planned_exercise_binary,
                         ema_steps_goal_number_no_NA,
                         ema_veg_portions_goal,
                         ema_group_exercise_participation_binary,
                         ema_morning_exercise_plan_binary,
                         ema_steps_goal_binary
                        )

model1 <- lm(daily_total_steps_scaled ~., data = dfPredictors_1)

summary(model1)
glance(model1) %>%
  dplyr::select(r.squared, adj.r.squared, sigma, AIC, BIC, p.value)
```

Figure 32: R-code for using linear model function to obtain a list of statistically significant predictors for steps count

```
Call:
lm(formula = daily_total_steps_scaled ~ ., data = dfPredictors_1)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.2558 -1.9286 -0.1351  1.8786 11.9774 

Coefficients:
                                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)                             4.5984430  0.9304201   4.942 2.17e-06 ***
ema_achieved_planned_exercise_binary    4.0571342  0.6338586   6.401 2.18e-09 ***
ema_steps_goal_number_no_NA             0.0008611  0.0001370   6.283 3.93e-09 ***
ema_veg_portions_goal                   0.2074569  0.1584069   1.310    0.192    
ema_group_exercise_participation_binary 0.1578031  0.7899710   0.200    0.842    
ema_morning_exercise_plan_binary        0.8877301  0.7103092   1.250    0.213    
ema_steps_goal_binary                  -6.0648677  1.4786929  -4.102 6.93e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.424 on 140 degrees of freedom
Multiple R-squared:  0.5257,	Adjusted R-squared:  0.5054 
F-statistic: 25.86 on 6 and 140 DF,  p-value: < 2.2e-16
```

Figure 33: Identifying statistically significant time-varying predictors for steps count

8.3.2.1.1 Optimised Set of BCTs for Steps Count

From the intervention design’s 34 BCTs selected to increase steps count, the FS RFE algorithm identified six time-varying predictors (from a set of 22 predictors) relevant to steps count outcome (**Figure 29**). These six predictors were linked to groups of BCTs (e.g., setting goals-step predictor is linked to 3 BCTs of goal setting, commitment, and graded tasks). With some of the BCTs repeating for different features, there are 9 unique BCTs used in predicting steps count (**Table 40**), representing 26% (9/34) of intervention BCTs. Therefore, these nine BCTs theoretically represent optimised set of BCTs for increasing steps count.

Table 40: Optimised set of BCTs for steps count based on FS time-varying predictors

BCTs	**Time-varying predictors**
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning
2.3 Self-monitoring, 3.3 Social support (emotional)	Joined group exercise
1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring, 8.7 Graded tasks	Setting goals-steps (yes/no)
1.6 Discrepancy between current behaviour and goal, 2.3 Self-monitoring, 15.1 Verbal persuasion about capability, 15.3 Focus on past success	Achieved planned exercise (self-reported)

8.3.2.2 Time-Varying Predictors for Steps Count with Correlation Matrix

The Correlation Matrix feature ranking produced six statistically significant ($p<0.05$) time-varying predictors with medium correlation with steps count outcome (with the rest of the ranked predictors not being statistically significant). The selected predictors reveal that answering daily EMA surveys, accessing education library, setting goals for vegetable portions, setting goal to exercise in the afternoon, setting goals for steps, and quality of sleep all significantly contributed to steps count prediction (**Table 41**).

Table 41: Time-varying predictors for steps count with Correlation Matrix

Predictors	r_s	**p-value**
Total EMA surveys answered	0.3515	0.0485
Accessing education library	-0.4424	0.0112
Setting goals-vegetables consumption	0.5678	0.0007
Setting goals-exercise-afternoon	-0.3754	0.0343
Setting goals-steps (yes/no)	0.5088	0.0029
Sleep quality (self-reported)	0.5755	0.0006

8.3.2.3 Time-Constant Predictors for Steps Count

The best-fit RFE model ranked and selected seventeen (85%; 17/20) time-constant predictors, with the lowest RMSE (3.754) and MAE (2.884). The RMSE score indicates that the average difference between the model's prediction and the actual steps count is 3,754 steps (see **Figure 34** for code in R and **Figure 35** for output of the RFE results of iterating through different sets of predictors to select the best model). The NRMSE (0.1370) (3.754/27.411) represents a low average error rate of 13.70%, and therefore a high prediction accuracy of 86.30%. This indicates that the model (with a Random Forest estimator in R) fits the dataset well and produces acceptable predictions for steps count.

```
# define the control using a random forest selection function
control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the RFE algorithm.  Use 20 time-constant predictors.
results <- rfe(dfPredictors_constant[, 1:20], dfPredictors_constant[[21]], sizes=c(1:20),
rfeControl=control)
# summarize the results
print(results)
# list the chosen features
predictors(results)
```

Figure 34: R-code to create a model with 20 time-constant predictors for predicting steps count outcome

	Variables <S3: AsIs>	RMSE <S3: AsIs>	Rsquared <S3: AsIs>	MAE <S3: AsIs>	RMSESD <S3: AsIs>	RsquaredSD <S3: AsIs>	MAESD <S3: AsIs>	Selected <S3: AsIs>
1	1	4.587	0.08589	3.597	0.8333	0.0820	0.6522	
2	2	3.940	0.31591	3.000	0.7237	0.1438	0.6212	
3	3	3.924	0.33455	3.044	0.7903	0.1759	0.6238	
4	4	3.812	0.37321	2.950	0.8097	0.1937	0.6390	
5	5	3.799	0.38145	2.976	0.8241	0.1910	0.6285	
6	6	3.793	0.36610	2.932	0.7623	0.1704	0.6213	
7	7	3.772	0.37218	2.911	0.7478	0.1702	0.6185	
8	8	3.787	0.36649	2.926	0.7532	0.1702	0.6224	
9	9	3.762	0.37673	2.896	0.7773	0.1714	0.6379	
10	10	3.766	0.37583	2.889	0.7622	0.1657	0.6295	
11	11	3.769	0.37399	2.897	0.7687	0.1634	0.6229	
12	12	3.763	0.37663	2.892	0.7695	0.1620	0.6297	
13	13	3.771	0.37561	2.897	0.7695	0.1639	0.6338	
14	14	3.778	0.37290	2.898	0.7662	0.1666	0.6294	
15	15	3.778	0.37388	2.899	0.7770	0.1672	0.6384	
16	16	3.764	0.37844	2.892	0.7711	0.1676	0.6354	
17	17	3.754	0.38075	2.884	0.7718	0.1662	0.6378	*
18	18	3.762	0.38067	2.898	0.7729	0.1680	0.6256	
19	19	3.772	0.37712	2.906	0.7814	0.1656	0.6428	
20	20	3.765	0.37870	2.891	0.7796	0.1666	0.6519	

20 rows

Figure 35: RFE results for selecting the best performing model with time-constant predictors for steps count

The top 5 time-constant predictors identified by the RFE algorithm included: UK county of residence, ethnicity, perspective on the menopause (e.g., not looking forward to it, have not thought about it, feeling neutral about the menopause), menopause stage (e.g., pre-, peri-, surgical menopause, post-menopause), and using CBT to manage menopause symptoms (**Figure 36**).

```
Recursive feature selection

Outer resampling method: Cross-Validated (10 fold)

Resampling performance over subset size:


The top 5 variables (out of 17):
   survey_pre_location_fct, survey_pre_meno_perspective_fct,
survey_pre_ethnicity_fct, survey_pre_meno_stage_fct, survey_pre_CBT_fct

 [1] "survey_pre_location_fct"              "survey_pre_meno_perspective_fct"
 [3] "survey_pre_ethnicity_fct"             "survey_pre_meno_stage_fct"
 [5] "survey_pre_CBT_fct"                   "survey_pre_income_fct"
 [7] "ema_group_exercise_participation_fct" "survey_pre_meno_knowledge_fct"
 [9] "survey_pre_age_group_fct"             "survey_pre_health_status_fct"
[11] "survey_pre_HRT_fct"                   "survey_pre_antidepressants_fct"
[13] "survey_pre_generation_british_fct"    "survey_pre_num_children_fct"
[15] "survey_pre_smoking_fct"               "survey_pre_marital_status_fct"
[17] "survey_pre_qualification_fct"
```

Figure 36: RFE results for selecting and ranking a subset of relevant time-constant predictors for steps count

Using linear model function, R-squared (0.4505) indicates that the model explains 45% of the variability in the outcome (i.e., steps count) and adjusted R-squared (0.3894) indicates 39% in variability with added penalty for the number of predictors (see **Figure 37** for code and **Figure 38** for output in R using linear model function). The RFE best-fit model (**Figure 35**) included 23.5% (4/17) of statistically significant predictors (i.e., UK county of residence, menopause perspective, menopause stage, participating in a group exercise prior in the past). More specifically, residing in 6 counties (i.e., London, NW England, Scotland, SE England, SW England, West Midlands, Yorkshire and the Humber), having a perspective on the menopause (e.g., “neutral perspective about the menopause”, or “not looking forward to it”), post-menopause stage (e.g., being post-menopause naturally or by having a surgical menopause), and participating in group exercises prior to the intervention (**Figure 38**). This outcome may indicate that different counties have varied opportunities to exercise (e.g., access to convenient gyms, healthy foods), and possibly support and education on menopause, and therefore these characteristics impacts the amount of physical activity (steps) the participants perform.

```
dfPredictors_0 <- data.frame(dfPredictors_constant[c(1:20,21)])

dfPredictors_1 <- select(dfPredictors_0, daily_total_steps_scaled,
                         survey_pre_location_fct,
                         survey_pre_meno_perspective_fct,
                         survey_pre_ethnicity_fct,
                         survey_pre_meno_stage_fct,
                         survey_pre_CBT_fct,
                         ema_group_exercise_participation_fct,
                         survey_pre_income_fct,
                         survey_pre_meno_knowledge_fct,
                         survey_pre_age_group_fct,
                         survey_pre_health_status_fct,
                         survey_pre_HRT_fct,
                         survey_pre_antidepressants_fct,
                         survey_pre_generation_british_fct,
                         survey_pre_num_children_fct,
                         survey_pre_smoking_fct,
                         survey_pre_marital_status_fct,
                         survey_pre_qualification_fct
                         )
model_constant1 <- lm(daily_total_steps_scaled ~., data = dfPredictors_1)

summary(model_constant1)

glance(model_constant1) %>%
  dplyr::select(r.squared, adj.r.squared, sigma,statistic, AIC, BIC, p.value)
```

Figure 37: R-code for using linear function model to obtain a list of statistically significant time-constant predictors for steps count outcome

```
                                                     Pr(>|t|)
(Intercept)                                          < 2e-16 ***
survey_pre_location_fctLondon                       0.133475
survey_pre_location_fctNorth West England           2.29e-05 ***
survey_pre_location_fctScotland                     0.108095
survey_pre_location_fctSouth East England           0.014317 *
survey_pre_location_fctSouth West England           0.646917
survey_pre_location_fctWales                        0.074585 .
survey_pre_location_fctWest Midlands                0.000400 ***
survey_pre_location_fctYorkshire and the Humber     0.134093
survey_pre_meno_perspective_fctHave not thought about it 0.855962
survey_pre_meno_perspective_fctNeutral              0.002499 **
survey_pre_meno_perspective_fctNot looking forward to it 0.004873 **
survey_pre_meno_perspective_fctUnsure               0.764222
survey_pre_meno_stage_fctPost-menopause             0.000535 ***
survey_pre_meno_stage_fctPre-menopause              0.044563 *
survey_pre_meno_stage_fctSurgical menopause         0.004967 **
survey_pre_meno_stage_fctUnsure                     0.202582
ema_group_exercise_participation_fctYes             0.011494 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.717 on 153 degrees of freedom
Multiple R-squared:  0.4505,    Adjusted R-squared:  0.3894
F-statistic: 7.378 on 17 and 153 DF,  p-value: 5.25e-13
```

Figure 38: Time constant predictors for significant contribution to steps count (R output)

8.3.2.4 Cross-Validation of The Steps Count

As described in the methods (**Section 8.2**), although RFE performs cross-validation automatically, this section demonstrates performing cross-validation to assess performance of the model on unseen test data (see **Figure 39** for R code to explicitly split the data to training and validation set, in which the validation set represents the unseen data). Three cross-validation methods were explored (e.g., leave one out cross validation (see **Figure 40** for code), k-fold cross validation (see **Figure 41** for code), and repeated k-fold cross validation (see **Figure 42** for code)) on the RFE selected best-fit (6-predictor) model for steps count (**Figure 28**). The leave-one-out method resulted in the lowest R-squared (0.48), while the 10-Fold (not repeated) resulted in the highest R-squared (0.527) and the lowest RMSE (3.385) (**Table 42**). Overall, the cross-validation on unseen (validation) data resulted in a slightly lower R-squared (0.41) and higher RMSE (3.79) (**Figure 43**), compared to the RFE results on training data with R-squared (0.49) and RMSE (3.60) (**Figure 28**), indicating that the RFE feature selection model is slightly over-fitting. This is often the case in predictions using small training datasets (Guyon et al., 2010).

```
# Split the data into training and test set
set.seed(123)
training.samples <- dfPredictors_2$daily_total_steps_scaled %>%
  createDataPartition(p = 0.8, list = FALSE)
train.data <- dfPredictors_2[training.samples, ]
test.data <- dfPredictors_2[-training.samples, ]
# Build the model
model <- lm(daily_total_steps_scaled ~., data = train.data)
# Make predictions and compute the R2, RMSE and MAE
predictions <- model %>% predict(test.data)
data.frame( R2 = R2(predictions, test.data$daily_total_steps_scaled),
            RMSE = RMSE(predictions, test.data$daily_total_steps_scaled),
            MAE = MAE(predictions, test.data$daily_total_steps_scaled))
```

Figure 39: R-code to create test and validation dataset for steps count

R2 <dbl>	RMSE <dbl>	MAE <dbl>
0.4094561	3.786733	2.915238

Figure 40: Output of the validation dataset prediction for steps count (from code in Figure 37)

```
# Define training control
train.control <- trainControl(method = "LOOCV")
# Train the model
model <- train(daily_total_steps_scaled ~., data = dfPredictors_2, method = "lm",
               trControl = train.control)
# Summarize the results
print(model)
```

Figure 41: R-code for leave-one-out cross validation for steps count

```r
# Define training control
set.seed(123)
train.control <- trainControl(method = "cv", number = 5)
# Train the model
model <- train(daily_total_steps_scaled ~., data = dfPredictors_2, method = "lm",
               trControl = train.control)
# Summarize the results
print(model)
```

Figure 42: R-code for 5-fold cross validation for steps count (for 10-fold, change 'number' = 10)

```r
# Define training control
set.seed(123)
train.control <- trainControl(method = "repeatedcv",
                              number = 10, repeats = 10)
# Train the model
model <- train(daily_total_steps_scaled ~., data = dfPredictors_2, method = "lm",
               trControl = train.control)
# Summarize the results
print(model)
```

Figure 43: R-code for 10-fold repeated 10 times cross validation for steps count (for 3 and 5 repeats, change 'repeats')

Table 42: Cross-validation results using 5 methods for steps

Cross-validation method	**Best-fit model (6 predictors)**		
	R-squared	**RMSE**	**MAE**
Leave-one-out	0.482	3.497	2.592
5-Fold	0.488	3.501	2.614
10-Fold	0.527	3.385	2.611
5-Fold, repeated 3 times	0.502	3.464	2.589
10-Fold, repeated 3 times	0.508	3.426	2.626
10-Fold, repeated 10 times	0.507	3.434	2.608

8.3.3 Diet

8.3.3.1 Vegetables Consumption

8.3.3.1.1 Time-Varying Predictors for Vegetables Consumption With RFE

The best-fit RFE model ranked and selected ten (45%; 10/22) time-varying predictors (e.g., setting goals for portions of vegetables, rating dinner, rating lunch, rating breakfast, setting goals to exercise in the evening, setting steps goals, counselling, setting goals to exercise in the morning) (see **Figure 44** for code). This group of predictors resulted in the lowest RMSE (2.139) and MAE (1.749), indicating that the average difference between the model's prediction and the portions of vegetables is 2 portions (see **Figure 45** for RFE results of iterating through different sets of predictors to select the best model and **Figure 46** for results of the RFE selected predictors). The NRMSE (0.1426) (2.139/15) represents a low average error rate of 14.26%, and therefore a high prediction accuracy of 85.74%. This indicates that the RFE model (with a Random Forest estimator in R) fits the dataset well and produces acceptable predictions for portions of vegetables consumed.

```r
# define the control using a random forest selection function
control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the RFE algorithm
results <- rfe(dfPredictors[, 1:22], dfPredictors[[26]], sizes=c(1:22), rfeControl=control)
# summarize the results
print(results)
# list the chosen features
predictors(results)
```

Figure 44: R-code to create a model with 22 time-varying predictors for predicting vegetables consumption outcome

	Variables <S3: AsIs>	RMSE <S3: AsIs>	Rsquared <S3: AsIs>	MAE <S3: AsIs>	RMSESD <S3: AsIs>	RsquaredSD <S3: AsIs>	MAESD <S3: AsIs>	Selected <S3: AsIs>
1	1	2.670	0.3753	2.172	0.4025	0.1375	0.3070	
2	2	2.769	0.3383	2.265	0.4668	0.2313	0.4178	
3	3	2.527	0.4651	2.085	0.4292	0.2063	0.3435	
4	4	2.532	0.4737	2.116	0.3655	0.2195	0.3150	
5	5	2.404	0.5463	1.944	0.3314	0.1931	0.2731	
6	6	2.192	0.5919	1.772	0.4418	0.2075	0.4002	
7	7	2.204	0.5974	1.788	0.3830	0.1904	0.3414	
8	8	2.182	0.6142	1.781	0.3813	0.1877	0.3705	
9	9	2.171	0.6197	1.790	0.3531	0.1765	0.3507	
10	10	2.139	0.6307	1.749	0.3471	0.1809	0.3264	*
11	11	2.142	0.6348	1.753	0.3645	0.1812	0.3455	
12	12	2.141	0.6311	1.756	0.3496	0.1809	0.3356	
13	13	2.143	0.6294	1.759	0.3591	0.1908	0.3208	
14	14	2.161	0.6278	1.772	0.3387	0.1757	0.3043	
15	15	2.183	0.6133	1.801	0.3439	0.1850	0.3112	
16	16	2.172	0.6223	1.785	0.3514	0.1906	0.3295	
17	17	2.173	0.6207	1.778	0.3534	0.1897	0.3101	
18	18	2.174	0.6194	1.771	0.3492	0.1883	0.2971	
19	19	2.165	0.6280	1.759	0.3529	0.1944	0.3192	
20	20	2.175	0.6235	1.763	0.3470	0.1901	0.3153	
21	21	2.154	0.6303	1.758	0.3284	0.1864	0.3052	
22	22	2.161	0.6313	1.756	0.3440	0.1865	0.3148	

22 rows

Figure 45: RFE results for selecting the best performing model with time-varying predictors for vegetables consumption

```
Recursive feature selection

Outer resampling method: Cross-Validated (10 fold)

Resampling performance over subset size:


The top 5 variables (out of 10):
   ema_veg_portions_goal, ema_dinner_colourful_rating_no_NA,
ema_lunch_colourful_rating_no_NA, ema_breakfast_colourful_rating_no_NA,
ema_evening_exercise_plan_binary

 [1] "ema_veg_portions_goal"               "ema_dinner_colourful_rating_no_NA"
 [3] "ema_lunch_colourful_rating_no_NA"    "ema_breakfast_colourful_rating_no_NA"
 [5] "ema_evening_exercise_plan_binary"    "ema_dinner_colourful_rating_binary"
 [7] "ema_lunch_colourful_rating_binary"   "ema_steps_goal_number_no_NA"
 [9] "ema_daily_total_education_shown"     "ema_morning_exercise_plan_binary"
```

Figure 46: RFE results for selecting and ranking a subset of relevant time-varying predictors for vegetables consumption

For comparison, RFE with Gradient Boosting regressor in Python selected twenty predictors with eight predictors being the same as RFE in R (see **Figure 47** for Python code and **Figure 48** for output).

```
#using RFE feature selection for veg portions
import warnings
warnings.filterwarnings("ignore")
from sklearn.feature_selection import RFECV
from sklearn.model_selection import RepeatedKFold
from sklearn.ensemble import GradientBoostingRegressor
import matplotlib.pyplot as plt
import pandas as pd
import random

random.seed(500)


data = pd.read_csv("C:/R_code/study4/dfPredictors.csv")
X = data.iloc[:,0:22]  #independent columns
y = data.iloc[:,-8]    #target column veg portions

rfecv = RFECV(estimator=GradientBoostingRegressor(),
              step=1,
              cv=RepeatedKFold(n_splits=10, n_repeats=3, random_state=1),
              scoring='neg_root_mean_squared_error')
rfecv.fit(X, y)
print("Optimum number of features: %d" % rfecv.n_features_)
print("Selected feature names:",rfecv.get_feature_names_out())

plt.figure( figsize=(16, 6))
plt.title('Total features selected for vegetables portions versus RMSE')
plt.xlabel('Total features selected')
plt.ylabel('Model accuracy using neg RMSE')
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()


rfecv_df = pd.DataFrame(rfecv.ranking_,index=X.columns,columns=['Rank']).sort_values(by='Rank',ascending=True)
rfecv_df.head(22)
```

Figure 47: Python-code to create a model with 22 time-varying predictors for predicting vegetables consumption outcome

```
Optimum number of features: 20
Selected feature names: ['ema_daily_total_surveys_answered' 'ema_daily_total_education_shown'
 'ema_daily_total_education_read'
 'ema_daily_education_library_accessed_binary' 'ema_veg_portions_goal'
 'ema_fruit_portions_goal' 'ema_breakfast_colourful_rating_no_NA'
 'ema_lunch_colourful_rating_no_NA' 'ema_dinner_colourful_rating_no_NA'
 'ema_dinner_colourful_rating_binary' 'ema_had_alcohol_last_night'
 'ema_achieved_planned_exercise_binary'
 'ema_group_exercise_participation_binary'
 'ema_morning_exercise_plan_binary' 'ema_afternoon_exercise_plan_binary'
 'ema_evening_exercise_plan_binary' 'ema_steps_goal_binary'
 'ema_steps_goal_number_no_NA' 'ema_human_coach_interaction'
 'ema_sleep_quality_transformed_scale']
```

Figure 48: RFE results (in Python) for selecting and ranking a subset of relevant time-varying predictors for vegetables consumption

Using a linear model function, R-squared (0.5855) indicates that the model explains 59% of the variability in the outcome (i.e., vegetables consumption) and adjusted R-squared (0.555) indicates 56% in variability with added penalty for the number of predictors (see **Figure 49** for code and **Figure 50** for output in R using linear model function). The RFE best-fit model (see **Figure 45**) included 60% (6/10) statistically significant predictors (i.e., setting goals for portions of vegetables to be consumed, eating colourful breakfast and lunch, rating dinner, setting goals to exercise in the evening, and receiving counselling), indicating that these predictors had the greatest impact on consumption of vegetables (**Figure 50**).

```
dfPredictors_0 <- data.frame(dfPredictors[c(1:22,26)])
dfPredictors_1 <- select(dfPredictors_0, daily_total_veg,
                         ema_veg_portions_goal,
                         ema_dinner_colourful_rating_no_NA,
                         ema_lunch_colourful_rating_no_NA,
                         ema_breakfast_colourful_rating_no_NA,
                         ema_evening_exercise_plan_binary,
                         ema_dinner_colourful_rating_binary,
                         ema_lunch_colourful_rating_binary,
                         ema_steps_goal_number_no_NA,
                         ema_daily_total_education_shown,
                         ema_morning_exercise_plan_binary
                        )
model1 <- lm(daily_total_veg ~., data = dfPredictors_1)
summary(model1)
glance(model1) %>%
  dplyr::select(r.squared, adj.r.squared, sigma, AIC, BIC, p.value)
```

Figure 49: R-code for using linear model function to obtain a list of statistically significant time-varying predictors for vegetables consumption

```
Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)                         1.374e+00  1.568e+00   0.876 0.382439    
ema_veg_portions_goal               5.998e-01  1.078e-01   5.566 1.34e-07 ***
ema_dinner_colourful_rating_no_NA   1.138e-02  9.403e-03   1.210 0.228340    
ema_lunch_colourful_rating_no_NA    2.055e-02  8.162e-03   2.517 0.012982 *  
ema_breakfast_colourful_rating_no_NA 2.251e-02  6.679e-03   3.370 0.000978 ***
ema_evening_exercise_plan_binary   -1.583e+00  4.000e-01  -3.958 0.000121 ***
ema_dinner_colourful_rating_binary  3.675e+00  9.868e-01   3.724 0.000286 ***
ema_lunch_colourful_rating_binary   6.297e-01  7.940e-01   0.793 0.429089    
ema_steps_goal_number_no_NA         8.751e-06  5.090e-05   0.172 0.863759    
ema_daily_total_education_shown    -6.697e-01  3.381e-01  -1.981 0.049661 *  
ema_morning_exercise_plan_binary   -5.765e-01  4.406e-01  -1.308 0.192950    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.222 on 136 degrees of freedom
Multiple R-squared:  0.5855,	Adjusted R-squared:  0.555 
F-statistic: 19.21 on 10 and 136 DF,  p-value: < 2.2e-16
```

Figure 50: RFE results for selecting the best performing model with time-varying predictors for vegetables consumption

8.3.3.1.1.1 Optimised Set of BCTs for Vegetables Consumption

From the intervention design's 34 BCTs, the FS RFE algorithm identified 10 time-varying predictors (from a set of 24 predictors) relevant to vegetables consumption outcome (see **Figure 46**). These 10 predictors were linked to groups of BCTs (e.g., setting goals-step predictor is linked to 3 BCTs of goal setting, commitment, and graded tasks). With some of the BCTs repeating for different features, there are 20 unique BCTs used in predicting vegetables consumption (**Table 43**), representing 59% (20/34) of intervention BCTs. Therefore, these 20 BCTs theoretically represent optimised set of BCTs for increasing vegetables consumption.

Table 43: Optimised set of BCTs for vegetables consumption based on FS time-varying predictors

BCTs	**Time-varying predictors**
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning

1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-evening
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (yes/no)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (yes/no)

8.3.3.1.2 Time-Varying Predictors for Vegetables Consumption with Correlation Matrix

The Correlation Matrix produced 11 statistically significant ($p<0.05$) time-varying predictors with medium correlation with vegetables portions outcome. The selected predictors reveal that for example, receiving EMA education, accessing education library, setting goals for fruit and vegetables portions, rating meals for colourfulness, all significantly contributed to prediction for consumption of vegetables (**Table 44**).

Table 44: Time-varying predictors for vegetables consumption with Correlation Matrix

Predictors	**r_s**	**p-value**
Accessing education library	0.4410	0.0115
Accessing education library (yes/no)	0.3768	0.0335
Setting goals-vegetables consumption	0.4315	0.0137
Setting goals-fruit consumption	0.4080	0.0204
Rating meal colourfulness-breakfast (yes/no)	0.6166	0.0002
Rating meal colourfulness-lunch	0.6305	0.0001
Rating meal colourfulness-dinner (yes/no)	0.5865	0.0004
Achieved planned exercise (self-reported)	0.4608	0.0080
Joined group exercise	0.5304	0.0018
Setting goals-exercise-morning	0.3622	0.0417
Setting goals-exercise-evening	-0.3783	0.0328

8.3.3.1.3 Time-Constant Predictors for Vegetables Consumption

The RFE algorithm identified a model with a subset of 8 predictors resulting in the best-fit model with 40% (8/20) of time-varying predictors and the lowest RMSE (2.925) and MAE (2.426), indicating that the average difference between the model's prediction and the actual portions of vegetables is 3 portions (see **Figure 51** for code in R and **Figure 52** for output of the RFE results of iterating through different sets of predictors to select the best model). The NRMSE (0.1950) (2.925/15) represents a low average error rate of 19.50%, and therefore a high prediction accuracy of 80.50%. This indicates that the model (with a Random Forest estimator in R) fits the dataset well and produces acceptable predictions for vegetables consumption.

```
# define the control using a random forest selection function
control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the RFE algorithm.  Use 20 time-constant predictors.
results <- rfe(dfPredictors_constant[, 1:20], dfPredictors_constant[[24]], sizes=c(1:20),
rfeControl=control)
# summarize the results
print(results)
# list the chosen features
predictors(results)
```

Figure 51: R-code to create a model with 20 time-constant predictors for predicting vegetables consumption outcome

	Variables <S3: AsIs>	RMSE <S3: AsIs>	Rsquared <S3: AsIs>	MAE <S3: AsIs>	RMSESD <S3: AsIs>	RsquaredSD <S3: AsIs>	MAESD <S3: AsIs>	Selected <S3: AsIs>
1	1	3.204	0.2279	2.594	0.4579	0.1934	0.4521	
2	2	2.995	0.3133	2.476	0.4153	0.1824	0.3344	
3	3	2.976	0.3353	2.471	0.4297	0.1857	0.3449	
4	4	2.966	0.3348	2.478	0.4547	0.1894	0.3615	
5	5	2.959	0.3376	2.455	0.4637	0.1932	0.3881	
6	6	2.984	0.3362	2.491	0.5415	0.1903	0.4467	
7	7	2.944	0.3523	2.449	0.5715	0.1993	0.4722	
8	8	2.925	0.3570	2.426	0.5819	0.2066	0.4858	*
9	9	2.932	0.3604	2.444	0.6038	0.2093	0.4975	
10	10	2.949	0.3524	2.457	0.5945	0.2066	0.4860	
11	11	2.937	0.3576	2.447	0.6036	0.2075	0.5084	
12	12	2.946	0.3564	2.460	0.6050	0.2085	0.5033	
13	13	2.946	0.3545	2.452	0.6064	0.2098	0.5067	
14	14	2.942	0.3566	2.454	0.6073	0.2100	0.5057	
15	15	2.938	0.3577	2.446	0.6004	0.2096	0.5006	
16	16	2.941	0.3566	2.451	0.5957	0.2089	0.4966	
17	17	2.935	0.3579	2.441	0.6043	0.2131	0.5031	
18	18	2.939	0.3569	2.450	0.5993	0.2123	0.4993	
19	19	2.934	0.3592	2.442	0.5966	0.2077	0.4982	
20	20	2.934	0.3575	2.444	0.5895	0.2087	0.4938	

20 rows

Figure 52: RFE results for selecting the best performing model with time-constant predictors for vegetables consumption

The top 8 time-constant predictors identified by the RFE algorithm included: ethnicity, menopause stage, participating in group exercise in the past, perspective on the menopause, knowledge about the menopause, UK county of residence, generation British, and age group (**Figure 53**).

```
Recursive feature selection

Outer resampling method: Cross-Validated (10 fold)

Resampling performance over subset size:


The top 5 variables (out of 8):
   survey_pre_ethnicity_fct, survey_pre_meno_stage_fct,
ema_group_exercise_participation_fct, survey_pre_meno_perspective_fct,
survey_pre_meno_knowledge_fct

[1] "survey_pre_ethnicity_fct"             "survey_pre_meno_stage_fct"
[3] "ema_group_exercise_participation_fct" "survey_pre_meno_perspective_fct"
[5] "survey_pre_meno_knowledge_fct"        "survey_pre_location_fct"
[7] "survey_pre_generation_british_fct"    "survey_pre_num_children_fct"
```

Figure 53: RFE results for selecting and ranking a subset of relevant time-constant predictors for vegetables consumption

Using linear model function, R-squared (0.4599) indicates that the model explains 46% of the variability in the outcome (i.e., vegetables consumption) and adjusted R-squared (0.3754) indicates 38% in variability with added penalty for the number of predictors (see **Figure 54** for code and **Figure 55** for output in R using linear model function). The RFE best-fit model (see **Figure 52**) included 63% (5/8) statistically significant predictors (e.g., UK county of residence, ethnicity, menopause perspective, attending group exercise classes in the past, having some knowledge about the menopause) (see **Figure 55**). This may indicate that ethnicity of women impacts the quantity of vegetables they consume, but also where they live, how they feel about menopause and their knowledge about menopause.

```r
dfPredictors_0 <- data.frame(dfPredictors_constant[c(1:20,24)])
dfPredictors_1 <- select(dfPredictors_0, daily_total_veg,
                         survey_pre_ethnicity_fct,
                         survey_pre_meno_perspective_fct,
                         survey_pre_meno_stage_fct,
                         ema_group_exercise_participation_fct,
                         survey_pre_meno_knowledge_fct,
                         survey_pre_location_fct,
                         survey_pre_generation_british_fct,
                         survey_pre_num_children_fct
                         )
model_constant_1 <- lm(daily_total_veg ~., data = dfPredictors_1)
summary(model_constant_1)

glance(model_constant_1) %>%
  dplyr::select(r.squared, adj.r.squared, sigma, AIC, BIC, p.value)
```

Figure 54: R-code for using linear model function to obtain a list of statistically significant time-constant predictors for vegetables consumption

```
                                                              Pr(>|t|)
(Intercept)                                                   9.34e-09 ***
survey_pre_ethnicity_fctChinese                                0.58237
survey_pre_ethnicity_fctIndian                                 0.13947
survey_pre_ethnicity_fctLatin American                         0.54011
survey_pre_ethnicity_fctOther White background                 0.00400 **
survey_pre_ethnicity_fctWhite and Black Caribbean              0.00389 **
survey_pre_ethnicity_fctWhite British                          0.08871 .
survey_pre_ethnicity_fctWhite Irish                            0.05057 .
survey_pre_meno_perspective_fctHave not thought about it            NA
survey_pre_meno_perspective_fctNeutral                         0.04539 *
survey_pre_meno_perspective_fctNot looking forward to it       0.35997
survey_pre_meno_perspective_fctUnsure                          0.13285
survey_pre_meno_stage_fctPost-menopause                        0.43518
survey_pre_meno_stage_fctPre-menopause                         0.52541
survey_pre_meno_stage_fctSurgical menopause                    0.17314
survey_pre_meno_stage_fctUnsure                                0.13691
ema_group_exercise_participation_fctYes                        0.00839 **
survey_pre_meno_knowledge_fctSome knowledge                    0.00127 **
survey_pre_meno_knowledge_fctVery informed                          NA
survey_pre_location_fctLondon                                  0.31301
survey_pre_location_fctNorth West England                           NA
survey_pre_location_fctScotland                                0.34777
survey_pre_location_fctSouth East England                      0.24498
survey_pre_location_fctSouth West England                      0.18182
survey_pre_location_fctWales                                   0.17666
survey_pre_location_fctWest Midlands                           0.30655
survey_pre_location_fctYorkshire and the Humber                0.04779 *
survey_pre_generation_british_fctNative                             NA
survey_pre_generation_british_fctSecond generation                  NA
survey_pre_generation_british_fctThird generation or more           NA
survey_pre_num_children_fct1-2                                      NA
survey_pre_num_children_fct3 or more                                NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.795 on 147 degrees of freedom
Multiple R-squared:  0.4599,	Adjusted R-squared:  0.3754
F-statistic: 5.442 on 23 and 147 DF,  p-value: 5.392e-11
```

Figure 55: Time constant predictors for significant contribution to vegetables consumption (R output)

8.3.3.2 Fruit Consumption

8.3.3.2.1 Time-Varying Predictors for Fruit Consumption With RFE

The best-fit model ranked and selected 16 (72%; 16/22) time-varying predictors (e.g., setting goals for portions of fruit consumed, eating highly colourful breakfast, setting goals for number of steps, eating highly colourful dinner, and rating breakfast) (see **Figure 56** for R-code). This group of predictors resulted in the lowest RMSE (1.796) and MAE (1.439), indicating that the average difference between the model's prediction and the portion of fruit is less than 2 portions (see **Figure 57** for RFE results of iterating through different sets of predictors to select the best model, see and **Figure 58** for results). The NRMSE (0.120) (1.796/15) represents a low average error rate of 12.00%, and therefore a high prediction accuracy of 88.00%. This indicates that the RFE model (with a Random Forest estimator in R) fits the dataset well and produces acceptable predictions for portions of fruit consumed.

```
# define the control using a random forest selection function
control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the RFE algorithm
results <- rfe(dfPredictors[, 1:22], dfPredictors[[27]], sizes=c(1:22), rfeControl=control)
# summarize the results
print(results)
# list the chosen features
predictors(results)
```

Figure 56: R-code to create a model with 22 time-varying predictors for predicting fruit consumption outcome

	Variables <S3: AsIs>	RMSE <S3: AsIs>	Rsquared <S3: AsIs>	MAE <S3: AsIs>	RMSESD <S3: AsIs>	RsquaredSD <S3: AsIs>	MAESD <S3: AsIs>	Selected <S3: AsIs>
1	1	1.840	0.4058	1.433	0.4941	0.1788	0.3990	
2	2	1.903	0.3362	1.501	0.5028	0.2160	0.3673	
3	3	1.887	0.3719	1.460	0.4645	0.2395	0.3453	
4	4	1.862	0.3932	1.450	0.4648	0.2324	0.3668	
5	5	1.855	0.4066	1.444	0.4029	0.2024	0.3072	
6	6	1.821	0.3854	1.418	0.4783	0.1880	0.3746	
7	7	1.860	0.3585	1.452	0.4860	0.1957	0.3503	
8	8	1.874	0.3375	1.483	0.4459	0.1680	0.2886	
9	9	1.839	0.3584	1.465	0.4690	0.1833	0.3199	
10	10	1.819	0.3728	1.435	0.4819	0.1946	0.3296	
11	11	1.824	0.3682	1.458	0.4626	0.1979	0.3161	
12	12	1.818	0.3805	1.447	0.4956	0.2046	0.3476	
13	13	1.838	0.3631	1.468	0.4874	0.2113	0.3395	
14	14	1.826	0.3714	1.455	0.4811	0.2047	0.3314	
15	15	1.811	0.3772	1.454	0.5073	0.2151	0.3518	
16	16	1.796	0.3919	1.439	0.4937	0.2177	0.3529	*
17	17	1.796	0.3901	1.434	0.4927	0.2114	0.3444	
18	18	1.807	0.3817	1.466	0.4840	0.2045	0.3329	
19	19	1.805	0.3851	1.458	0.4772	0.2084	0.3348	
20	20	1.810	0.3849	1.444	0.4696	0.2082	0.3316	
21	21	1.813	0.3815	1.450	0.4681	0.2025	0.3412	
22	22	1.832	0.3703	1.463	0.4570	0.1940	0.3200	

22 rows

Figure 57: RFE results for selecting the best performing model with time-varying predictors for fruit consumption

```
Outer resampling method: Cross-Validated (10 fold)

Resampling performance over subset size:


The top 5 variables (out of 16):
   ema_fruit_portions_goal, ema_breakfast_colourful_rating_binary,
ema_steps_goal_number_no_NA, ema_dinner_colourful_rating_binary,
ema_breakfast_colourful_rating_no_NA

 [1] "ema_fruit_portions_goal"
 [2] "ema_breakfast_colourful_rating_binary"
 [3] "ema_steps_goal_number_no_NA"
 [4] "ema_dinner_colourful_rating_binary"
 [5] "ema_breakfast_colourful_rating_no_NA"
 [6] "ema_daily_total_education_shown"
 [7] "ema_veg_portions_goal"
 [8] "ema_daily_total_education_read"
 [9] "ema_morning_exercise_plan_binary"
[10] "ema_lunch_colourful_rating_no_NA"
[11] "ema_daily_total_surveys_answered"
[12] "ema_lunch_colourful_rating_binary"
[13] "ema_steps_goal_binary"
[14] "ema_group_exercise_participation_binary"
[15] "ema_had_alcohol_last_night"
[16] "ema_daily_education_library_accessed_binary"
```

Figure 58: RFE results for selecting and ranking a subset of relevant time-varying predictors for fruit consumption

For comparison, RFE with Gradient Boosting regressor in Python selected only 3 predictors (e.g., fruit portions goal, rating breakfast, and rating dinner) with two predictors being the same as RFE using Random Forest algorithm in R. The results between ML algorithms used in R and Python were not in alignment, except for the first ranked predictor (i.e., setting goals for portions of fruit) (see **Figure 59** for Python code and **Figure 60** for output).

```
#using RFE feature selection for fruit portions
import warnings
warnings.filterwarnings("ignore")
from sklearn.feature_selection import RFECV
from sklearn.model_selection import RepeatedKFold
from sklearn.ensemble import GradientBoostingRegressor
import matplotlib.pyplot as plt
import pandas as pd
import random

random.seed(400)


data = pd.read_csv("C:/R_code/study4/dfPredictors.csv")
X = data.iloc[:,0:22]  #independent columns
y = data.iloc[:,-9]    #target column fruit portions

rfecv = RFECV(estimator=GradientBoostingRegressor(),
              step=1,
              cv=RepeatedKFold(n_splits=10, n_repeats=3, random_state=1),
              scoring='neg_root_mean_squared_error')
rfecv.fit(X, y)
print("Optimum number of features: %d" % rfecv.n_features_)
print("Selected feature names:",rfecv.get_feature_names_out())

plt.figure( figsize=(16, 6))
plt.title('Total features selected for fruit portions versus RMSE')
plt.xlabel('Total features selected')
plt.ylabel('Model accuracy using neg RMSE')
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()


rfecv_df = pd.DataFrame(rfecv.ranking_,index=X.columns,columns=['Rank']).sort_values(by='Rank',ascending=True)
rfecv_df.head(22)
```

Figure 59: Python-code to create a model with 22 time-varying predictors for predicting fruit consumption outcome

```
Optimum number of features: 3
Selected feature names: ['ema_fruit_portions_goal' 'ema_breakfast_colourful_rating_no_NA'
 'ema_dinner_colourful_rating_no_NA']
```

Figure 60: RFE results (in Python) for selecting and ranking a subset of relevant time-varying predictors for fruit consumption

Using a linear model function, R-squared (0.5098) indicates that the model explains 51% of the variability in the outcome (i.e., fruit consumption) and adjusted R-squared (0.4494) indicates 45% in variability with added penalty for the number of predictors (see **Figure 61** for code and **Figure 62** for output in R using linear model function). The RFE best-fit model (**Figure 57**) included 19% (3/16) statistically significant ($p<0.05$) predictors (i.e., setting goals for portions of fruit to be consumed, rating breakfast and dinner), indicating that these predictors had the greatest impact on consumption of fruit (**Figure 62**).

```r
dfPredictors_0 <- data.frame(dfPredictors[c(1:22,27)])

dfPredictors_1 <- select(dfPredictors_0, daily_total_fruit,
                    ema_fruit_portions_goal,
                    ema_breakfast_colourful_rating_binary,
                    ema_steps_goal_number_no_NA,
                    ema_dinner_colourful_rating_binary,
                    ema_breakfast_colourful_rating_no_NA,
                    ema_daily_total_education_shown,
                    ema_veg_portions_goal,
                    ema_daily_total_education_read,
                    ema_morning_exercise_plan_binary,
                    ema_lunch_colourful_rating_no_NA,
                    ema_daily_total_surveys_answered,
                    ema_lunch_colourful_rating_binary,
                    ema_steps_goal_binary,
                    ema_group_exercise_participation_binary,
                    ema_had_alcohol_last_night,
                    ema_daily_education_library_accessed_binary

                   )
model1 <- lm(daily_total_fruit ~., data = dfPredictors_1)
summary(model1)
glance(model1) %>%
  dplyr::select(r.squared, adj.r.squared, sigma, AIC, BIC, p.value)
```

Figure 61: R-code for using linear model function to obtain a list of statistically significant time-varying predictors for fruit consumption

```
Coefficients:
                                             Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                 3.128e+00  2.176e+00   1.438  0.15296    
ema_fruit_portions_goal                     9.977e-01  1.499e-01   6.656 7.13e-10 ***
ema_breakfast_colourful_rating_binary       1.203e+00  5.423e-01   2.219  0.02821 *  
ema_steps_goal_number_no_NA                -8.385e-05  7.417e-05  -1.130  0.26036    
ema_dinner_colourful_rating_binary          1.911e+00  6.092e-01   3.138  0.00211 ** 
ema_breakfast_colourful_rating_no_NA        8.534e-03  5.998e-03   1.423  0.15722    
ema_daily_total_education_shown            -1.377e-01  3.300e-01  -0.417  0.67712    
ema_veg_portions_goal                      -3.454e-02  8.249e-02  -0.419  0.67615    
ema_daily_total_education_read              1.719e-01  9.963e-02   1.725  0.08682 .  
ema_morning_exercise_plan_binary           -6.132e-01  3.564e-01  -1.721  0.08770 .  
ema_lunch_colourful_rating_no_NA            7.751e-03  6.373e-03   1.216  0.22609    
ema_daily_total_surveys_answered           -8.286e-01  5.105e-01  -1.623  0.10700    
ema_lunch_colourful_rating_binary           5.683e-02  6.436e-01   0.088  0.92978    
ema_steps_goal_binary                       6.915e-01  8.096e-01   0.854  0.39458    
ema_group_exercise_participation_binary     5.240e-01  3.954e-01   1.325  0.18738    
ema_had_alcohol_last_night                  2.280e-01  3.610e-01   0.632  0.52871    
ema_daily_education_library_accessed_binary -6.345e-01  5.634e-01  -1.126  0.26217    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.669 on 130 degrees of freedom
Multiple R-squared:  0.5098,    Adjusted R-squared:  0.4494 
F-statistic: 8.449 on 16 and 130 DF,  p-value: 1.101e-13
```

Figure 62: RFE results for selecting the best performing model with time-varying predictors for fruit consumption

8.3.3.2.1.1 Optimised Set of BCTs for Fruit Consumption

From the intervention design's 34 BCTs selected to increase fruit consumption the FS RFE algorithm identified sixteen time-varying predictors (from a set of 24 predictors) relevant to fruit consumption outcome (**Figure 58**). These 16 predictors were linked to 20 unique BCTs, representing 59% (20/34) of all intervention BCTs, with many of the BCTs linked to counselling predictor that was identified (**Table 45**). Therefore, these 20 BCTs theoretically represent optimised set of BCTs for increasing fruit consumption.

Table 45: Optimised set of BCTs for fruit consumption based on FS time-varying predictors

BCTs	**Time-varying predictors**
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning
1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
1.1 Goal setting, 1.9 Commitment	Setting goals-fruit consumption
2.3 Self-monitoring, 3.3 Social support (emotional)	Joined group exercise

2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (yes/no)
2.3 Self-monitoring	Alcohol consumed last night
1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring, 8.7 Graded tasks	Setting goals-steps (yes/no)
4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 9.1 Credible sources, 12.1 Restructuring the physical environment	Accessing education library
5.1 Information about health consequences	Accessing education library (yes/no)
2.2 Feedback on behaviour, 2.3 Self-monitoring, 8.3 Habit formation	Total EMA surveys answered
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (yes/no)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (yes/no)

8.3.3.2.2 Time-Varying Predictors for Fruit Consumption with Correlation Matrix

The Correlation Matrix produced 4 statistically significant ($p<0.05$) time-varying predictors with medium correlation with fruit portions outcome. The selected predictors reveal that for example, answering EMA surveys, receiving EMA education, accessing education library, and rating dinner for colourfulness, all significantly contributed to prediction for consumption of fruit (**Table 47**).

Table 46: Time-varying predictors for fruit consumption with Correlation Matrix

Predictors	r_s	**p-value**
Total EMA surveys answered	-0.4439	0.0109
EMA education received (counselling)	-0.6111	0.0002
Accessing education library (yes/no)	0.4227	0.0160
Rating meal colourfulness-dinner	0.6250	0.0001

8.3.3.2.3 Time-Constant Predictors for Fruit Consumption

The RFE algorithm identified a model with a subset of 4 predictors resulting in the best-fit model with 20% (4/20) of time-constant predictors and the lowest RMSE (2.427) and MAE (1.858), indicating that the average difference between the model's prediction and the actual portion of fruit is two (see **Figure 63** for code in R and **Figure 64** for output of the RFE results of iterating through different sets of predictors to select the best model). The NRMSE (0.187) (2.427/13) represents a low average error rate of 18.70%, and therefore a high prediction accuracy of 81.30%. This indicates that the model (with a Random Forest estimator in R) fits the dataset well and produces acceptable predictions for portions of fruit consumed.

```r
# define the control using a random forest selection function
control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the RFE algorithm.  Use 20 time-constant predictors.
results <- rfe(dfPredictors_constant[, 1:20], dfPredictors_constant[[25]], sizes=c(1:20),
rfeControl=control)
# summarize the results
print(results)
# list the chosen features
predictors(results)
```

Figure 63: R-code to create a model with 20 time-constant predictors for predicting fruit consumption outcome

	Variables <S3: AsIs>	RMSE <S3: AsIs>	Rsquared <S3: AsIs>	MAE <S3: AsIs>	RMSESD <S3: AsIs>	RsquaredSD <S3: AsIs>	MAESD <S3: AsIs>	Selected <S3: AsIs>
1	1	2.572	0.02916	1.998	0.2737	0.04827	0.1874	
2	2	2.436	0.10075	1.898	0.2924	0.12198	0.2115	
3	3	2.446	0.13214	1.888	0.3501	0.14236	0.2489	
4	4	2.427	0.14682	1.858	0.3437	0.14182	0.2574	*
5	5	2.431	0.14483	1.865	0.3327	0.14351	0.2416	
6	6	2.490	0.15610	1.948	0.4402	0.17693	0.3365	
7	7	2.483	0.16168	1.940	0.4649	0.17750	0.3524	
8	8	2.472	0.16434	1.930	0.4552	0.17237	0.3435	
9	9	2.484	0.16633	1.946	0.4785	0.18192	0.3652	
10	10	2.480	0.16901	1.941	0.4868	0.18646	0.3760	
11	11	2.475	0.17059	1.938	0.4836	0.18699	0.3703	
12	12	2.475	0.16645	1.940	0.4659	0.18927	0.3638	
13	13	2.474	0.16671	1.935	0.4648	0.18637	0.3566	
14	14	2.481	0.16331	1.942	0.4652	0.18710	0.3608	
15	15	2.490	0.16074	1.952	0.4716	0.18764	0.3699	
16	16	2.478	0.16345	1.938	0.4673	0.19429	0.3637	
17	17	2.471	0.16652	1.933	0.4658	0.19007	0.3659	
18	18	2.484	0.16188	1.948	0.4634	0.18815	0.3583	
19	19	2.478	0.16476	1.940	0.4677	0.19251	0.3604	
20	20	2.473	0.16868	1.939	0.4714	0.18990	0.3647	

20 rows

Figure 64: RFE results for selecting the best performing model with time-constant predictors for fruit consumption

The top four time-constant predictors identified by the RFE algorithm included: UK county of residence, marital status, joining group exercise classes in the past, and age group (**Figure 65**).

```
Recursive feature selection

Outer resampling method: Cross-Validated (10 fold)

Resampling performance over subset size:


The top 4 variables (out of 4):
   survey_pre_location_fct, survey_pre_marital_status_fct,
ema_group_exercise_participation_fct, survey_pre_age_group_fct

[1] "survey_pre_location_fct"              "survey_pre_marital_status_fct"
[3] "ema_group_exercise_participation_fct" "survey_pre_age_group_fct"
```

Figure 65: RFE results for selecting and ranking a subset of relevant time-constant predictors for fruit consumption

Using linear model function, R-squared (0.2699) indicates that the model explains 27% of the variability in the outcome (i.e., fruit consumption) and adjusted R-squared (0.1992) indicates 20% in variability with added penalty for the number of predictors (see **Figure 66** for code and **Figure 67** for output in R using linear model function). The RFE best-fit model included 75% (3/4) statistically significant predictors (e.g., UK county of residence, marital status, participating in group exercises in the past) that significantly contributed to the variability in portions of fruit consumed. This may indicate that women living in different countries, whether they are married or not and joining groups to exercise consume different amount of fruit (**Figure 67**).

```
dfPredictors_0 <- data.frame(dfPredictors_constant[c(1:20,25)])
dfPredictors_1 <- select(dfPredictors_0, daily_total_fruit,
                         survey_pre_location_fct,
                         survey_pre_marital_status_fct,
                         ema_group_exercise_participation_fct,
                         survey_pre_age_group_fct
                         )


model_constant_1 <- lm(daily_total_fruit ~., data = dfPredictors_1)
summary(model_constant_1)

glance(model_constant_1) %>%
  dplyr::select(r.squared, adj.r.squared, sigma, AIC, BIC, p.value)
```

Figure 66: R-code for using linear model function to obtain a list of statistically significant time-constant predictors for fruit consumption

```
                                                               Pr(>|t|)
(Intercept)                                                    1.4e-05 ***
survey_pre_location_fctLondon                                  0.78262
survey_pre_location_fctNorth West England                      0.05066 .
survey_pre_location_fctScotland                                0.21519
survey_pre_location_fctSouth East England                      0.16345
survey_pre_location_fctSouth West England                      0.48414
survey_pre_location_fctWales                                   0.47553
survey_pre_location_fctWest Midlands                           0.03541 *
survey_pre_location_fctYorkshire and the Humber                0.69850
survey_pre_marital_status_fctMarried, living as married        0.74587
survey_pre_marital_status_fctNever married                     0.01319 *
survey_pre_marital_status_fctPrefer not to say                 0.09392 .
ema_group_exercise_participation_fctYes                        0.00617 **
survey_pre_age_group_fct45-49                                  0.75363
survey_pre_age_group_fct50-54                                  0.66518
survey_pre_age_group_fct55-59                                  0.79129
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.252 on 155 degrees of freedom
Multiple R-squared:  0.2699,    Adjusted R-squared:  0.1992
F-statistic: 3.819 on 15 and 155 DF,  p-value: 9.172e-06
```

Figure 67: Time constant predictors for significant contribution to fruit consumption (R output)

8.3.4 Feasibility of Predicting Target Behaviours

Overall, using both methods, 1) feature ranking with correlation matrix (CM) and 2) selecting subset of features methods with recursive feature elimination (RFE) was feasible in identifying relevant groups of time-varying predictors for each outcome (i.e., output was generated in R or Python). Furthermore, using the RFE method, it was feasible to identify optimised sets of BCTs for each time-varying predictor, for each target outcome.

8.3.4.1 Summary of RFE Selected Time-Varying Predictors for All Target Behaviours

The feature selection RFE algorithm used time-varying predictors to predict each target outcome, with the objective to use as few predictors as possible to predict an outcome. From the 24 time-varying predictors used in the ML models, the RFE algorithm selected between 6 and 21 predictors, depending on the type of target outcome. For example, predicting steps count required 6 predictors, while alcohol consumption required 21 predictors (see a summary of time-varying predictors selected by RFE for each outcome, **Appendix D, Table 90**). Furthermore, predicting target outcomes that were measured objectively in the intervention (**Chapter 7**), using fitness tracker (i.e., steps, sleep) and not subjectively by user’s input, required fewer predictors. Additionally, two predictors: daily Goal setting for steps, and Goal setting for portions of vegetables were selected in predicting all ten outcomes.

8.3.4.2 Optimised Sets of BCTs Linked to Time-Varying Predictors for All Target Behaviours

As described in the Methods (**Section 8.2**), the time-varying predictors are theoretically linked to BCTs (see **Table 39** for mapping of BCTs to features). Therefore, by identifying relevant time-varying predictors for each outcome, their corresponding groups of BCTs could also be identified. Based on this theoretical link, the results of RFE show that the 24 time-varying predictors were linked to between 9 and 24 unique BCTs. For example, the RFE selected 6 predictors for steps count that were linked to 9 unique BCTs, while RFE selected 16 predictors for fruit consumption and 10 predictors for vegetables consumption, each equally linked to 20 unique BCTs. These BCTs therefore represent the optimised set of BCTs for each target behaviour, from the initial 34-BCTs used in the intervention design (see a summary of optimised sets of BCTs for all target behaviours in **Appendix D, Table 91**).

8.3.4.3 Summary of RFE Selected Time-Constant Predictors for all Target Outcomes

In all target outcomes, the county of residence (i.e., locally available options) was selected as a time-constant predictor, followed by ethnicity that was selected in all outcomes except for fruit consumption, water intake, and number of meals consumed. Views and perspectives on menopause, in terms of accepting of it, or not looking forward to it also influenced most of the target outcomes, except for consumption of fruit, alcohol consumption, and sleep quality (see a summary of time-constant predictors used in RFE, **Appendix D, Table 92**)

8.3.5 Acceptability of Accuracy and Predictive Power

The acceptability of prediction accuracy (i.e., Normalised RMSE) and power (i.e., R-squared) of the feature selection was performed in R using RFE with Random Forest algorithm. In all outcomes, except for sleep (total and deep), the prediction power was acceptable (R-squared ≥ 0.10), and R-squared was on average 46.6% and 33.9% for time-varying and time-constant predictions, respectively. The prediction accuracy (NRMSE) was high, on average 85.7% and 82.6% for time-varying and time-constant predictions, respectively. However, although the power and accuracy results are acceptable, the sample size and the number of events (observations) available in the dataset was very small, resulting in overfitting and therefore acceptable results are very likely (see **Limitations, Section 8.4.1**).

8.4 Discussion

This chapter demonstrates a novel use of ML FS to identify group-level predictors that are linked to theoretical constructs in the context of healthy lifestyle behaviours in UK-residing midlife women. These constructs are represented by groups of BCTs that were identified in a multimethod design (Study 1, 2, co-production) and tested in a DHBCI (Study 3). This study (Study 4) used FS to optimise (and therefore further personalise) the intervention design by identifying the most relevant features and therefore the most relevant BCTs that were involved in predicting each intervention outcome (e.g., steps, fruit and vegetables consumption). Existing literature used FS successfully in the context exercise pose prediction (Puvanendran and Thangasundram, 2023) and in eating behaviours to predict 'about to eat' moments (Rahman et al., 2016). Another application of FS used monitoring of eating behaviour using necklace-worn wearables to detect swallowing (Alshurafa et al., 2014) and a correlation classification ML model was applied in prediction of respective high-risk time to prevent binge eating using EMA intervention dataset (Arend et al., 2023). Although the use of FS in optimising predictors is not novel, there is a gap in literature in the application of FS in health-promoting behaviour change and identifying most impactful BCTs to further personalise DHBCIs.

Using the longitudinal intervention dataset (see **Chapter 7**), the FS using Random Forest (RF) algorithm and Gradient Boosting Regressor (GB) produced similar results overall, with 13 (range 6 to 21) and 12 (range 3 to 20) average number of time-varying predictors selected across all ten target behaviours, respectively. Generally, using only relevant and fewer features in a model results in a better performance and the objective in building a model is to find the right balance between the best-fit and simplicity of the model (Bolón-Canedo, Sánchez-Maroño and Alonso-Betanzos, 2013). The greatest discrepancies (between RF and GB algorithms) were in predicting fruit consumption and vegetables consumption with a difference of 10 and 13 predictors, respectively (with RF using more predictors than GB). Although these two target behaviours were the primary focus of the intervention, the selected features may not have provided the best representation for these two intervention outcomes. In another study, RFE with logistic regression model, Random Forest (RF), and Gradient Boosting Trees (GBT) algorithms were used to identify feature importance based on a longitudinal data of electronic health record and genetic data (e.g., age, blood pressure, total cholesterol) (Zhao et al., 2019). The results show that each model prioritised different features, for example, RF chose BMI in multiple years, whereas GBT prioritised medical conditions obtained from the most recent year prior to the prediction window (Zhao et al., 2019). Although differences in FS using different algorithms should be expected, the choice of the selected algorithm should include domain expert knowledge (e.g., a nutritionist in dietary interventions, an exercise physiologist in physical activity interventions), with many aspects to consider in selecting the best estimator (e.g., the problem, data, number of parameters). Additionally, quantifying the stability of the FS methods is needed, also acknowledged in another study evaluating FS algorithms (López et al., 2021).

Furthermore, objectively measured data (using Garmin fitness tracker) for steps and sleep quantity and sleep quality required lower number of predictors (between 6 and 7) to predict their outcome, compared to data that was provided subjectively through EMAs. Specifically, EMA survey used for providing input on consumption of alcoholic beverages, number of snacks and number of meals used the highest number of predictors (between 18 and 21 predictors) to predict their outcomes. Results from a meta-analysis of personalised lifestyle DHIs show that interventions that used system-captured data for personalisation were associated with higher effectiveness than those that used user-reported data (Tong et al., 2021a). Although using JITAI, including EMAs, has been widely used in behavioural research to produce more frequent assessments of behaviour change (Spruijt-Metz, Wen, et al., 2015), high-frequency data captured from multiple modalities can potentially offset any misrepresentations and inaccuracies in data obtained from subjective user data input. Furthermore, although this study evaluated group-level predictors, making predictions by utilising data from the entire dataset, (Perski et al., 2023) identified improved performance with hybrid algorithms (group-level and individual-level data), compared to only group-level but not individual-level algorithms using longitudinal dataset. However, one of the main limitations in both, the (Perski et al., 2023) study and this research is in their small datasets. In this research, there was no separate test data used in the model testing to verify performance of the models on unseen data. The small dataset also has an impact on overfitting of the models to the dataset, influencing high acceptability of the predictive models' accuracy (RMSE) and goodness-of-fit (R-squared). Therefore, future optimisation phases in this research will require larger datasets to address overfitting of the selected models to data.

As the objective of feature selection is to find the optimal number of relevant features (Saeys, Inza and Larrañaga, 2007), fewer predictors with a higher proportion of statistically significant predictors may signify a better model. The most frequently selected predictors were setting goals for steps, setting goals for vegetables consumption, setting goals to exercise in the morning, counselling prompts, and rating breakfast and lunch for colourfulness. Most of these predictors targeted capability and motivation components of COM-B (see **Appendix D, Table 90** for a summary of time-varying predictors selected in RFE for each outcome). With the theoretical link to BCTs, the RFE identified predictors provided groups of the most relevant and therefore optimised BCTs. Overall, the optimised sets of BCTs identified for each target behaviour included between 9 and 24 BCTs, from the 34-BCT intervention design. For example, steps count outcome was predicted in RFE using six predictor that were linked to 9 unique BCTs. This means that these 9 BCTs represent an optimised set of BCTs, from the 34-BCT design tested in the intervention (**Chapter 7**). The rest of the 25 (34-9) intervention BCTs although included in the intervention design, were not relevant in predicting steps count outcome, at a group-level. Most of the BCTs used in the optimised set of BCTs were in Repetition and substitution BCT group (e.g., behavioural practice/rehearsal, graded tasks), followed by Goals and Planning BCT group (e.g., Goal setting, action planning) (see a summary of optimised BCTs, **Appendix D, Table 91**). The groups of most frequent BCTs (e.g., goal setting, self-monitoring, feedback on behaviour, action planning, graded tasks) represented by predictors in FS were also identified in other studies focusing on diet and physical activity (Samdal et al., 2017; Mahdi, Michalik-Denny and Buckland, 2022). Furthermore, the correlation matrix revealed that increasing access to the education content had a significant strong positive correlation with outcomes, such as daily portions of fruit and daily portions of vegetables consumed. However, it is important to note that these outcomes were based on the 22 time-varying features that were selected to be used in the ML models. Therefore, different sets of features are likely to produce different results, although the principles behind this research should remain regardless of the types of features used in ML models. Other research pointed out that in FS, individual irrelevant features may become relevant in the context of other features (Fogelman-Soulié, 2008). Furthermore, a feature may be independent of the outcome variable but be conditionally dependent on another feature (Fogelman-Soulié, 2008). Therefore, future research should focus on utilising feature engineering techniques (e.g., feature creation, transformation, splitting, extraction) to improve the model's performance, robustness, generalisation, and interpretability (Verdonck et al., 2024).

This research explored new ways to achieve improved personalisation of DHBCIs. Although it focused on a group-level personalisation, there is a need for better personalisation through individual-level predictor selection with many other individual factors to consider. In this research, a set of 20 time-constant predictors (representing characteristics of individuals) were used in the RFE model. The results suggest that living in a particular part of the UK has an influence on health behaviours, which could be linked to access to fresh fruit and vegetables, convenient access to gyms, and outdoors to engage in more walking. These barriers were also acknowledged in a systematic review (Kelly et al., 2016) which revealed that the provision of locally available, affordable, and easy access to integrating health behaviours into daily lives of midlife adults are needed. Improving local environment to encourage walking, cycling, active transport and healthier food outlets were also identified (Kelly et al., 2016). Ethnicity, which may represent different cultures, appears to influence consumption of vegetables, alcohol and coffee consumption, as well as walking (see a summary of time-constant predictors used in RFE, **Appendix D, Table 92**). Furthermore, (Kaiser and Butter, 2024) examined whether data from two weeks of EMA questionnaires on stress and emotions alongside smartphone sensor data would be able to predict food cravings approximately 2.5 hours into the future. The study concluded that prediction of food craving has proved quite difficult when based on generalised models on the population level with influential factors that include stress (Chao et al., 2015), negative emotions (Christensen, 2007) but also positive emotions (Moore and Konrath, 2015), circadian patterns (Reichenberger et al., 2018), and several more. While the number of influential variables is high, their interactions are not fully clear. Other factors, such as past psychological (i.e., personality and affective states), situational (i.e., objective situations and psychological situation cues), and time (i.e., trends, time of day, and day of the week) were explored in a study using ML classification algorithms to predict future behaviours and experiences (i.e., loneliness, procrastination, and studying) (Beck and Jackson, 2022). The study found that a majority of participants' future behaviours are predicted by both person and situation features, and that the most important features vary greatly across people (Beck and Jackson, 2022).

Although personalisation is thought to improve user adherence in DHBCIs, it is still far from reaching its full potential (Monteiro-Guerra et al., 2020). A review of personalisation strategies in DHBCIs (Monteiro-Guerra et al., 2020) concluded that future work should consider theory and leverage the needs of the target users for personalisation. Advanced personalisation methods utilising ML models have been suggested to further improve personalisation effectiveness in DHIs (Hornstein et al., 2023). Furthermore, although there is an agreement in the scientific community that nomothetic models are less useful, group-level models (e.g., UK-residing midlife women) have the potential to be effective for most of the target population, on average. At this point in time, no other studies incorporated regression-based predictive models in the context of health-promoting behaviour change targeting midlife women. This research is therefore addressing this gap in the literature and provides novel methods to further personalise DHBCIs at a group-level.

8.4.1 Strengths and Limitations

Although using feature selection to identify subsets of features that are the most relevant in predicting outcome is not novel, this study applied a novel method to identify predictors that are linked to groups of theoretical constructs (i.e., BCTs). Therefore, the identified predictors could also be linked back to theory, to the intervention BCTs, to identify optimised sets of BCTs that were the most relevant in each target outcome. These theoretical constructs were defined through a theory and evidence-based design (Study 1, Study 2, co-production). Additionally, the predictions are based on a real intervention dataset consisting of longitudinal high-frequency data, providing greater level of granularity in capturing behaviour change in time. The prompted study design supported uniform frequency (i.e., EMA prompts at the same time daily) between data entries across all participants. Additionally, combining data from multiple modalities (i.e., EMAs, fitness tracker, survey data) provides a holistic view on behaviour change and can therefore create more robust predictions.

The main limitation of this study is the small sample size (N=24) and limited number of total observations (k=171) with individual observations capturing on average 7 days of data per participant (range 3 – 13 days) (see **Chapter 7, Section 7.3.2.3.2**). Thus, ML model that is trained on a small dataset may perform with a high degree of accuracy at training time, but performs poorly, with low degree of accuracy in making predictions on previously unseen data (known as overfitting). This was also acknowledged in another study (Perski et al., 2023) and although the algorithm performed well, it was tested only on a dataset with small number of (entries) observations (k=37,002) and a sample (N=791). Models consisting of mixed predictors (i.e., time-varying and time-constant) as well as individual-level or hybrid (i.e., group-level and individual-level) predictions were out of scope for this feasibility study. The features constructed in this study do not represent an exhaustive list of all possible features that may be available in the intervention dataset and should therefore not be considered the best features. Additionally, given the small dataset, some of the ML models did not effectively identify a strong set of predictors. For example, in predicting sleep target behaviour, the model fit was less than 10%. It is therefore recommended that for a reliable generalisation error estimate (e.g., RMSE), an independent validation dataset and another modelling algorithm are used on the final FS subset (Jović, Brkić and Bogunović, 2015). Although optimising the predictive model was not in scope of this study, it is important to address in future studies. Furthermore, the evaluation technique performed by the FS is limited to only this exploratory study and it has not been validated to be extended to other studies. Secondly, only two ML algorithms were explored, and their selection did not involve extensive selection of other possible regression-based models. Other larger ML studies (Perski et al., 2023) include identification of a best-performing group-level algorithm.

8.4.2 Conclusions

This chapter demonstrated a novel use of supervised feature selection ML algorithm to evaluate the feasibility of identifying groups of features, theoretically linked to groups of BCTs, that have a significant effect (determined by the feature selection algorithm, $p<0.05$) on the intervention target behaviours. This study demonstrated that selecting groups of predictors that are linked to BCTs is feasible and acceptable in accuracy and goodness-of-fit (i.e., explainability) in predicting target behaviours. These findings confirm the assumption that ML algorithms can efficiently identify the most relevant features and therefore the most relevant groups of BCTs that are operationalised in the intervention designs. The findings indicate that time-constant predictors, including ethnicity and cultural background should be considered in the designs to improve personalisation. Additionally, conducting human-supported digital health lifestyle intervention (as opposed to digital only or human-only) may provide additional real-life benefits in personalisation and continuous adaptation of the intervention at an individual level. Thus, a theory-based design followed by a group-level identification of predictors linked to behavioural constructs provides an opportunity to improve personalisation and potentially effectiveness of DHBCIs targeting UK-residing midlife women. These findings have an important implication for future research that are discussed in the next concluding chapter. In addition, next chapter will present key findings for each study within this research and conclude with overall recommendations on ways to achieve adaptive, continuous and personalised DHBCIs at an individual level.

9. Discussion and Future Research

9.1 Overview of Chapter

The aim of this thesis was to personalise a digital health behaviour change intervention (DHBCI) for a sub-population of midlife women, in the UK. The research methodology was based on identifying theory and evidence-based behavioural factors that have the potential to improve diet and physical activity for the target population. This thesis presented a series of empirical studies beginning with a systematic review (Study 1), mixed method focus groups (Study 2), and co-production, which collectively informed the identification of behavioural factors (e.g., goal setting, knowledge, motivation) that were subsequently operationalised in an experimental study ("intervention") (Study 3). The intervention evaluated the feasibility and acceptability of the design in a DHBCI with the target population. The thesis concluded with an exploration of the feasibility to identify the most relevant intervention features and behavioural factors predicting lifestyle improvements, utilising ML models (Study 4) (see **Chapter 1, Figure 1**).

Together, these findings can in future research guide the designs of personalised lifestyle health-promoting interventions that may also include other theory and evidence-based design methods (e.g., women's health expert panel, Delphi method), other data collection modalities (e.g., more sophisticated sensors capturing eating episodes and biometrics), reach other healthy lifestyle behaviours (e.g., diet with intermittent fasting and exercise with physical-cognitive exercises, weight loss) and domains (e.g., stress, cognitive functioning), and other population groups of midlife women (e.g., within the UK, in other countries). In this concluding chapter, a summary of the key findings of this research is presented. The discussion centres around the novel contribution to the existing literature. The limitations of the empirical investigations included in this thesis are provided, along with recommendations for how to overcome them in the future research. Lastly, future research recommendations are taken into consideration in light of the conclusions of this thesis.

*Note: Relevant supplementary materials for this chapter are presented in **Appendix E** of this thesis.*

9.2 Summary of Key Findings and Contributions to Existing Literature

9.2.1 Study 1: Behaviour Change Techniques in Digital Health Interventions for Midlife Women: A Systematic Review (Population-Level Design)

The systematic review is the first published study to systematically evaluate designs of digital health-promoting interventions targeting midlife women. The study was published in the JMIR mHealth and uHealth journal (Sediva et al., 2022) and cited by several authors since its publication. This chapter highlighted that the synthesis of behavioural factors that may play a role in improving diet and physical activity in DHIs for midlife women is limited with several methodological weaknesses. Overall, the reviewed interventions 1) lacked theoretical grounding, 2) had low levels of treatment fidelity, and 3) did not specify what components (e.g., BCTs) were used in the DHIs and how these components were activated. The novel aspects of this review include annotating behavioural components of the included thirteen studies to the BCW framework (including COM-B/TDF) and BCTs, evaluating treatment fidelity and the extent of using behaviour change theory in the intervention designs. It has been established that having theoretical understanding of behaviour change is necessary to maximise the potential efficacy of interventions (Michie and Johnston, 2012; Prestwich et al., 2014; Davis et al., 2015). While designing health behaviour change interventions is inherently a complex process, the most convincing results are currently obtained when interventions are explicitly based on behaviour change theory, formally identifying intervention techniques, components, and theory-driven mechanism of action, while ensuring validity and fidelity at each step of the way (Teixeira, 2016). Although the systematic review findings indicate what (groups of) BCTs are used more frequently in DHI designs, the apparent heterogeneity in the designs of DHIs, selection of techniques and their modes of delivery, target populations and target behaviours, do not support identification of effective BCTs for generalisability of the designs.

Although researchers often refer to effective BCTs as BCTs known to change behaviour (Teixeira, 2016), it is important to note that effectiveness of any BCT depends on a number of parameters, including the target behaviour, population, setting, mode of delivery, presence of any interaction with other operating BCTs and related mechanisms of action (Kok et al., 2016). Therefore, the identified set of 33 BCTs that were annotated from the reviewed interventions in this systematic review provide a generic set of BCTs that have been used more frequently in DHBCIs with midlife women and are therefore referred to in this research as generic population-level intervention techniques that lack personalisation. Although, behavioural science lacks evidence to identify what combinations of BCTs and related mechanisms work best in which circumstances (Teixeira, 2016), this review identified a set of BCTs that have the potential to serve as a foundational (generalisable) model for developing other DHIs for midlife women. The identified set of BCTs in this study is used as the initial group of BCTs in the design of the three-workstream intervention (described in **Chapter 7**) and it is further merged and refined with the combined inputs from the lived experiences of UK-residing midlife women (study 2), and co-production.

9.2.2 Study 2: Designing a Digital Health Behaviour Change Intervention for Midlife Women in the UK: A Mixed Method Study (Group-Level Personalisation)

This mixed-method study aimed to understand lived experiences of UK-residing midlife women with healthy eating and regular physical activity, and to provide input for the next level of granularity in the personalisation of the intervention design. Novel aspects of this study include the process of representing lived experiences of midlife women using both inductive TA and a deductive approach by applying the BCW framework. The qualitative focus group discussions identified barriers and facilitators to lifestyle health behaviours (i.e., healthy diet, regular physical activity, sleep) and the impact of menopause on these lifestyle behaviours, with a pre-focus group survey capturing individual experiences on diet, physical activity, sleep, and menopause symptoms.

Although other studies also explored barriers and facilitators to health behaviours in midlife women (Kowal and Fortier, 2007; Teixeira et al., 2010; McGuire, Anderson and Fulbrook, 2014; Chopra et al., 2022) and midlife adults (Kelly et al., 2016), the application of the BCW framework and identification of BCTs to systematically describe lived experiences with both healthy eating and physical activity is novel. Overall, the inductively identified barriers and enablers were deductively annotated to 39 BCTs and cross-validated by a second reviewer (resulting in an acceptable inter-rater validity). The COM-B component of Motivation was the primary influencer of health behaviours, also highlighted in other research (Timlin, McCormack and Simpson, 2021) that focused on barriers and facilitators in the adoption of a healthy diet in UK-residing midlife adults. Furthermore, four TDF domains of social influences, behavioural regulation, reinforcement, and beliefs about capabilities, had the highest number of BCTs, indicating that more support may be needed in these domains to improve health behaviours. The domain of social influences particularly was highlighted in other studies (Lawton et al., 2016; Cardol et al., 2022). Uncertainty around what health foods are and how to adjust one’s diet in midlife (revealed in the focus groups) indicate that nutrition knowledge is consistently reported as the main factor influencing healthy eating. Other research confirms that knowledge is a substantial barrier to healthy eating in midlife adults (Kelly et al., 2016; Timlin, McCormack and Simpson, 2021), however, knowledge alone is insufficient to improve healthy eating behaviours (Spronk et al., 2014) and other BCTs may need to be incorporated.

Overall, the discussions revealed that influences on health behaviours are multi-factorial and require not only increasing knowledge, but also progressive goal setting through graded-tasks, self-monitoring, and commitment (Van Achterberg et al., 2011) to improve self-efficacy, enjoyment, and health outcomes. This study provided a more granular group-level personalisation for the intervention design specific to UK-residing midlife women, and as such, it further expanded on the generic set of BCTs identified in the systematic review (Study 1) to further tailor the intervention to this population. Only one other study explored personalised and adaptive DHIs targeting midlife women, focusing on increasing physical activity (Arigo, Lobo, et al., 2022), although no other study has identified BCTs to inform the design of a DHI targeting midlife women. Therefore, the identified BCTs and their corresponding mechanism of action have the potential to be replicated in other studies targeting UK-residing midlife women. Designing a DHI based on the results of this study has the potential to address the unique needs of this population and achieve a group-level intervention personalisation.

9.2.3 Co-Production of a DHBCI for Midlife Women in the UK (Group-Level Personalisation)

A recent taxonomy of approaches to developing interventions includes not only theory and evidence, but also partnerships, in which people for whom the intervention aims to help are involved in decision-making about the intervention through the development process, having at least equal decision-making contribution as the research team (O'Cathain et al., 2019). This is the first study that combined the use of co-production and the BCW to design a health behaviour intervention targeting midlife women. A recent systematic review identified only 24 studies that involved co-production in the health context, achieving wider perspective and shared understanding of the specific problem, identifying and meeting needs of diverse groups, giving the public voice and active role in research, creating a sense of ownership and common purpose, and deepening trust and confidence (Grindell et al., 2022). Despite providing numerous benefits, no co-production study with midlife women was included in the review (Grindell et al., 2022). A literature search revealed one recent study in which posters and booklets about menopause were co-produced with midlife women (N=40) in Zimbabwe and South Africa (Drew et al., 2022). Additionally, a study protocol has been recently published to co-produce a BCI with midlife women (i.e., who are consumers of higher amounts of alcohol) using a Delphi method to reduce alcohol consumption (Davies et al., 2023).

In this study, a group of UK-residing midlife women (N=7) were equal partners in co-designing the intervention through a series of workshops to select target behaviours, what needs to change and how, and to ensure all content was relevant, meeting the needs of midlife women. The in-depth reporting of how a co-production approach was combined with the BCW framework (see **Chapter 7**), including the availability of the designed bespoke materials for all workshop activities, and feedback to these materials from the PPI group, should prove useful to other researchers in co-designing similar health behavioural interventions with midlife women. Additionally, although the BCW framework was instrumental in providing structure to the co-production workshops and intervention development, it is important to note that not all steps of the BCW guide were appropriate within the co-production approach, also acknowledged in other studies (Hall et al., 2020b). The BCW approach helped to develop milestones for each workshop and ensured the clearly defined objectives were completed after each workshop (Hall et al., 2020b). However, the BCW stage of defining TDF from COM-B components and also identification of BCTs felt too complex and constrained to the PPI group and these steps were consequently removed from the group workshops and completed by the researcher, incorporating only COM-B level discussions in the group workshops. A similar observation was acknowledged in other research describing a degree of tension between stage two and three of the BCW guide, in which working directly with intervention functions and BCTs within the workshops felt restrictive and stunted creativity (Hall et al., 2020b). Although co-production is founded on the principles of greater equality (in the relationship between PPI and researchers (Price et al., 2022), there are no set procedures or methods for using a co-production approach in designing an intervention (Hall et al., 2020b). It remains unclear whether planned activities (Wolstenholme, Kidd and Swift, 2019) or less structure (Whitham et al., 2019) allows for better involvement and better adoption of co-produced interventions (Smith et al., 2022).

Nonetheless, the adapted co-production process in this study identified all components of the BCW, including 34 BCTs that were further incorporated in the final intervention design. A group of health experts (N=3) consisting of a nutritionist, an exercise physiologist, and a GP, also co-produced the educational content for the intervention EMA app. In addition to identifying key intervention components through group workshops, the PPI-group reviewed, and usability tested all aspects of the intervention prior to its launch and involvement of participants. Usability testing is frequently used to pilot the acceptability and feasibility of a technology-based programme, and it is also commonly used in a human-computer interaction (HCI) design to facilitate positive experience for people (Søgaard Neilsen and Wilson, 2019). The PBA approach (Yardley et al., 2015) guidance was instrumental in the person-centred iterative process used in co-production. The PPI requested changes were tracked using the PBA's Table of Changes template (Yardley et al., 2015) and the prioritised changes were implemented (e.g., improving visual aesthetics, instructions and guidance of the EMA prompts) to iteratively improve the intervention experience. While qualitative research using PBA alone has been incorporated in other interventions to improve their acceptability, feasibility, appropriateness, and optimal engagement of the target population who will use them, combining PBA with PPI has been explored only in limited recent studies (Morton et al., 2021; Rai et al., 2021; Santillo et al., 2023). Combining the co-production approach in this study with the primary qualitative research (Study 2) allowed for greater diversity of feedback than it would be possible with PPI or qualitative research alone (Muller et al., 2019), and therefore further refining personalisation of the intervention design.

Another study that followed a framework in co-production and prototyping of a (non-digital) public health intervention developed a three-stages framework (Hawkins et al., 2017) that is closely aligned with the PBA approach (Yardley et al., 2015), and therefore it is also closely aligned with this research that followed the PBA approach. The 18-month design study included three stages of 1) evidence review and stakeholder consultation, 2) co-production, and 3) prototyping (Hawkins et al., 2017). The stage one included review of existing literature and included focus groups with young adults (N=47), interviews with the delivery team, observations of current practice, and stakeholder consultations with opportunity samples (N=9) of young people and practitioners (Hawkins et al., 2017). Stage two included co-production of the intervention materials and resources with members of the research team and key stakeholders, consisting of group meetings over a four-month period (Hawkins et al., 2017). The prototyping stage included reviews of draft intervention manuals and associated resources that were expert-reviewed by the lead authors of the intervention (Hawkins et al., 2017). Feasibility and acceptability of the intervention content was further tested with an opportunity sample of young adults (N=5) and the intervention delivery team (Hawkins et al., 2017).

Although the stages of the framework by (Hawkins et al., 2017) involved additional stakeholders than those involved in this thesis, the three-stages framework is similar to the

PBA approach (e.g., collecting evidence from systematic reviews and key stakeholders, followed by prototyping). The PBA authors recently published an agile co-production and evaluation framework for developing public health interventions (ACE) (Yardley et al., 2023), which has been evaluated in a qualitative study to inform public guidance and messaging around the Mpox epidemic (May et al., 2023). The ACE framework allows for rapid co-production and evaluation of interventions, meeting the priorities of the public, particularly those from seldom-heard communities. It combines three key activities of 1) an agile approach to intervention development, 2) co-production with target communities, and 3) evaluation (Yardley et al., 2023). The feasibility of co-producing these interventions indicate that future co-production design studies may involve other stakeholders (e.g., public health delivery teams, target population, health professionals) and include agile co-production frameworks. Based on ACE authors (Yardley et al., 2023), the ACE framework has the potential to support systematic development of effective, inclusive, and timely public health interventions. It provides researcher with an opportunity for further framework refinement by applying it to a range of different health challenges, interventions and populations (Yardley et al., 2023).

9.2.4 Study 3: The Feasibility and Acceptability of a Multimethod DHBCI for Midlife Women in the UK (Group-Level Personalisation Design Testing)

The experimental study is the first study that evaluated design of a multi-behavioural DHBCI aimed to assess its feasibility and its acceptability among UK-residing midlife women. From the intervention design perspective, combining the three-design methods (i.e., theory and evidence based, lived experiences, and co-production) in an intervention targeting lifestyle improvements in midlife women is novel. Such combination approach has the potential to add value beyond what can be achieved by either method independently (Hall et al., 2020b). The intervention design is underpinned by the BCW framework, COM-B model, TDF framework and BCTs that were merged, and ten PPI-identified target behaviours were prioritised for the intervention. The combined design included 34 BCTs, primarily focusing on goal setting and self-monitoring, and a large set of 11 BCTs involved in counselling (e.g., action planning, problem solving, behavioural practice/rehearsal, social support). Similarly, in a recent multimodal lifestyle intervention, a set of 35 BCTs was implemented, with four BCTs on average being exposed simultaneously to the participants (Englund, Sommar and Krachler, 2024).

The longitudinal high-frequency data provided greater level of granularity in capturing behaviour change in time. The prompted study design (i.e., using EMA prompts) supported uniform frequency (i.e., EMA prompts at the same time daily), between data entries across all participants. Additionally, combining data from multiple modalities (i.e., EMAs, fitness tracker, survey data) provided a holistic view on behaviour change, which can potentially support further optimisation and improved personalisation. With no dropouts, high response rate (e.g., average 77% of EMAs answered, 81% of Garmin steps and 85% of sleep data recorded, and 97% surveys completed), and the education content reviews (accessed by 62% of the participants), the intervention resulted in high feasibility and acceptability. The participants found the intervention enjoyable and engaging. However, it is important to note that the intervention participants were extensively supported throughout the interventions and at the start of each new phase, with the impact of this human-coach interaction being explored in the ML model prediction (see **Study 4**, **Chapter 8**). The intermediate outcomes revealed group-level improvements in all ten target behaviours. Multilevel modelling analysis showed greater between and within person variability across all target behaviours. The findings from this study indicate that individual tailoring and personalisation of the intervention is needed to account for individual trajectories in health behaviour change.

9.2.5 Study 4: Predicting Health Behaviours in UK-Residing Midlife Women using Machine Learning with EMA and Fitness Tracker Data: An Exploratory Study (Optimisation of Group-Level Personalisation)

Many intervention designs include BCTs that do not add to the effectiveness of the intervention but happen to be included (Michie, West, et al., 2018b). Although the selected group of 34 BCTs were operationalised in the intervention (Study 3) to achieve group-level personalisation, not all BCTs or subgroups of BCTs were expected to have an equal contribution to changing health behaviours in all individuals (Prestwich et al., 2014; Michie, West, et al., 2018a). Previous attempts to identify generalisable groups of BCTs that are the most effective in specific health behaviours have not been successful (Michie, Abraham, et al., 2009a; McDermott et al., 2016; Michie, West, et al., 2018a; Sediva et al., 2022) due to many factors that influence their effectiveness, including various contexts (populations, settings), the way they are delivered, and other features of BCIs not captured by the BCT classification (Michie, West, et al., 2018b). Previous research also acknowledged that change in health behaviours is idiosyncratic (i.e., differs between individuals), dynamic (i.e., fluctuates over time) and multi-factorial (i.e., driven by multiple variables, such low energy, poor sleep, social environment) (Arend et al., 2023; Perski et al., 2024). Consequently, tailoring of BCTs or groups of BCTs to individuals based on their theory-relevant characteristics (Prestwich et al., 2014) and behavioural factors is needed to develop effective interventions.

This final study demonstrates a novel use of ML feature selection (FS) to identify group-level predictors that are linked to theoretical constructs in the context of healthy lifestyle behaviours in UK-residing midlife women. These constructs are represented by groups of BCTs that were identified in the design phase of this thesis (i.e., Study 1, Study 2, co-production) and tested in the intervention (Study 3). This study (Study 4) applied ML FS to optimise and therefore further personalise the intervention design by identifying the most relevant features and therefore the most relevant BCTs (linked to the most relevant features) that were involved in predicting each intervention outcome (e.g., steps, vegetables consumption). Although using FS to identify subsets of features that are the most relevant in predicting outcome is not novel, this study applied a novel method to identify predictors that are linked to groups of theoretical constructs (i.e., BCTs). Therefore, the identified time-varying predictors could also be linked back to theory through the intervention BCTs, to identify optimised sets of BCTs that were the most influential in behaviour change for each target behaviour. Other similar efforts to link intervention components (e.g., content and delivery, population, setting, outcome, study methodology) to ML model features used the Behaviour Change Intervention Ontology (BCIO) (Hastings et al., 2023) to facilitate the linking.

To achieve the study objectives, two ML models (i.e., Recursive Feature Elimination (REF) with Random Forest and Gradient Boosting Regressor) were selected based on their performance in previous studies (Perski et al., 2023), utilising the longitudinal dataset created in Study 3. With the objective of FS to use as fewer predictors as possible to predict an outcome, the RFE algorithm selected between 6 and 21 predictors, from a sample group of 24 time-varying predictors used in the ML models. For example, predicting steps count required 6 predictors, while alcohol consumption required 21 predictors. Interestingly, predicting target outcomes that were measured objectively in the intervention using fitness tracker (i.e., steps, sleep) and not subjectively by user's input through EMA, required fewer predictors. This result may indicate that objectively captured input improves prediction and combining multiple modalities to capture data, together with subjectively captured data, may offset data inconsistencies. The most frequently selected predictors were setting goals for steps, setting goals for vegetables consumption, setting goals to exercise in the morning, counselling prompts, and rating breakfast and lunch for colourfulness. Most of these predictors targeted capability and motivation components of COM-B, indicating their influence on the target behaviours and therefore the opportunity to strengthen capability and motivation for further personalisation. With the theoretical link to BCTs, the RFE-identified predictors provided groups of the most relevant and therefore optimised BCTs. Overall, the optimised sets of group-level BCTs identified for each target behaviour included between 9 and 24 BCTs, from the 34-BCT intervention design. For example, steps count outcome required six predictors that were linked to nine unique BCTs (i.e., 1.1 Goal setting (behaviour), 1.4 Action planning, 1.6. Discrepancy between current behaviour and goal, 1.9. Commitment, 2.3. Self-monitoring of behaviour, 3.3. Social support (emotional), and 8.7. Graded tasks). This implies that these 9 BCTs represent an optimised set of BCTs for improving steps count, from the initial 34-BCT design, tested in the intervention. Therefore, by including these 9 BCTs and not necessarily the remainder of the 34 BCTs, the intervention effectiveness may improve through this next level of optimisation. Across all ten outcomes, most of the optimised set of BCTs corresponded to the BCT categories of 'Repetition and substitution' (e.g., behavioural practice/rehearsal, graded tasks), followed by 'Goals and planning' (e.g., Goal setting, action planning).

Furthermore, the correlation matrix revealed that increasing access to the education content (i.e., consisting of diet, physical activity, and menopause) had a significant correlation with outcomes, such as daily portions of fruit and vegetables consumed. The participants in the intervention (Study 3) were frequently encouraged by the researcher to review the educational content that was made available on-demand on the EMA app. This researcher interaction was represented by a 'human coach interaction' predictor and it appeared to be influential in behaviour change. From the time-constant predictors linked to sociodemographic and other characteristics of the participants (and therefore were not expected to change), the most frequently RFE-selected predictors corresponded to county of residence, ethnicity, and views and perspectives on menopause. Improving local environment to encourage walking, providing affordable access to fresh fruit and vegetables, and developing local communities for social support may be influential and helpful and improving health behaviour change outcomes. Although more research is needed in the ongoing efforts of behavioural/health scientists to improve personalisation of DHBCIs, this research provides promising new methods to identify the most relevant intervention components that are linked to behavioural theory, and therefore supporting better explainability of ML models. By incorporating regression-based predictive models in the context of lifestyle health behaviour change targeting midlife women, this research is addressing this gap in the literature and provides novel methods to further personalise DHBCIs at a group-level. This study contributes to research focused on advancing the development of adaptive and dynamic DHBCIs that are providing continuous re-calibration and individualisation to potentially reach greater efficacy and effectiveness at an individual level.

9.2.6 Overall Contribution to Knowledge

The overall contribution to knowledge of this thesis is in describing the process of designing and optimising a digital health-promoting intervention with a group-level intervention personalisation, representing the next level of granularity from a generic population-level design. The design process is based on combined components from three mixed methods of intervention design that progress from the most generic to the most specific input level, including: 1) existing evidence and theory, 2) views and lived experienced of the target population, and 3) partnership (co-production) with members of the public (PPI) and health experts. It's has been previously recognised that synthesising information and evidence from diverse sources are recommended to make decisions about effectiveness of specific behavioural factors (Michie, West, et al., 2018b). Furthermore, although the three designs methods are interrelated (i.e., having the same target behaviours and population focus), they are also independent, allowing for interventions to be based on any of the method combinations. Individually and combined, these studies assisted in 1) designing and developing a digital health programme, 2) understanding how the intervention works, 3) advancing the research into future optimisation phases, 4) allowing for replicability of the design by other researchers. All three studies, underpinned by the BCW framework, describe their unique perspective on defining intervention components and therefore, having the same design structure (in the same framework format) facilitated efficient consolidation of all components into one intervention design. The combined design was actioned (operationalised) through rule-based (if-then) scenarios and developed into a multi-modal intervention (collecting behavioural and physiological data from surveys, EMAs and fitness tracker) that was tested for feasibility and acceptability. Although the intervention was personalised at the group-level, minor individual-level personalisation was implemented in the content and communication dimension. However, identifying effective BCTs or groups of BCTs for a given behaviour in a given context continues to present a major challenge (Michie, West, et al., 2018b). Intervention designs, including the design in the feasibility study in this research, include BCTs that do not add to the effectiveness but happen to be included in the intervention (Michie, West, et al., 2018b). Therefore, the final study (Study 4) went a step further to address this limitation, and evaluated the performance (i.e., accuracy and goodness-of-fit) of the intervention BCTs, by utilising ML models to select features, linked to theoretical constructs. This novel method of identifying the most relevant theoretical constructs linked to predictors generated groups of the most relevant sets of BCTs involved in predicting the intervention target behaviours of healthy eating and regular physical activity.

To my knowledge, this is the first multi-behavioural health-promoting intervention designed by following a proven behaviour change intervention design framework included in all three multimethod designs that resulted in a combined identification of the intervention components that were evaluated for their relevance in predicting the intervention outcomes (using ML FS). The methodology in this thesis supports the development of rigorous and epistemologically coherent research design, which requires capturing experiential phenomena through the use of multiple perspectives (Larkin, Shaw and Flowers, 2019). Although the design is specific to meeting the needs of the population of UK-residing midlife women, the principles behind identifying and operationalising the intervention components to a group-level population can be potentially applied to other contexts and populations. Another single-behavioural (physical activity) multi-study intervention targeting midlife women involved a three-study pilot testing followed by an iterative intervention refinement (Arigo et al., 2021), however it focused merely on feedback through user testing to achieve better adoption and acceptability from the participants. The BCW framework was also used in another study to guide a multi-study design (e.g., focus groups, interviews, expert stakeholder engagement) to identify intervention content for a cross-sectional and multi-modal intervention to enhance influenza vaccination uptake among adults with chronic respiratory conditions (Gallant et al., 2023).

Although several other qualitative studies explored identifying intervention components in a multi-study BCW-guided designs, empirical evidence is still lacking. This thesis demonstrated that co-designing and operationalising a health-promoting intervention that is theory and evidence based and designed for the population of midlife women, in the UK, is both feasible and acceptable. By applying systematic and rigorous design methods based on a framework of multiple behaviour change theories, the intervention design captured robust and integrated view on the needs of midlife women to improve their dietary and physical activity behaviours. This approach aligns with the MRC framework for designing complex interventions, which suggests that components included in the intervention design should be both theory and evidence based to clearly understand the intervention's process of change (Craig et al., 2008; Skivington et al., 2021). Furthermore, this research demonstrated that using multiple modalities (e.g., survey, mobile app, fitness tracker) to collect diverse sources of data is feasible and can be successfully used by regression-based ML models. Using ML feature selection algorithms to identify group-level intervention features linked to theoretical constructs that are the most relevant in activating behaviour change is both feasible and acceptable. With this, the thesis demonstrated a novel method of integrating theoretical BCTs with actual intervention features to allow for repeatability and personalisation of the intervention components in future studies.

9.3 Overall Limitations

The systematic review (Study 1) included only a small number of interventions that matched the search criteria, which also limited the number of RCTs that evaluated effectiveness of BCTs. Most of the studies were conducted in the USA and involved primarily white midlife women. Therefore, the designs and outcomes of the included interventions included a limited view on the experiences of diverse populations of midlife women. Also as mentioned in another scoping review of BCTs, the descriptions of the included interventions were limited and did not provide clear view on how specific BCTs were activated (Arigo, Romano, et al., 2022b). Furthermore, the sample of midlife women participating in focus groups (Study 2) was recruited opportunistically and lacked diversity. Societal norms and views on midlife and the menopause, and openness to engage in the topic might have possibly impacted the recruitment process. Additionally, as the study recruitment took place three-months after COVID-19 lockdown restrictions were lifted, it might have also impacted recruitment. The PPI group involved in co-production of the intervention design, although diverse (in ethnicity, gender identification, marital status, parity), they were not necessarily representative of women with disadvantaged background. As such, it is a common concern related to co-production in that it may reinforce inequalities as more educated public is more likely to be receptive to engaging due to their capability to contribute (Steen, Brandsen and Verschuere, 2018) . More research is required to understand how to best engage more disadvantaged individuals within co-production research (Hall et al., 2020a). Additionally, the planning of the thesis took place during COVID-19 lockdown and the entire design phase took place shortly after COVID-19 lockdown restrictions were lifted in the UK. Consequently, all empirical studies were planned to be conducted online and a large part of the focus group discussions and also PPI-group input naturally reflected the experience of lifestyle changes during the lockdown and as a result of the lockdown. Therefore, as a result of this, the barriers and enablers of lifestyle behaviours may have been different to how they were pre-lockdown (e.g., consuming more alcoholic beverages, engaging in more planning due to limited shopping opportunities, emphasising social connections), which was also acknowledged in other studies with UK populations (Davies et al., 2022; Solomon-Moore et al., 2022).

As the intervention in this thesis was designed during a peculiar period of post COVID-19, it had an impact on the focus group discussion topics and increased utilisation of technologies. It is assumed that other influences (e.g., rapid acceptability of AI in people's daily lives, future global pandemics, changes in food supply) may arise in 5-10 years, and therefore, the findings in this thesis may be less applicable to women who are currently in their 30's and early 40's.

Therefore, the stability of the findings, influenced by the shifts in the accruing evidence about whether such DHI works over time needs to be considered. It has been suggested that cumulative meta-analysis of findings from future studies that are added may aid interpretation of stability of findings (Muellerleile and Mullen, 2006). While the modular design (e.g., consisting of multiple methods that can be used in any combination) of the intervention can be applied, additional qualitative and co-design activities may need to be conducted to gather new requirements from UK-residing midlife women. Therefore, the stability of findings from this thesis can be strengthened by conducting additional co-design studies to capture changing needs arising from new technological, environmental, social, and economic influences impacting health behaviours of midlife women.

Furthermore, the main limitations of the intervention design (Study 1, Study 2, and co-production) is that it is based on the first version of the BCT taxonomy (BCTTv1) (Michie et al., 2013) that has since been updated with Behaviour Change Technique Ontology (BCTO) (Marques et al., 2023), providing additional techniques and groups of techniques. Future research should therefore incorporate the updated BCTO into intervention designs and also utilise the newly available BCIO (Michie, West, et al., 2021) guidance to improve how studies are reported and intervention components specified (see **Appendix E** for a short synthesis of these Ontologies). Additionally, the researcher completed mapping of BCTs and the components of the BCW using self-prepared spreadsheets. This process might have led to potential errors or omissions despite having an acceptable inter-rater reliability from a second reviewer. Additionally, qualitative analysis relies on the coder's understanding and interpretation of the data and there are multiple ways of interpreting both, transcribed focus groups discussions, and reports included in the systematic review. To minimise potential bias, a second reviewer (for Study 1 and Study 2) completed the review of themes and annotated themes to BCTs with an acceptable level of inter-rater validity.

Furthermore, the intervention (Study 3) was a feasibility study with a single-arm with limited-efficacy testing (Bowen et al., 2009), and therefore drawing conclusions on the effectiveness of the intervention on improving health outcomes is not accessible. The intermediate outcomes in the short-term intervention involving a convenience sample are provided to a limited extent as secondary aims. Furthermore, although other healthy diet and regular physical activity target behaviours were identified in co-production, not all behaviours were included in the intervention. A subset of ten target behaviours were selected to establish feasibility and acceptability of the intervention and to implement intervention design that could be delivered within the two-week intervention period without overwhelming the participants with too many prompts that would be needed to capture high-frequency behavioural data.

The primary limitation in the final study (Study 4) is in using only group-level predictors and not individual-level predictors to explore potential improvements in the personalisation of the intervention design. This decision was driven by the nature of the explorative feasibility study that focused primarily on evaluating whether any predictors linked to BCTs could be identified in predicting the target behaviours. The time-varying predictors linked to groups of BCTs were used only for evaluation purposes and the study did not involve an extensive process of feature creation and validation. Additionally, it is important to note that the dataset used in the ML feature selection was small (consisting of a small sample and a limited number of observations) and showed potential overfitting of the model too closely to the dataset. Future studies should review and compare results generated by other ML algorithms and identify the most suitable ML models with acceptable prediction power and accuracy. Additional combinations of predictors (group-level, individual-level, time-varying, time-constant, mixed) should also be explored to fine-tune personalisation of interventions.

Overall, the reliability and validity of the claims of contributions to knowledge of this research should take into consideration 1) limited number of prior studies used to select the initial set of BCTs, 2) focus group participants with limited diversity in sociodemographic background, 3) limited number of target behaviours discussed in co-production due to restrictions on timeline and scope, 4) small sample size and single-arm design used in the intervention, 5) exploration of a limited number of supervised ML algorithms and predictors to test feasibility of feature selection, based on a small intervention dataset that indicated potential overfitting. Therefore, although each study resulted in a novel contribution to knowledge, more research is needed to grow the body of evidence specifically benefiting the population of midlife women, in the UK.

9.4 Future Research Recommendations

There is a clear need to understand the effectiveness of health-promoting behaviour change interventions on health and wellbeing in short term at midlife, and in longer term in old age. However, to replicate such interventions, it is important to define how they work. Understanding how to explain, influence, and predict behaviours is one of the most pressing issues facing health/behavioural scientists (Perski et al., 2024). The use of behaviour change theory is needed to improve our understanding and devise effective interventions which can engender improved health and wellbeing for all (Perski et al., 2024). Additionally, in contrast with low-occurrence behaviours (e.g., vaccination update, cancer screening), repeated-occurrence behaviours (e.g., physical activity, healthy eating, smoking cessation, alcohol reduction) are performed regularly over the entire lifespan and across different contexts (Dunton, 2018). Therefore, repeated-occurrence behaviours tend to be dynamic, multi-factorial, and idiosyncratic. Behaviours such as healthy eating (Dohle and Hofmann, 2019), and physical activity and sleep (Bernard et al., 2016) vary from day to day at the individual level (Resnicow and Vaughan, 2006) in response to multiple factors, including intra-individual (e.g., motivation), inter-individual (e.g., social support), and environmental (e.g., weather) and their dynamic interplay (Chevance, Perski and Hekler, 2021). Given these dynamic, idiosyncratic manifestations with various combinations of specific influences (e.g., weather, social support), interventions may be more effective for some individuals and less effective for others (Fisher, Medaglia and Jeronimus, 2018).

Thus, the future research recommendations presented in this section are grouped into three themes that are at the forefront of health/behavioural research in efforts to improve long-term effectiveness of DHBCIs. The themes include 1) individual-level personalisation of interventions, 2) designing adaptive and continuous DHBCIs for long-term support, and 3) improving retention and engagement of users to ensure people fully benefit from DHBCIs (see to **Chapter 2** for literature review on these three themes). This research delivers the groundwork for the transition from i) generic population-level interventions to personalised based on group-level only intervention designs to both group and individual-level statistical inference, ii) static behaviour change theories (frameworks, and models) to dynamic computational models, and iii) from static to adaptive and continuous-tuning interventions, iv) from infrequent assessments to more intensive assessments in future health behaviour change interventions targeting midlife women. Finally, although DHBCIs have the potential to improve health behaviours for many, not everyone is able to benefit from them (see **Appendix E** for a short synthesis on barriers to adopting digital health).

9.4.1 Personalisation of Interventions at Individual-Level

Personalisation of DHBCIs has the potential to improve health behaviours and consequently health outcomes. However, personalisation of health-promoting interventions (e.g., providing personalised nutrition advice), is a complex undertaking that requires not only personalisation of the intervention's digital technology with ML predictions, but it also requires consideration of many other influences. These include physiological factors (e.g., anthropometric, phenotypic and genotypic variation) and underlying inter-individual variability in health perceptions, beliefs, and other psychological factors that influence variability in response to personalised advice (Gibney, 2020). Personalisation can be applied to different aspects of an intervention (see **Chapter 2**) for example, in the intervention content, the content order, level of guidance, and communication with users. The underlying mechanisms that trigger personalisation can be based on user choice, provider/coach choice, decision rules, or ML-based approaches (Hornstein et al., 2023). The personalisation of the DHBCI in this thesis included tailoring the times of five daily EMA messages based on each individual's preferences and skipping questions that did not apply to the individual (e.g., questions about alcohol consumption for individuals who are abstinent). However, although such personalisation is desirable, it provides the basic level of personalisation that does not include predictions on what types of activities should be applied to each individual (Vesanen, 2005). The personalisation of intervention features in this thesis was based on identified intervention components, aggregated at a group-level. Personalisation of these features required understanding of the intervention components, and therefore a design that is theory-based.

Moreover, to predict and explain health behaviours and to inform the development of effective BCIs, theories of health behaviours need to apply to individuals (Johnston and Johnston, 2013). It has been argued that most behavioural theories emphasise group-level and largely static generalisations, implying that theory supports explanations and predictions about average changes in outcomes in groups (Spruijt-Metz, Hekler, et al., 2015). Nevertheless, it has been shown that theory also has the potential to generate insights for specific individuals, particularly what might occur in the future for specific individuals (Hekler et al., 2016). Ideally, a theory selected in designing a DHBCI would provide both group-level and individual-level generalisations (Chevance, Perski and Hekler, 2021). This thesis demonstrated that identifying theory- and evidence-based multi-behavioural factors is feasible and supports developing a design that is personalised at a group-level (Study 1, Study 2, and co-production). It also demonstrated that such design can be operationalised (activated) in a DHBCI (Study 3). With the identified intervention features (Study 4) being linked to theoretical constructs (BCTs), activating a particular set of features could potentially be further optimised based on predictions obtained from additional data about an individual.

Moreover, future research in promoting health behaviours needs to focus not only on innovations in behaviour change theory to reflect a more dynamic perspective on behaviour (Hekler et al., 2016; Chevance et al., 2021), but also on methods that take into account the complexity of the dynamic, multi-factorial, and idiosyncratic nature of health behaviour change (Chevance, Perski and Hekler, 2021). The benefit of data-driven prediction techniques (i.e., ML models) is that they can facilitate effective personalisation (Ghanvatkar, Kankanhalli and Rajan, 2019). In efforts to achieve improved personalisation, latest research in this area examined a novel approach of capturing user's exposure time. In this recent five-week multi-behavioural (e.g., physical activity, food habits, stress management, and general self-care) lifestyle intervention used a set of 35 BCTs and estimated the exposure time to various BCTs as a novel method to potentially identify the relative importance of different BCTs in the intervention (Englund, Sommar and Krachler, 2024). The intervention revealed that BCTs of behavioural practice and social support were having the longest exposure time, although the authors acknowledged experiencing difficulties in estimating exact times of exposure (Englund, Sommar and Krachler, 2024). Predicting outcomes of BCIs is extremely challenging but the results of recent studies provide proof of principle that it can be achieved using latest transparent ML models with the level of accuracy that exceed other previously used approaches (Hastings et al., 2023).

9.4.2 Delivering Adaptive and Continuous Digital Health Interventions

Ample evidence suggests that health behaviours are complex and that adaptive and continuous adjustment ("tuning") of interventions is necessary to support healthy behaviour changes over time and across contexts, similarly to what a clinician or a health coach would do (Chevance, Perski and Hekler, 2021). Instead of delivering generic (not including specific individualisation components) and static interventions (measured at single time point), tailored (personalised) interventions are aimed to reach one specific individual, based on specific characteristics of that person that have been measured through formal assessments (Chevance, Perski and Hekler, 2021). Additionally, targeted interventions that take into account demographics, personality traits, physical fitness, and are captured at baseline to support decision-making, have been used and further explored in this thesis in identifying time-constant predictors to target behaviours (Chapter 8). Adaptative interventions take it a step further to provide dynamics decision-making over time, with adaptive algorithms generated based data from previous individuals (Collins, Murphy and Bierman, 2004). Such interventions can be delivered via micro-randomised trials (MRT) using digital technologies (Chevance, Perski and Hekler, 2021). Finally, to take it a step further, continuous interventions are similar to adaptive, however, the tuning is based on previous data from the same individual and includes real-time optimisation algorithms (Chevance, Perski and Hekler, 2021). It delivers content based on the needs of a specific individual, using methods such as N-of-1 study design or reinforcement learning (Chevance, Perski and Hekler, 2021).

JITAI, including EMAs, have been widely used in behavioural research to produce more frequent assessments of behaviour change (Spruijt-Metz et al., 2015), which can help accelerate the development of adaptive interventions. To achieve such level of granularity in data, dynamic models require high-frequency data collected from multiple modalities to capture different aspects of behaviour. A meta-analysis of personalised lifestyle DHIs shows that interventions that used system-captured data for personalisation were associated with higher effectiveness than those that used user-reported data (Tong et al., 2021a). Similarly, in this thesis (Study 4), predictors based on objectively measured data (captured by devices) (e.g., steps count, sleep data) were selected by ML models more frequently than predictors using subjectively measured data (based on survey responses) (e.g., number of units of alcohol entered). This suggests that utilising multiple modalities to capture data is needed to offset any misrepresentations and inaccuracies in data. This also suggests that it is vital to design interventions that are theory-based, considering both qualitative methods to collect data that provide information about an individual's subjective context, but also quantitative methods to collect data that provides objective measures. For future personal healthcare, data quality will be critical requiring reliable data sources, better accuracy and stability of sensors (and other IoT technologies), and data collection devices that collect and aggregate data and communicate reliable information (Cai et al., 2019).

Traditional ML models are based on regression or classification and this this thesis utilised regression-based ML models. However, traditional ML is primarily concerned with prediction given a set of input features and the ML algorithm learns a function from the data that can predict an outcome (Rubin, 2005). Although it is efficient in finding patterns and correlations in data, it doesn't know about the cause-and-effect relationships between variables (Feuerriegel et al., 2024). In a healthcare setting, a physician may be interested in predicting diabetes risk in a patient with a higher BMI for whom the physician recommends quitting smoking. Traditional ML would suggest using both the BMI and smoking behaviour to predict the diabetes risk under smoking versus no-smoking scenario. However, this approach would ignore that stopping smoking would also change the patient's BMI. To address this issue, ML needs to be embedded in a causal framework (Feuerriegel et al., 2024) to capture these cause-end-effect relationships. Causal ML therefore aims to predict the causal quantity, namely changes in an individual's intervention outcome due to the treatment (Kaddour et al., 2022). Therefore, in modelling these potential outcomes (i.e., counterfactuals), causal ML tries to understand cause-end-effect relationship and how much change in one variable will affect the outcome. It can estimate these effects from both experimental data obtained through RCTs and observational data obtained from clinical registries, health records, or other real-world data (Feuerriegel et al., 2024). While traditional ML is effective in predictions, causal ML goes beyond prediction and provides additional level of understanding in the difference in outcomes due to interventions.

This thesis (Study 4) used traditional ML techniques (e.g., feature selection) to identify which BCTs were more influential in determining the outcomes. However, although this technique was feasible, it was unable to determine what the intervention outcomes would be if the intervention exposed individual participants to different sets of BCTs (e.g., counterfactuals). Therefore, in future studies, using causal ML could theoretically help to answer questions on "what if" we exposed different sets of BCTs to the same individual, how would their behaviours and consequently intervention outcomes change? Future research should therefore investigate causal ML in behavioural interventions by simulating interventions (or groups of interventions) and evaluate and compare their potential effects on an outcome (while inferring causality and utilising already available data). Behavioural interventions could therefore benefit from drawing novel conclusions about the efficacy of different treatment conditions (and with different sets of behavioural components and techniques) in a more efficient way compared to conducting lengthy and costly evaluations (e.g., RCTs) in the field. This is particularly relevant when RCTs are unavailable, or it is not possible to test every possible treatment combination scenario for each individual. Utilising causal ML has the potential to provide further granularity of personalised intervention strategies, and consequently improved health outcomes (Feuerriegel et al., 2024). This may involve assessing the feasibility of estimating individual-level intervention effects for different behavioural components, using existing multimodal datasets. At the outcome level, causal ML can help make personalised estimates of treatment effects for subpopulations (e.g., UK-residing midlife women) or even predict outcomes for individuals (Feuerriegel et al., 2024). However, cautious use with causal ML is important as causal inference is based on formal assumptions that cannot be tested (Feuerriegel et al., 2024), with potential intervention outcomes corresponding to treatment arms that weren't measured in the intervention. Therefore, ensuring reliability and robustness of these methods is essential (Feuerriegel et al., 2024). As of today, these novel methods still lack clinical use and therefore proof-of-concept studies involving cautious use in clinical practice should be prioritised as an important first step (Feuerriegel et al., 2024).

9.4.3 Improving Adherence to Digital Health Interventions

Retention and user engagement are known issues in DHIs, which has been acknowledged in several studies (Chien et al., 2020; Torous et al., 2020; Torous, Michalak and O'Brien, 2020; Jakob et al., 2022). There are a number of factors that influence the uptake of evidence-based interventions, including systematically identifying factors (e.g., barriers, enablers) that influence behaviour change processes by using theoretical frameworks and models (e.g., BCW, TDF) that explain various behaviours (Phillips et al., 2015). Although it is often challenging to determine what aspects of intervention design or procedures contributed to retention and engagement of the participants, this thesis applied several methods that were highlighted in previous research. For example, based on a review of factors influencing retention and adherence (Jakob et al., 2022), the recruitment process was primarily in-person with the researcher attending events targeting midlife women and topics around menopause. Each potential participant met with the researcher either in-person or in a video-call prior to recruitment. Additionally, the intervention start was on Mondays of the participant's selected week and not on weekends. According to (Jakob et al., 2022), first time enrollment on a weekend negatively impacts adherence to DHIs.

Other studies attempted to predict user dropouts by using ML models with feature selection (e.g., boosted decision trees) (Bremer et al., 2020a; Bennemann et al., 2022), achieving feasibility in predicting dropouts and with theory-driven handcrafted features increasing the prediction performance (e.g., area under the curve (AUC) values) (Bremer et al., 2020a). Therefore, the ability to predict dropouts at an individual level could be used to enhance decision making and inform dynamic intervention regimens (Bremer et al., 2020a). Moreover, to develop effective lifestyle DHBCIs, predictions alone are not enough (Teixeira, 2016) to link theory with ML models (Hastings et al., 2023), which requires transparency, explainability, and interpretability of these models (Hassija et al., 2024). One of the ways this is addressed is a proxy fairness method of using human-in-the-loop, in which incorporating human oversight into the decision-making process of AI systems (e.g., validating or adjusting the decisions made by an AI model to ensure fairness and ethicality) (Hassija et al., 2024). Therefore, human-supported interventions (e.g., health-coach) can potentially provide many benefits from improving retention and engagement to ensuring fairness in AI's decision-making. Although predicting health behaviours is extremely challenging, future research should incorporate ontologically informed interpretable ML prediction systems (Hastings et al., 2023) that can be used to predict other health behaviours across a wide range of scenarios.

Additionally, to improve retention and engagement could benefit from latest advancements in in virtual agents to provide coaching support. Potential hybrid models could be implemented by integrated real-time assessments that are supported by virtual health coaches (Acosta et al., 2022) as well as human health coaches. Virtual health coaches (i.e., chatbots) that are based on large language models (LLMs) (e.g., OpenAI's ChatGPT) have been tuned to provide safer and harmless content, although more work is still needed in this area (Ouyang et al., 2022; Dai et al., 2023) to solely rely on AI in providing intervention feedback. A recent qualitative study evaluated a virtual reality (VR) and AI (utilising GPT-4) program designed to simulate a human therapist and provide immersive mental health support to participants (N=20) with mild-to-moderate anxiety or depression (Spiegel et al., 2024). This study represents an important step forward in developing interventions that provide digital therapists/coaches, not to replace a human therapist/coach, but to augment this service by providing support that is accessible at anytime and anywhere, at scale and low cost. Similar programmes could be explored in the area of lifestyle health promoting interventions by offering users/patients an option to use self-administered AI-enabled digital avatar, resembling a human coach interaction. Future research should investigate longitudinal effects on clinical outcomes and adjust the program's AI to further enhance the therapeutic coach communication (Spiegel et al., 2024), providing adaptive, evidence-based intervention support. Although research on interactions between LLMs and patients have seen recent advancements, evaluation of such conversations using AI chat-interface is likely to underestimate the real-world value of human conversations (McDuff et al., 2023). Additional research is needed to transition from a LLM research prototype evaluations to a safe and robust tool, including health equity and fairness, privacy, and robustness (McDuff et al., 2023). It will be critical in the future to incorporate tools of human-machine interaction, such as safety, security, and reliability (Pedersen, Johansen and Jøsang, 2018) in addition to ensuring fairness, explainability, and accountability of AI algorithms to make decisions in digital health interventions.

9.5 Conclusion

This research sought to explore the feasibility of designing and optimising a personalised digital health behaviour change intervention (DHBCI) to promote healthy lifestyle behaviours for an under-researched population of midlife women, in the UK. Previous research in the field of nutrition and exercise has generally neglected this population. Midlife population is a demographic particularly deserving of inquiry, given their pivotal role in society and the substantial impact of their ill-health, both from economic and health care services cost perspective. Despite the large population of women currently experiencing menopause in the UK (estimated at thirteen million), to date no single research has given voice to this population in co-production of health-promoting research. Therefore, this research has addressed this gap within the co-produced digital health-promoting literature, contributing a novel perspective and extending existing knowledge. A person-centred approach was at the core of this thesis, giving voices to women to shape research on topics that directly affect them. Additionally, the utility of a multimethod approach, this research allowed a more comprehensive and holistic viewpoint on the experiences and needs of the target population in the context of healthy eating and regular physical activity. This research is built on a strong foundation of a behaviour change theory and a systematic description of the DHI components. It is enhanced by multimodal data, providing rich insight into human behaviour that can be linked back to the theory, from intervention features to groups of behavioural factors describing each feature. With a strong theoretical foundation, this research can be therefore used to facilitate our improved understanding and utility of a personalised group-level health-promoting support for midlife women, in the UK.

Taken together, this research extends the growing evidence base suggesting that personalised DHBCIs aimed to improve health behaviours are both feasible to design and operationalise, and that digital lifestyle health support is acceptable to midlife women, in the UK. Furthermore, the findings of the post-intervention optimisation study revealed that further improvements in personalisation of DHBCIs using ML models is feasible. This research is contributing to the growing literature seeking to identify methods to provide long-term health-promoting support though adaptive and continuous DHBCIs personalised to individuals. The contribution of this research is in developing a novel method of selecting the most relevant intervention features that are linked to behavioural constructs contributing to the intervention outcomes, with the potential of improved intervention effectiveness. Despite the current research providing evidence for the feasibility and acceptability and perceived benefits of DHBCI, providing such tools to support midlife women's health and wellbeing requires broader support, collaboration, and investment from policy makers and the industry to deliver these solutions to market. Nevertheless, the current findings highlight these interventions as a positive first step in research targeting midlife women, aimed to equip them with tools for effective self-management of lifestyle health behaviours. Designing personalised and adaptive DHBCIs is a complex task for all health behaviours and populations and requires further research into evaluating methods that can achieve effective long-term outcomes. This will require interactions among the fields of behavioural and health sciences, AI and devices capturing data, to advance current designs of behavioural health interventions that serve the individuals and therefore the society. Overall, the qualitative and quantitative methods of this thesis facilitated the utility of designing and optimising health-promoting support for midlife women in the UK.

Appendices

Appendix A: Chapter 5

The Quality Assessment

The quality assessment was completed using the Physiotherapy Evidence Database (PEDro) scale (Cashin and McAuley, 2020) and the Cochrane risk-of-bias tool for randomised trials (RoB 2) (Sterne et al., 2019) was used to assess the risk of bias in randomised trials. The majority (12/13, 92%) of the studies met the modified 6-point PEDro scale at 80-100% (5 points out of 6 points) (**Figure 68**).

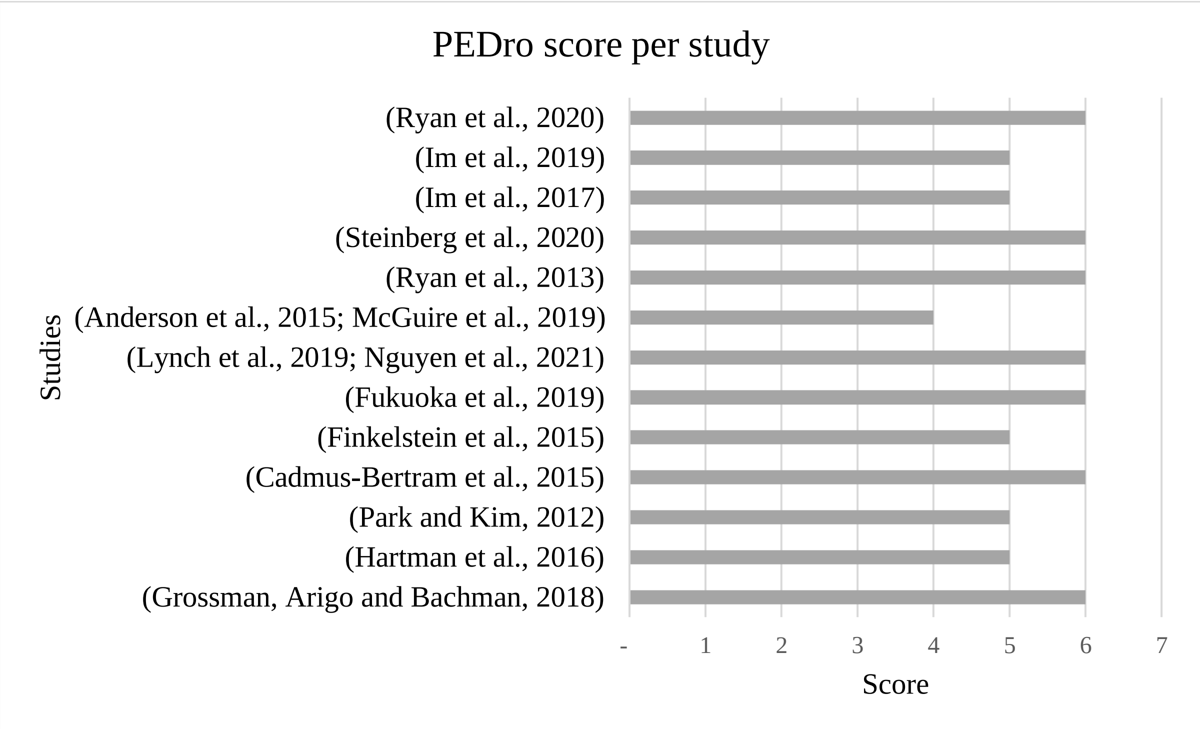


Figure 68: PEDro scale analysis of the included studies

The Cochrane's Risk Bias Analysis indicates that the overall risk of bias was low in 77% (10/13) of the studies, with some concerns in 23% (3/13) of the studies, primarily in the randomisation and deviations from the intended intervention (**Figure 69**).

Study	D1	D2	D3	D4	D5	Overall
(Grossman, Arigo and Bachman, 2018)	+	!	+	+	+	!
(Hartman et al., 2016)	-	+	+	+	+	!
(Park and Kim, 2012)	+	+	+	+	+	+
(Cadmus-Bertram et al., 2015a)	+	+	+	+	+	+
(Finkelstein et al., 2015)	+	+	+	+	+	+
(Fukuoka et al., 2019)	+	+	+	+	+	+
(Lynch et al., 2019) and (Nguyen et al., 2021)	+	+	+	+	+	+
(Anderson et al., 2015) and (McGuire et al., 2019)	-	!	!	+	+	!
(Ryan et al., 2018)	+	+	+	+	+	+
(Steinberg et al., 2020)	+	+	+	+	+	+
(Im et al., 2017)	+	!	+	+	+	+
(Im et al., 2019)	+	+	+	+	+	+
(Ryan et al., 2020)	+	+	+	+	+	+

Legend:

D1	Randomization process
D2	Deviations from the intended interventions
D3	Missing outcome data
D4	Measurement of the outcome
D5	Selection of the reported result

+	Low risk
!	Some concerns
-	High risk

Figure 69: Cochrane risk of bias analysis of the included studies using Rob2 tool

BCT Mappings for Each Included Study

Table 47: BCT mappings detailed analysis per intervention

BCTs and BCCs	(Grossman, Arigo and Bachman, 2018)	(Hartman et al., 2016)	(Park and Kim, 2012)	(Cadmus-Bertram et al., 2015a)	(Finkelstein et al., 2015)	(Fukuoka et al., 2019)	(Lynch et al., 2019; Nguyen et al., 2021)	(Anderson et al., 2015; McGuire et al., 2019)	(Ryan et al., 2013)	(Steinberg et al., 2020)	(Im et al., 2017)	(Im et al., 2019)	(Ryan et al., 2020)	BCTs per category, n	Studies scoring ≥1 BCT, %
1.Goals and planning, n	4	5	1	3	0	4	4	3	5	2	0	0	3	34	77
BCTs from all possible BCTs (9 BCTs), %	44	56	11	33	0	44	44	33	56	22	0	0	33	117	29
1.1. Goal setting (behaviour)	X	X		X		X	X	X	X				X	8	63
1.2. Problem solving						X	X	X	X	X			X	6	46
1.3. Goal setting (outcome)	X	X												2	15
1.4. Action planning		X	X	X		X	X	X	X	X			X	9	69
1.5. Review behaviour goal(s)	X	X				X	X		X					5	38

1.6. Discrepancy between current behaviour and goal								X					1	8
1.7. Review outcome goal(s)	X	X		X									3	23
1.8. Behavioural contract													0	0
1.9. Commitment													0	0
2.Feedback and monitoring, n	4	2	4	3	2	2	2	1	2	4	0	0	2	28	85
BCTs from all possible BCTs (7 BCTs), %	57	29	57	43	29	29	29	14	29	57	0	0	29	91	31
2.1. Monitoring of behaviour by others without feedback														0	0
2.2. Feedback on behaviour	X	X	X	X	X	X	X	X	X	X			X	11	85
2.3. Self-monitoring of behaviour	X	X	X	X			X		X	X			X	8	62
2.4. Self-monitoring of outcome(s) of behaviour														0	0

2.5. Monitoring of outcome(s) of behaviour without feedback														0	0
2.6. Biofeedback	X		X							X				3	23
2.7. Feedback on outcome(s) of behaviour	X		X	X	X	X				X				6	46
3. Social support, n	1	0	0	0	0	1	1	1	1	2	2	1	1	11	69
BCTs from all possible BCTs (3 BCTs), %	33	0	0	0	0	33	33	33	33	67	67	33	33	39	28
3.1. Social support (unspecified)	X					X		X	X					4	31
3.2. Social support (practical)										X	X	X	X	4	31
3.3. Social support (emotional)							X			X	X			3	23
4. Shaping knowledge	1	1	1	1	1	1	0	1	1	1	1	1	1	12	92
BCTs from all possible BCTs (4 BCTs), %	25	25	25	25	25	25	0	25	25	25	25	25	25	52	23

4.1. Instruction on behaviour	X	X	X	X	X	X		X	X	X	X	X	X	12	92
4.2. Information about Antecedents														0	0
4.3. Re-attribution														0	0
4.4. Behavioural experiments														0	0
5.Natural consequences, n	0	0	0	0	0	1	1	1	0	0	1	1	0	5	38
BCTs from all possible BCTs (6 BCTs), %	0	0	0	0	0	17	17	17	0	0	17	17	0	78	6
5.1. Information about health consequences						X	X	X			X	X		5	38
5.2. Salience of consequences														0	0
5.3. Information about social and environmental consequences														0	0

5.4. Monitoring of emotional consequences														0	0
5.5. Anticipated regret														0	0
5.6. Information about emotional consequences														0	0
6.Comparison of behaviour, n	1	0	0	0	0	0	0	1	1	1	0	0	1	5	38
BCTs from all possible BCTs (3 BCTs), %	33	0	0	0	0	0	0	33	33	33	0	0	33	39	13
6.1. Demonstration of the behaviour	X							X	X	X			X	5	38
6.2. Social comparison														0	0
6.3. Information about others' approval														0	0
7.Associations, n	0	2	1	0	1	1	2	1	1	2	0	1	0	12	69

BCTs from all possible BCTs (8 BCTs), %	0	25	13	0	13	13	25	13	13	25	0	13	0	104	12
7.1. Prompts/cues		X	X		X	X	X	X	X	X		X		9	69
7.2. Cue signalling reward														0	0
7.3. Reduce prompts/cues		X					X			X				3	23
7.4. Remove access to the reward														0	0
7.5. Remove aversive stimulus														0	0
7.6. Satiation														0	0
7.7. Exposure														0	0
7.8. Associative learning														0	0
8.Repetition and substitution, n	3	1	5	1	2	3	2	3	3	0	2	2	3	30	92
BCTs from all possible BCTs (8 BCTs), %	43	14	71	14	29	43	29	43	43	0	29	29	43	91	33

8.1. Behavioural practice/rehearsal	X		X		X	X	X	X	X		X	X	X	10	77
8.2. Behaviour substitution			X											1	8
8.3. Habit formation	X		X		X	X	X	X	X		X	X	X	10	77
8.4. Habit reversal			X											1	8
8.5. Overcorrection			X											1	8
8.6. Generalisation of target behaviour														0	0
8.7. Graded tasks	X	X		X		X		X	X				X	7	54
9.Comparison of outcomes, n	1	1	1	0	0	0	0	1	1	0	0	1	0	6	46
BCTs from all possible BCTs (3 BCTs), %	33	33	33	0	0	0	0	33	33	0	0	33	0	39	15
9.1. Credible source	X	X	X					X	X			X		6	46
9.2. Pros and cons														0	0
9.3. Comparative imagining of future outcomes														0	0
10.Reward and threat, n	2	0	0	2	0	2	0	0	2	2	0	0	3	13	46

BCTs from all possible BCTs (11 BCTs), %	18	0	0	18	0	18	0	0	18	18	0	0	27	143	9
10.1. Material incentive (behaviour)	X			X		X			X	X			X	6	46
10.2. Material reward (behaviour)	X			X		X			X	X			X	6	46
10.3. Non-specific reward														0	0
10.4. Social reward														0	0
10.5. Social incentive														0	0
10.6. Non-specific incentive														0	0
10.7. Self-incentive														0	0
10.8. Incentive (outcome)														0	0
10.9. Self-reward														0	0
10.10. Reward (outcome)														0	0
10.11. Future punishment													X	1	8
11.Regulation, n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

BCTs from all possible BCTs (4 BCTs), %	0	0	0	0	0	0	0	0	0	0	0	0	0	52	0
11.1. Pharmacological support														0	0
11.2. Reduce negative emotions														0	0
11.3. Conserving mental resources														0	0
11.4. Paradoxical instructions														0	0
12.Antecedents, n	3	1	1	1	1	1	1	0	0	0	0	0	1	10	62
BCTs from all possible BCTs (6 BCTs), %	50	17	17	17	17	17	17	0	0	0	0	0	17	78	13
12.1. Restructuring the physical environment	X													1	8
12.2. Restructuring the social environment														0	0

12.3. Avoidance/reducing exposure to cues for the behaviour														0	0
12.4. Distraction														0	0
12.5. Adding objects to the environment	X			X	X	X	X						X	6	46
12.6. Body changes	X	X	X											3	23
13. Identity, n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (5 BCTs), %	0	0	0	0	0	0	0	0	0	0	0	0	0	65	0
13.1. Identification of self as role model														0	0
13.2. Framing/reframing														0	0
13.3. Incompatible beliefs														0	0
13.4. Valued self-identify														0	0
13.5. Identity associated with changed behaviour														0	0

14. Scheduled consequences, n	1	0	0	1	0	0	0	0	0	0	0	0	1	3	23
BCTs from all possible BCTs (10 BCTs), %	10	0	0	10	0	0	0	0	0	0	0	0	10	130	2
14.1. Behaviour cost														0	0
14.2. Punishment														0	0
14.3. Remove reward													X	1	8
14.4. Reward approximation														0	0
14.5. Rewarding completion	X			X										2	15
14.6. Situation-specific reward														0	0
14.7. Reward incompatible behaviour														0	0
14.8. Reward alternative behaviour														0	0
14.9. Reduce reward frequency														0	0

14.10. Remove punishment														0	0
15.Self-belief, n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (4 BCTs), %	0	0	0	0	0	0	0	0	0	0	0	0	0	52	0
15.1. Verbal persuasion capability														0	0
15.2. Mental rehearsal of successful performance														0	0
15.3. Focus on past success														0	0
15.4. Self-talk														0	0
16. Covert learning, n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (3 BCTs), %	0	0	0	0	0	0	0	0	0	0	0	0	0	39	0
16.1. Imaginary punishment														0	0

16.2. Imaginary reward														0	0
16.3. Vicarious consequences														0	0
BCTs per study, n (%)	21 (23)	13 (14)	14 (15)	12 (13)	7 (8)	16 (17)	13 (14)	13 (14)	17 (18)	14 (15)	6 (6)	7 (8)	16 (17)	169 (14)	100

Each study was coded for BCT present (x) or absent [blank].

BCW Mapping for All Included Studies

Table 48: BCW mapping of all studies

		CAPABILITY					OPPORTUNITY		MOTIVATION							
		Physical	Psychological				Social	Physical	Reflective						Auto	
BCT Categories	Intervention Functions	Skills[a]	Know[b]	CogI S[c]	MA D[d]	BRe g[e]	Soc infl[f]	Env res[g]	B Cap[h]	B Con[i]	S/P ID[j]	Opti m[k]	Inte nt[l]	Goal s[m]	Rein f[n]	E m[o]
1.Goals and planning	Enablement		x	x		x			x	x	x			x		
2.Feedback and monitoring	Enablement, Persuasion		x			x			x	x		x			x	x
3. Social support	Enablement						x			x	x		x			x
4. Shaping knowledge	Education	x	x	x												
5.Natural consequences	Enablement, Persuasion		x	x						x						
6.Comparison of behaviour	Training	x	x					x								
7.Associations	Env restr [p], Enablement			x	x		x	x								
8.Repetition and substitution	Training, Skills	x	x	x		x				x					x	

9.Comparison of outcomes	Persuasion									x						
10.Reward and threat	Incentivisation, Coercion								x	x	x	x	x		x	
11.Regulation	N/A															
12.Antecedents	Env restr [p], Enablement	x			x			x								
13. Identity	N/A															
14. Scheduled consequences	Incentivisation, Coercion								x		x	x	x		x	X
15.Self-belief	N/A															
16. Covert learning	N/A															
TDF domains, n		8	13	10	3	15	3	5	6	10	7	4	4	3	4	3
COM-B sub-components, n (%)		8 (8)	41 (42)				3 (3)	5 (5)	34 (35)						7 (7)	
COM-B components, n (%)		49 (50)					8 (8)		41 (42)							

Each study was coded for BCT present (x) or absent [blank].

[a] Physical skills (Skills); [b] Knowledge (Know); [c] Cognitive and Interpersonal Skills (CogIS); [d] Memory, attention and decision processes (MAD); [e] Behavioural regulation (BReg); [f] Social influences (Soc infl); [g] Environmental context and resources (Env res); [h] Beliefs about capabilities (B Cap); [i] Beliefs about consequences (B Con); [j] Professional/Social role and identify (S/P ID); [k] Optimism (Optim); [l] Intentions (Intent); [m] Goals (Goals); [n] Reinforcement (Reinf); [o] Emotion (Em); [p] Environmental Restructuring (Env Restr)

TCS Categories Results for All Studies

Table 49: TCS categories results for all studies

Theory	TCS category	TCS Items included	Max score per category, n	Description	Studies, n (%)	Mean score, n (SD)
Mentioned	Reference to underpinning theory (C1)	1, 2, 3	3	Stated or suggested rather than demonstrated theoretical base	10 (77)	1.69 (1.25)
Application	Targeting of relevant theoretical constructs (C2)	2, 5, 7, 8, 9, 10, 11	7	Targeted theoretical construct predicted behaviour; theory or predictors explicitly used for designing the intervention; the extent to which the intervention targets particular theory-relevant constructs	13 (100)	3.00 (1.53)
	Using theory to select recipients or tailor interventions (C3)	4, 6	2	Theory used to select participants; or tailor the intervention to the needs of a particular individual	3 (23)	0.23 (0.44)
	Measurement of constructs (C4)	12a, 12b	2	Measured theory-based constructs or predictors	9 (69)	1.23 (0.93)
Testing	Testing of theory: mediation effect (C5)	15, 16a, 16b, 16c, 16d,	7	Measured theoretical constructs; the intervention changed the theoretical constructs; changes explain the effect	12 (92)	2.23 (1.36)

		17, 18				
Refining	Refining theory (C6)	19a, 19b	2	Intervention results refined theory	3 (23)	0.23 (0.44)
Totals			23			7.85 (3.87)

Composite scores were calculated for the six categories of theory used. An overall theory score for each included study was calculated as a sum of the total score with a maximum possible score of 23, representing 17 primary TCS items and six subitems.

Table 50: TCS item results for each study

TCS Item	Item category	(Grossman, Arigo and Bachman, 2018)	(Hartman et al., 2016)	(Park and Kim, 2012)	(Cadmus-Bertram et al., 2015a)	(Finkelstein et al., 2015)	(Fukuoka et al., 2019)	(Lynch et al., 2019; Nguyen et al., 2021)	(Anderson et al., 2015; McGuire et al., 2019)	(Ryan et al., 2013)	(Steinberg et al., 2020)	(Im et al., 2017)	(Im et al., 2019)	(Ryan et al., 2020)	TCS Items for all studies, n (%)
Theory mentioned (I1)	1	0	1	0	1	0	1	1	1	1	0	1	1	1	9 (69)
Targeted construct mentioned as predictor of behaviour (I2)	1 & 2	1	1	0	0	0	0	0	0	1	0	1	1	1	6 (46)
Intervention based on single theory (I3)	1	0	1	0	1	0	0	0	1	1	0	1	1	1	7 (54)
Theory or predictors used to select or develop recipients for the intervention (I4)	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0)
Theory or predictors used to select or develop intervention techniques (I5)	2	0	1	0	1	0	0	0	1	1	0	1	1	1	7 (54)
Theory or predictors used to tailor intervention techniques to recipients (I6)	3	0	0	1	0	0	1	0	0	1	0	0	0	0	3 (23)

All intervention techniques are explicitly linked to at least one theory relevant construct or predictor (I7)	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0)
At least one, but not all, of the intervention techniques are explicitly linked to at least one theory-relevant construct or predictor (I8)	2	1	1	0	0	0	0	0	0	1	0	1	1	1	6 (46)
Group of techniques are linked to a group of constructs or predictors (I9)	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0)
All theory-relevant constructs or predictors are explicitly linked to at least one intervention technique (I10)	2	0	0	0	0	0	0	0	0	1	0	1	1	1	4 (31)
At least one, but not all, of the theory relevant constructs are explicitly linked to at least one intervention technique (I11)	2	1	1	1	1	1	1	1	0	1	1	1	1	1	12 (92)
Theory-relevant constructs are measured: post-intervention (I12a)	4	0	0	1	0	1	1	1	0	1	0	1	1	1	8 (62)
Theory-relevant constructs are measured: post and pre intervention (I12b)	4	0	0	1	0	1	1	0	0	1	1	1	1	1	8 (62)
Changes in measured theory-relevant constructs (I15)	5	0	0	0	0	1	0	0	0	1	0	0	1	0	3 (23)
Mediator predicts the dependent variable (I16a)	5	0	0	0	0	1	0	1	1	1	1	1	1	1	8 (62)
Mediator predicts dependent variable, controlling for the independent variable (I16b)	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0(0)

Intervention does not predict the dependent variable when controlling the independent variable (I16c)	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0)
Mediated effect is statistically significant (I16d)	5	0	0	1	1	1	1	1	1	1	0	0	1	0	8 (62)
Results discussed in relation to theory (I17)	5	1	0	1	0	0	1	1	0	1	0	0	1	1	7 (54)
Appropriate support for theory (I18)	5	0	0	0	1	0	1	0	0	1	0	0	0	0	3 (23)
Results used to refine theory: adding or removing constructs to the theory (I19a)	6	0	0	0	0	0	0	0	0	0	0	1	1	1	3 (23)
Results used to refine theory: specifying that the interrelationships between the theoretical constructs should be changed (I19b)	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (0)
TCS items per study, n (%)		4 (17)	6 (26)	6 (26)	6 (26)	6 (26)	8 (35)	6 (26)	5 (22)	15 (65)	3 (13)	11 (48)	14 (61)	12 (52)	102 (34)

Each study was coded for TCS item present (1) or absent (0).

Summary of Technological and Non-Technological Components

Table 51: Summary of technological and non-technological components used

		Technology used									
Intervention Type [a]	Study	Wearable	Web	App	Email	Peripheral Device	Phone /Text	Electronic doc	Face - to-face	Hard copy	Tech per study, n
Weight loss	(Grossman, Arigo and Bachman, 2018)	x	x		x	x		x	x		6
Weight loss	(Hartman et al., 2016)	x	x	x			x			x	5
Weight loss	(Park and Kim, 2012)		x				x				2
Lifestyle (PA)	(Cadmus-Bertram et al., 2015a)	x	x							x	3
Lifestyle (PA)	(Finkelstein et al., 2015)	x		x			x				3
Lifestyle (PA)	(Fukuoka et al., 2019)	x		x			x		x	x	5
Lifestyle (PA, sleep)	(Lynch et al., 2019; Nguyen et al., 2021)	x					x		x		3
Lifestyle (PA), Meno Sympt	(Anderson et al., 2015; McGuire et al., 2019)		x					x	x	x	4
Lifestyle (Diet)	(Ryan et al., 2013)		x	x			x		x	x	5
Lifestyle (Diet)	(Steinberg et al., 2020)		x	x			x			x	4

Meno sympt	(Im et al., 2017)		x		x						2
Meno sympt	(Im et al., 2019)		x		x						2
Meno sympt	(Ryan et al., 2020)	x		x			x				3
Tech component across studies, n (%)		7(54)	9(69)	6(46)	3(23)	1(8)	8(62)	2(15)	5(38)	6(46)	

Each study was coded for technology present (x) or absent [blank].

[a] Intervention types included 1) Weight loss 2) Lifestyle physical activity (PA), 3) Lifestyle (Diet), 4) Lifestyle (Sleep), 5) Menopausal symptoms (Meno sympt).

Treatment Fidelity Results for Each Study

Table 52: Treatment fidelity results for all studies

Fidelity domains	(Grossman, Arigo and Bachman, 2018)	(Hartman et al., 2016)	(Park and Kim, 2012)	(Cadmus-Bertram et al., 2015a)	(Finkelstein et al., 2015)	(Fukuoka et al., 2019)	(Lynch et al., 2019; Nguyen et al., 2021)	(Anderson et al., 2015; McGuire et al., 2019)	(Ryan et al., 2013)	(Steinberg et al., 2020)	(Im et al., 2017)	(Im et al., 2019)	(Ryan et al., 2020)	Mean proportion (SD)	Median proportion
1. Treatment design	0.63	0.38	0.19	0.31	0.19	0.69	0.44	0.38	0.75	0.38	0.50	0.50	0.56	0.45 (0.18)	0.44
2. Training providers	0.14	0.57	0.14	0.14	0.00	0.14	0.43	0.57	0.71	0.43	0.29	0.29	0.57	0.34 (0.22)	0.29
3. Delivery	0.22	0.33	0.11	0.33	0.11	0.33	0.56	0.33	0.33	0.44	0.22	0.22	0.56	0.32 (0.14)	0.33
4. Receipt	0.00	0.50	0.00	0.50	0.00	0.00	0.00	0.25	0.50	0.25	0.40	0.20	0.75	0.26 (0.25)	0.25
5. Enactment	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50 (0.00)	0.50
Overall fidelity proportion per study	0.38	0.43	0.16	0.32	0.14	0.43	0.43	0.41	0.62	0.41	0.39	0.37	0.59	0.39 (0.14)	0.41

Table 53: Treatment fidelity for each study

Fidelity categories	(Grossman, Arigo and Bachman, 2018)	(Hartman et al., 2016)	(Park and Kim, 2012)	(Cadmus-Bertram et al., 2015a)	(Finkelstein et al., 2015)	(Fukuoka et al., 2019)	(Lynch et al., 2019; Nguyen et al., 2021)	(Anderson et al., 2015; McGuire et al., 2019)	(Ryan et al., 2013)	(Steinberg et al., 2020)	(Im et al., 2017)	(Im et al., 2019)	(Ryan et al., 2020)	Totals per domain, n (%)
Treatment design, n (%)	10 (63)	6 (38)	3 (19)	5 (31)	3 (19)	11 (69)	7 (44)	6 (38)	12 (75)	6 (38)	8 (50)	8 (50)	9 (56)	94 (45)
1. Intervention dose information (Intervention Group)														
a. Length of contact (minutes)	1	0	0	0	0	0	0	0	1	0	0	0	0	
b. Number of contacts	1	1	0	1	0	1	1	1	1	1	1	1	1	
c. Intervention content	1	1	1	1	1	1	1	1	1	1	1	1	1	
d. Duration of contact over time	1	0	0	0	0	0	0	0	1	0	0	0	0	
2. Intervention dose information (Comparison / Control Group)														
a. Length of contact (minutes)	1	0	0	0	0	0	0	0	1	0	0	0	0	
b. Number of contacts	1	1	0	1	0	0	1	1	1	1	1	1	1	

c. Intervention content	1	1	1	1	1	1	1	1	1	1	1	1	1	
d. Duration of contact over time	1	0	0	0	0	0	0	0	1	0	0	0	0	
e. Method to ensure that dose is equivalent between conditions.	0	0	0	0	0	0	0	0	0	0	0	0	0	
f. Method to ensure that dose is equivalent for participants within conditions	0	0	0	0	0	0	0	0	0	0	0	0	0	
3. Specification of provider credentials that are needed.	1	1	0	0	0	1	1	1	1	1	1	1	1	
4. Theoretical model upon which the intervention is based is clearly articulated.														
a. The active ingredients are specified and incorporated into the intervention	1	1	1	1	1	1	1	1	1	1	1	1	1	
b. Use of experts or protocol review group to determine whether the intervention protocol reflects the underlying	0	0	0	0	0	1	1	0	1	0	1	1	1	

theoretical model or clinical guidelines														
c. Plan to ensure that the measures reflect the hypothesized theoretical constructs/mechanisms of action	0	0	0	0	0	0	0	0	1	0	1	1	1	
5. Potential confounders that limit the ability to make conclusions at the end of the trial are identified?	0	0	0	0	0	0	0	0	0	0	0	0	0	
6. Plan to address possible setbacks in implementation (i.e., back-up systems or providers)	0	0	0	0	0	0	0	0	0	0	0	0	1	
6. If more than one intervention is described, all described equally well.	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	

Training Providers, n (%)	1 (14)	4 (57)	1 (14)	1 (14)	0 (0)	1 (14)	3 (43)	4 (57)	5 (71)	3 (43)	2 (29)	2 (29)	4 (57)	31 (34)
1. Description of how providers will be trained (manual of training procedures)	0	0	0	1	0	0	1	1	1	1	1	1	1	
2. Standardization of provider training (especially if multiple waves of training are needed for multiple groups of providers)	0	1	0	0	0	0	1	1	1	1	1	1	0	
3. Assessment of provider skill acquisition.	0	1	0	0	0	0	0	0	1	0	0	0	1	
4. Assessment and monitoring of provider skill maintenance over time	0	1	0	0	0	0	0	1	1	0	0	0	1	
5. Characteristics being sought in a treatment provider are articulated a priori. Characteristics that should be avoided in	0	0	0	0	0	0	0	0	0	0	0	0	0	

a treatment provider are articulated a priori.														
6. At the hiring stage, assessment of whether or not there is a good fit between the provider and the intervention (e.g., ensure that providers find the intervention acceptable, credible and potentially efficacious	1	1	1	0	0	1	1	1	1	1	0	0	1	
7. There is a training plan that takes into account trainees' different education and experience and learning styles	0	0	0	0	0	0	0	0	0	0	0	0	0	
Delivery of Treatment, n (%)	2 (22)	3 (33)	1 (11)	3 (33)	1 (11)	3 (33)	5 (56)	3 (33)	3 (33)	4 (44)	2 (22)	2 (22)	5 (56)	37 (32)
1. Method to ensure that the content of the	0	0	0	0	0	0	1	0	1	1	0	0	1	

intervention is delivered as specified.														
2. Method to ensure that the dose of the intervention is delivered as specified.	0	0	0	0	0	0	1	0	0	1	0	0	0	
3. Mechanism to assess if the provider actually adhered to the intervention plan or in the case of computer delivered interventions, method to assess participants' contact with the information.	1	1	0	1	0	1	1	1	0	1	0	0	1	
4. Assessment of non-specific treatment effects.	1	1	1	1	1	1	1	1	1	1	1	1	1	
5. Use of treatment manual.	0	1	0	1	0	0	0	1	1	0	1	1	1	
6. There is a plan for the assessment of whether or not the active	0	0	0	0	0	0	1	0	0	0	0	0	1	

ingredients were delivered.														
7. There is a plan for the assessment of whether or not proscribed components were delivered. (e.g., components that are unnecessary or unhelpful)	0	0	0	0	0	0	0	0	0	0	0	0	0	
8. There is a plan for how contamination between conditions will be prevented.	0	0	0	0	0	0	0	0	0	0	0	0	0	
9. There is an a priori specification of treatment fidelity (e.g., providers adhere to delivering >80% of components).	0	0	0	0	0	1	0	0	0	0	0	0	0	
Receipt of Treatment, n	0 (0)	2 (50)	0 (0)	2 (50)	0 (0)	0 (0)	0 (0)	1 (25)	2 (50)	1 (25)	2 (40)	1 (20)	3 (75)	14 (26)
1. There is an assessment of the	0	0	0	0	0	0	0	0	0	1	0	0	0	

degree to which participants understood the intervention.														
2. There are specification of strategies that will be used to improve participant comprehension of the intervention.	0	0	0	1	0	0	0	1	1	0	0	0	1	
3. The participants' ability to perform the intervention skills will be assessed during the intervention period.	0	1	0	1	0	0	0	0	1	0	0	0	1	
4. A strategy will be used to improve subject performance of intervention skills during the intervention period.	0	1	0	0	0	0	0	0	0	0	1	0	1	
5. Multicultural factors considered in the development and delivery of the	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1	1	NA	

intervention (e.g., provided in native language; protocol is consistent with the values of the target group)														
Enactment of Treatment Skills, n	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	1 (50)	13 (50)
1. Participant performance of the intervention skills will be assessed in settings in which the intervention might be applied.	1	1	1	1	1	1	1	1	1	1	1	1	1	
2. A strategy will be used to assess performance of the intervention skills in settings in which the intervention might be applied.	0	0	0	0	0	0	0	0	0	0	0	0	0	
Totals per study, n (%)	14 (38)	16 (43)	6 (16)	12 (32)	5 (14)	16 (43)	16 (43)	15 (41)	23 (62)	15 (41)	15 (39)	14 (37)	22 (59)	

Each study was coded for treatment fidelity item present (1) or absent (0)

Appendix B: Chapter 6

Additional Demographics of the Participants

Table 54: Demographics of the focus group participants including general health and lifestyle

Attribute	Scale of measure	n	Frequency (%)	Mean	SD	Range
Health status		29				
	Fair	4	13.79			
	Good	9	31.03			
	Very good	14	48.28			
	Excellent	2	6.90			
Age at menarche		29				
	12 or younger	10	34.50			
	13 to 14	16	55.20			
	15 to 16	3	10.30			
	17 or older	0	0.00			
Lifelong irregularity of your menstrual cycle		29				
	Yes	2	6.90			
	No	27	93.10			
Age at first full-term pregnancy		29				
	25 or younger	2	6.90			
	26 to 30	10	34.48			
	31 or older	11	37.93			
	Not applicable	6	20.69			
Menopausal status (self-reported)		29				
	Pre-menopause	3	10.34			
	Peri-menopause	15	51.72			
	Menopause or post-menopause	10	34.48			
	Not sure	1	3.45			
Age at natural menopause		18				
	40 to 44	7	38.89			
	45 to 50	5	27.78			

	51 or older	6	33.33			
HRT user		29				
	Never	16	55.17			
	In the past	1	3.45			
	Currently	12	41.38			
Smoking		29				
	Never	15	51.72			
	In the past	13	44.83			
	Currently	1	3.45			
Sleep (hrs/night)		29		6.98	0.88	4.00 - 8.00

Table 55: General technology use questionnaire feedback from focus groups participants

Question	Response	n	Frequency (%)
Using technology for lifestyle support	Yes	24	82.80
	No	5	17.20
Using - wearable fitness tracker devices (faceless, i.e., Oura ring, Whoop)	Yes	0	0.00
Using - smart watch (apple watch, Samsung galaxy, Polar, Garmin, Fitbit)	Yes	19	63.30
Using - nutrition/recipes apps or websites	Yes	11	36.70
Using exercise apps or websites	Yes	9	30.00
Using apps or websites to track menopausal symptoms	Yes	6	20.00
Using other technology	Yes	3	
	Calm	1	3.30
	Slimming World	1	3.30
	Strava	1	3.30
Outcomes experienced using technology			
	Weight loss	8	26.70
	Increased physical activity	14	46.70
	Eating healthier diet	9	30.00
	Living a healthier lifestyle	11	36.70
	Other outcomes	5	16.70
	Attending yoga and Pilates classes	1	3.30
	Better sleep	3	10.00
Reasons for not using technology			

	Because I manage my health well without.	1	3.33
	Cumbersome and unnecessary	1	3.33
	I exercise for pleasure. I run until I'm tired and am satisfied with a vague idea of distance as opposed to an exact mileage	1	3.33
	Never considered using one, don't like style of some of them. May be useful now I attend a gym	1	3.33
	Never tried it	1	3.33
Interested in using technology in the future			
	No	2	6.70
	Yes	3	10.00
	Something simple. Apps possible.	1	
	Not sure	2	

Appendix C: Chapter 7

Co-Production Workshops

Table 56: Co-production activities summary

Activity name	Activity objective
Focus-group survey review (Chapter 5)	Review focus group survey questions
Focus group session testing (Chapter 5)	Provide feedback on focus group test session experience
Pre-workshop 1	Preparation for Workshop 1, following provided guidance
Workshop 1a	Identify target behaviours for improving diet
Workshop 1b	Identify target behaviours for improving physical activity
User technology experience	Experience how intervention technologies (EMA, fitness tracker) work
Pre-workshop 2	Preparation for Workshop 2, following provided guidance
Workshop 2	Identify COM-B components
Pre-workshop 3	Preparation for Workshop 3, following provided guidance
Workshop 3	Identify mode of delivery and intervention functions
Prototype testing	Provide feedback on the intervention prototype

Table of Changes from the Intervention Prototype Testing

Table 57: Table of Changes based on PPI usability testing feedback

The feasibility and acceptability of a co-produced health-promoting lifestyle intervention for midlife women						
Intervention element	Negative Comments	Positive Comments	Possible Change	Reason for change	Agreed change / NC	MoScoW [a]
EMA	Needing to remember to charge the Garmin when battery was low without waiting to be fully out		Include in the training and weekly reminders	Data capturing	Agreed	REP, EAS
EMA	I struggled a little with my phone as I kept having to delete the app and reconnect		Include in the training, troubleshooting tips	Data capturing	Agreed	EAS
EMA	I understood the importance of responding to the daily surveys. I think these are excellent to get people into a healthy routine. It would become stressful if at a social event and not able to respond to the survey in a timely manner		Provide individualised setting for 90-minute survey response blocks	Personalisation of the intervention prompts for each individual	Agreed	EAS
EMA	The alert of stress levels or the heart rate levels ended up stressing me out even more so I took it off at some point but put it back on later		Turned off for all users in Garmin Connect	Turn off intrusive triggers	Agreed	EAS
EMA	The portions number to be more easily usable. When asking for colourful, I just thought it might not suit a colourblind person		Add text specifying that if enable to determine colour, skip the question	Unable to determine colour	Agreed	EAS
EMA	An option to remove alcohol related questions? I don't drink alcohol for health reasons, so it didn't bother me. I do wonder if someone is a		Alcohol entry was made optional and could be skipped.	Users who do not use alcohol may find daily question on	Agreed	EAS

	recovering alcoholic, that the questions could be triggering?			alcohol intrusive. Personalisation of what is being asked of users.		
EMA		I think the bite sized education info was helpful and relevant and I looked forward to seeing these		No change		NC
EMA		I found the Garmin of some interest but much like the rest of the group, exercise is an important part of my life and although I absolutely set and monitored activities such as daily steps and looked forward to seeing my daily achievement, I don't personally		No change		NC

		need this as a tool to make me exercise. However, if new to exercise I can see why it would be both helpful and motivational				
EMA		Add more visuals wherever you can as visuals are helpful to remember.	Although technically challenging, images and visuals were added to all reminders and educational content.	Improve engagement by adding visuals instead of only text	Agreed	EAS
Survey	In the section how many portions of fruit, meat, units of water etc it would be good to have a range rather than an exact number.		Add checkboxes to tick a range from 0 to 10.	Easier data entry	Agreed	EAS
Survey	I couldn't t say 2/3 portions as it created error so had to give a single digit.		Portion sizes are kept as whole numbers, portions size text to be added.	No change	Agreed	NC
Survey	The only comment would be that it is slightly odd to rate on 0-6 as opposed to 0-10 but it is easy to accommodate.		Using standardised questionnaire, therefore keeping scale 0-6.	No change	Agreed	NC
Survey	I am sure there is a difference with how much sleep you think you get and what you actually getting! Questions are all good.		Text clarification in the survey to indicate actual sleep minutes, not perceived.	Improve data entry.	Agreed	EAS

[a] Coding Framework codes, see **Table 59**

Table 58: Coding Framework for Table of Changes (Yardley et al., 2015)

Coding Framework for Table of Changes		
Code	**Stands for**	**Means**
IMP	Important for behaviour change	This is an important change that is likely to impact behaviour change or a precursor to behaviour change (e.g. acceptability, feasibility, persuasiveness, motivation, engagement), and/or is in line with the Logic Model, and/or is in line with the Guiding Principles For example, participants appear unconvinced by an aspect of the intervention, so you decide to add motivational examples.
EAS	Easy and uncontroversial	An easy and feasible change that doesn't involve any major design changes. For example, a participant was unsure of a technical term, so you add a definition.
REP	Repeatedly	This was said repeatedly, by more than one participant.
EXP	Experience	This is supported by experience. Please specify what kind of experience, for example: 1. PPIs agree this would be an appropriate change. 2. Other stakeholders (e.g. practitioners, providers, topic specialists) agree that this would be an appropriate change. 3. Literature: This is supported by evidence in the literature.
NCON	Does not contradict	This does not contradict experience (e.g. evidence), or the Logic Model, or the Guiding Principles
NC	Not changed	It was decided not to make this change. Please explain why (e.g. it would not be feasible; or only one person said this).

Education Topics

Table 59: Education topics selected for mEMA app content

Category	Num	Topic	Target behaviour
Diet	1	Healthy recipes	Increase consumption of fruit and vegetables.
Diet	2	Types/quantity of water	Increase hydration
Diet	3	Healthy snacks	Replace unhealthy snacks with healthy options
Diet	4	Meal frequency	Consume meals regularly
Diet	5	Meal portions (Energy amounts per meal per day)	Reduce meal portions
Diet	6	Food group portions (Energy amounts per food group)	Increase portion of plant foods and healthy protein
Diet	7	Macronutrient proportions	Types of macronutrients. How much to consume from each type and best options to include.
Diet	8	Plants (Fruit, vegetables, grains, pulses, nuts and seeds)	Increase consumption of plant foods (in addition to increasing consumption of fruit and vegetables)
Diet	9	Fruit	Increase consumption of fruit
Diet	10	Take aways	Cook more at home.
Diet	11	Protein (linked to macronutrient proportions)	Increase healthy protein consumption.
Diet	12	Alcohol	Limit consumption of alcoholic beverages.
Diet	13	Anti-Inflammatory foods	Reduce ultra processed foods consumption.
Diet	14	Eating when on holidays	Consume healthy meals and snacks. Reduce consumption of ultra processed foods.

Diet	15	Gut health	Consume healthy meals and snacks. Reduce consumption of ultra processed foods.
Menopause	1	Evidence based information on HRT and non-HRT support during peri/post menopause	Guidance from a medical professional (GP)
Menopause	2	Perimenopause (definition, symptoms, how to cope with)	Guidance from a medical professional (GP)
Menopause	3	Menopause (definition, long term health implications)	Guidance from a medical professional (GP)
Menopause	4	Menopause symptoms	Guidance from a medical professional (GP)
Menopause	5	Gut health (ways to improve)	Guidance from a medical professional (GP)
Menopause	6	Supplements for menopause	Guidance from a medical professional (GP)
Menopause	7	Sleep (tips for improving sleep for women in midlife)	Guidance from a medical professional (GP)
Menopause	8	Supplements recommendations for women in midlife	Guidance from a medical professional (GP)
Exercise	1	Suggested types of exercises for women in midlife	Increase physical activity
Exercise	2	Tips to increase walking	Increase physical activity (steps count)
Exercise	3	Strength building guidance for women in midlife	Increase physical activity
Exercise	4	Cardio guidance for women in midlife	Increase physical activity
Exercise	5	Mobility exercise guidance for women in midlife	Increase physical activity

Combined Intervention Design

Combined BCT Mappings Across Three Workstreams

Table 60: Combined BCT mappings across three workstreams

BCT categories and BCTs	PPI: Increase walking	PPI: Reduce caffeine	PPI: Reduce alcohol	PPI: Healthy meals and snacks	Focus groups: Physical activity and healthy eating	Systematic review: weight loss, lifestyle, menopause symptoms	Systematic review: BCTs used most frequently, %	BCTs across all sources, Mean n
1.Goals and planning, n	6	6	6	6	6	7	3	6
BCTs from all possible BCTs (9 BCTS), %	67%	67%	67%	67%	67%	78%	33%	69%
1.1. Goal setting (behaviour)	X	X	X	X	X	X	62%	100%
1.2. Problem solving	X	X	X	X	X	X	46%	100%
1.3. Goal setting (outcome)						X		17%
1.4. Action planning	X	X	X	X	X	X	69%	100%
1.5. Review behaviour goal(s)	X	X	X	X	X	X		100%
1.6. Discrepancy between current behaviour and goal						X		17%
1.7. Review outcome goal(s)						X		17%
1.8. Behavioural contract	X	X	X	X	X			83%
1.9. Commitment	X	X	X	X	X			83%
2.Feedback and monitoring, n	2	2	2	2	3	4	3	3
BCTs from all possible BCTs (7 BCTs), %	29%	29%	29%	29%	43%	57%	43%	36%
2.1. Monitoring of behaviour by others without feedback								0%
2.2. Feedback on behaviour	X	X	X	X	X	X	85%	100%
2.3. Self-monitoring of behaviour	X	X	X	X	X	X	62%	100%
2.4. Self-monitoring of outcome(s) of behaviour								0%

2.5. Monitoring of outcome(s) of behaviour without feedback								0%
2.6. Biofeedback					X	X		33%
2.7. Feedback on outcome(s) of behaviour						X	46%	17%
3. Social support, n	3	3	3	3	3	3	0	3
BCTs from all possible BCTs (3 BCTs), %	100%	100%	100%	100%	100%	100%	0%	100%
3.1. Social support (unspecified)	X	X	X	X	X	X		100%
3.2. Social support (practical)	X	X	X	X	X	X		100%
3.3. Social support (emotional)	X	X	X	X	X	X		100%
4. Shaping knowledge	3	2	2	2	1	1	1	2
BCTs from all possible BCTs (4 BCTs), %	75%	50%	50%	50%	25%	25%	25%	46%
4.1. Instruction on behaviour	X	X	X	X	X	X	92%	100%
4.2. Information about Antecedents	X	X	X	X				67%
4.3. Re-attribution								0%
4.4. Behavioural experiments	X							17%
5.Natural consequences, n	4	3	3	4	4	1	0	3
BCTs from all possible BCTs (6 BCTs), %	67%	50%	50%	67%	67%	17%	0%	53%
5.1. Information about health consequences	X	X	X	X	X	X		100%
5.2. Salience of consequences	X	X	X	X	X			83%
5.3. Information about social and environmental consequences	X			X				33%
5.4. Monitoring of emotional consequences					X			17%
5.5. Anticipated regret								0%
5.6. Information about emotional consequences	X	X	X	X	X			83%
6.Comparison of behaviour, n	1	1	1	1	0	1	0	1
BCTs from all possible BCTs (3 BCTs), %	33%	33%	33%	33%	0%	33%	0%	28%
6.1. Demonstration of the behaviour	X	X	X	X		X		83%
6.2. Social comparison								0%
6.3. Information about others' approval								0%
7.Associations, n	1	1	1	1	1	2	1	1

BCTs from all possible BCTs (8 BCTs), %	13%	13%	13%	13%	13%	25%	13%	15%
7.1. Prompts/cues	X	X	X	X	X	X	69%	100%
7.2. Cue signalling reward								0%
7.3. Reduce prompts/cues						X		17%
7.4. Remove access to the reward								0%
7.5. Remove aversive stimulus								0%
7.6. Satiation								0%
7.7. Exposure								0%
7.8. Associative learning								0%
8.Repetition and substitution, n	5	5	5	5	6	5	3	5
BCTs from all possible BCTs (7 BCTs), %	71%	71%	71%	71%	86%	71%	43%	74%
8.1. Behavioural practice/rehearsal	X	X	X	X	X	X	77%	100%
8.2. Behaviour substitution	X	X	X	X	X	X		100%
8.3. Habit formation	X	X	X	X	X	X	77%	100%
8.4. Habit reversal	X	X	X	X	X	X		100%
8.5. Overcorrection								0%
8.6. Generalisation of target behaviour					X			17%
8.7. Graded tasks	X	X	X	X	X	X	54%	100%
9.Comparison of outcomes, n	1	1	1	1	0	1	0	1
BCTs from all possible BCTs (3 BCTs), %	33%	33%	33%	33%	0%	33%	0%	28%
9.1. Credible source	X	X	X	X		X	46%	83%
9.2. Pros and cons								0%
9.3. Comparative imagining of future outcomes								0%
10.Reward and threat, n	2	1	1	1	3	3	0	2
BCTs from all possible BCTs (11 BCTs), %	18%	9%	9%	9%	27%	27%	0%	17%
10.1. Material incentive (behaviour)						X	46%	17%
10.2. Material reward (behaviour)						X	46%	17%
10.3. Non-specific reward					X			17%
10.4. Social reward	X	X	X	X	X			83%
10.5. Social incentive								0%
10.6. Non-specific incentive								0%
10.7. Self-incentive								0%
10.8. Incentive (outcome)								0%
10.9. Self-reward	X				X			33%
10.10. Reward (outcome)								0%
10.11. Future punishment						X		17%

11.Regulation, n	0	0	0	0	1	0	0	0
BCTs from all possible BCTs (4 BCTs), %	0%	0%	0%	0%	25%	0%	0%	4%
11.1. Pharmacological support								0%
11.2. Reduce negative emotions					X			17%
11.3. Conserving mental resources								0%
11.4. Paradoxical instructions								0%
12.Antecedents, n	3	3	4	4	3	3	1	3
BCTs from all possible BCTs (6 BCTs), %	50%	50%	67%	67%	50%	50%	17%	56%
12.1. Restructuring the physical environment	X	X	X	X	X	X		100%
12.2. Restructuring the social environment	X	X	X	X	X			83%
12.3. Avoidance/reducing exposure to cues for the behaviour			X	X				33%
12.4. Distraction								0%
12.5. Adding objects to the environment	X	X	X	X	X	X	46%	100%
12.6. Body changes						X		17%
13. Identity, n	1	1	1	1	3	0	0	1
BCTs from all possible BCTs (5 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%
13.1. Identification of self as role model								0%
13.2. Framing/reframing	X	X	X	X	X			83%
13.3. Incompatible beliefs								0%
13.4. Valued self-identify					X			17%
13.5. Identity associated with changed behaviour					X			17%
14. Scheduled consequences, n	0	0	0	0	1	2	0	1
BCTs from all possible BCTs (10 BCTs), %	0%	0%	0%	0%	10%	20%	0%	5%
14.1. Behavior cost					X			17%
14.2. Punishment								0%
14.3. Remove reward						X		17%
14.4. Reward approximation								0%
14.5. Rewarding completion						X		17%
14.6. Situation-specific reward								0%
14.7. Reward incompatible behaviour								0%

14.8. Reward alternative behaviour								0%
14.9. Reduce reward frequency								0%
14.10. Remove punishment								0%
15.Self-belief, n	2	3	4	3	4	0	0	3
BCTs from all possible BCTs (4 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%
15.1. Verbal persuasion capability	X	X	X	X	X			83%
15.2. Mental rehearsal of successful performance			X		X			33%
15.3. Focus on past success		X	X	X	X			67%
15.4. Self-talk	X	X	X	X	X			83%
16. Covert learning, n	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (3 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%
16.1. Imaginary punishment								0%
16.2. Imaginary reward								0%
16.3. Vicarious consequences								0%
BCTs per use case, n	34	32	34	34	39	33	12	34
BCTs from all possible BCTs (93 BCTs), %	37%	34%	37%	37%	42%	35%	13%	37%

EMA App Development Template

Table 61: mEMA app development template

Mode of delivery	Interaction #	Interaction type	Task category	Interaction with the user	Input options	Questionnaire source	BCTs
EMA (Morning)	1	Input 1	Review	**Good morning! How was your sleep last night?**	4-scale slider (Very good, Fairly good, Fairly bad, Very bad)	PSQI, question 6 (Buysse et al., 1989)	2.3. Self-monitoring of behaviour
	2	Input 2	Review	**How bothersome is your energy level this morning?**	7-scale slider (scale 0 to 6)	MENQOL, question 18 (Hilditch et al., 1996; Lewis, Hilditch and Wong, 2005)	2.3. Self-monitoring of behaviour
	3	Input 3	Review	**Did you drink any alcohol yesterday?**	Radio button (Yes/No)	SFFFQ question 6 (Cleghorn et al., 2016)	2.3. Self-monitoring of behaviour

	4	Sub-input 1 to Input 3	Assess Counselling	**How much alcohol did you have?**	If yes, a free textbox (number of drinks or units) '- If the reported consumption is at optimal level, congratulate. '- If consumption if higher, provide link to education on how to reduce alcohol consumption.	SFFFQ question 6a	1.2. Problem solving 2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 4.1. Instruction on behaviour 10.4 Social Reward
	5	Input 4	Assign	**How many portions of fruit and vegetables do you plan to consume today?**	o A number of portions_______ o Skip this goal	SFFFQ, question 2 and 3.	1.1. Goal setting (behaviour) 1.4. Action planning
	6	Prompt 1	Assign Assess	**Open your Garmin connect to set your goals for hydration, steps, and intensity minutes so that Garmin can help you keep track of your progress:**	A prompt with options to:	N/A	1.1. Goal setting (behaviour) 1.9. Commitment 2.2. Feedback on behaviour 4.1. Instruction on behaviour 7.1. Prompts/cues 8.3. Habit formation
					o Set/update hydration goals		
				1) Set your hydration goal for today (see instructions on how to do this).	o Set/update step goals		

				2) Set your step goals (see instructions on how to do this)	o Set/update intensity minutes		
				3) Set your intensity exercise minutes for the week (see instructions on how to do this). The default/minimum is 150 of moderate-intensity minutes per week (this is the same as 75 vigorous-intensity minutes per week).	o Dismiss and move to next question (prefer not have Garmin track my progress)		
				How can you increase your steps? Join a challenge on Garmin Connect.	Joined a challenge Skip		1.2. Problem solving 1.4 Action planning
				When do you plan to exercise?	Early morning before 9am Late morning 9am to 11:59am Afternoon: 12 - 5pm Evening: after 5pm In small exercise 'snacks' throughout the day Not sure yet Skip	Questions from	1.2. Problem solving 1.4 Action planning

	7	Input 5	Assign	**How many millilitres (ml) of water would you like to drink today?** (Please provide the same goal you entered into your Gamin device, under Health Status/Hydration)	o A slider (1 cup = 250 ml) o Skip this goal	SFFFQ, additional question 5.	1.1. Goal setting (behaviour) 1.9. Commitment 8.7. Graded tasks
	8	Input 6	Assign	**How many steps would you like to commit to achieving today?** (Please provide the same goal you entered into your Garmin device, under Activities/Steps)**.** **Joining a group exercise class such as Zumba or walking with a friend can be a good way to reach your step goals.**	o Free textbox (a number of steps) o Skip this goal	N/A (related to IPAQ-SF). *Baseline steps will be determined from Garmin fitness tracker the participants will wear for one week prior to starting the intervention.*	1.1. Goal setting (behaviour) 1.9. Commitment 4.1. Instruction on behaviour 8.7. Graded tasks
	9	Input 7	Assign (on Mondays each week)	**How many moderate-intensity minutes would you like to commit to achieving this week?** (Please provide the same goal you entered into your Garmin device, under Activities/Intensity minutes)**.** **This is shown only on Mondays each week.**	o Free textbox (a number of minutes) o Skip this goal	IPAQ-SF (Craig et al., 2003)	1.1. Goal setting (behaviour) 1.9. Commitment 8.7. Graded tasks
	1	Prompt 1	Assign	**Remember to fill up your water bottle in the morning after you wake up. Keep hydrated.**	Diet 2 – types/quantity of water	Linked to SFFFQ, additional question 5.	7.1. Prompts/cues 8.3. Habit formation 12.5. Adding objects to the environment

EMA (Late morning)	1	Input 1	Review	**How would you rate your <u>breakfast</u> this morning?**	Options:	· Skipped meals: SFFFQ, question 7	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
					o No breakfast (skip to the next question)	· Colourful meal: Based on (König and Renner, 2019), to prompt for colourful meals to increase fruit and vegetables intake.	
					o **Colourful (scale (1) colour to (100) many colours)**		
					o **Portions of:**	· Portions of fruit and veg: SFFFQ, question 2 and 3.	
					· **Fruit**		
					· **Vegetables**		
	1	Prompt 1	Assign	**How about adding a side of colourful vegetables to your lunch.**	Diet 8 – increase consumption of plant foods.	Based on the Fogg Behaviour Model (Fogg, 2002, 2009) that emphasises using simple and easy prompts, to build 'tiny habits'.	7.1. Prompts/cues 8.1. Behavioural practice/rehearsal 8.3. Habit formation
	2	Prompt 1	Assign	**Keep hydrated. Remember to drink water throughout the day.**	Diet 2 – types/quantity of water.	SFFFQ, question 6. Encouragement to increase water intake.	7.1. Prompts/cues 8.1. Behavioural practice/rehearsal 8.3. Habit formation

EMA (Early afternoon)	1	Input 1	Review	**How would you rate your <u>lunch</u> today?**	Options:	· Skipped meals: SFFFQ additional questions 7.	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
					o No lunch (skip to next question)	· Colourful meals: related to portions of fruit and vegetables to increase intake.	
					o **Colourful (scale low, medium, high)**	· Portions of fruit and vegetables: SFFFQ (question 2 and 3)	
					o **Portions of:**		
					· **Fruit**		
					· **Vegetables**		
EMA (Late afternoon)	1	Prompt 1	Assign	**Have an apple at your afternoon coffee break or any other fruit that you like.**	Diet 9 - Best options for fruit intake.	Related to SFFFQ, question 2	7.1. Prompts/cues 8.1. Behavioural practice/rehearsal 8.3. Habit formation 8.4. Habit reversal
	2	Prompt 2	Assign	**Replace coffee with water after 3pm and remember to keep hydrating.**	Diet 2 – Types and quantity of water.	Related to SFFFQ, question 4 and 5	7.1. Prompts/cues 8.1. Behavioural practice/rehearsal 8.3. Habit formation 8.4. Habit reversal
	3	Prompt 3 (triggered Thurs, Fri, Sat, Sun)	Assign	**Reduce alcohol consumption this weekend and remember to keep hydrating.**	Diet 2 – Alcohol	Related to SFFFQ, question 4 and 5	7.1. Prompts/cues 8.1. Behavioural practice/rehearsal 8.3. Habit

							formation 8.4. Habit reversal
EMA (Evening)	1	Input 1	Review Counselling	**How would you rate your <u>dinner</u> this evening?**	Options:	· Skipped meals: SFFFQ additional questions 7.	2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation
					o No dinner (skip to next question)	· Colourful meals: related to portions of fruit and vegetables to increase intake.	
					o **Colourful (scale 1 - 10)**	· Portions of fruit and vegetables: SFFFQ (question 2 and 3)	
					o **Portions of:**		
					· **Fruit**		
					· **Vegetables**		
	2	Input 2	Assess Counselling	**How many cups of coffee** (or other caffeinated beverages) **did you have today?** (a cup is approx. 250 ml)	o Number of cups_____ o Skip Link to education if input is higher than recommended amount.	SFFFQ (additional question 4)	2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 10.4. Social reward

	3	Input 3	Assess Counselling	**How many cups / ml of water did you drink today?** (a glass is approx. 250 ml)	o Number of cups/ml____ o Skip Link to education if input is lower than recommended amount.	SFFFQ (additional question 5)	2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 10.4. Social reward
	4	Input 4	Assess Counselling	**How many snacks did you have today?**	Scale (0 – 10) o Skip Link to education on healthy snack options.	SFFFQ, additional question 8	2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 10.4. Social reward
	5	Input 5	Assess Counselling	**Did you participate in a Garmin group exercise challenge, a group exercise class or any exercise activity with a group or a friend?**	Options: o Yes o No o Not available o Skip If Yes: Congratulate! If No: No problem, you can always join another day.	IPAQ-SF, additional question 8. Optional activity for goal setting and social support.	2.3. Self-monitoring of behaviour 3.1. Social support (unspecified)
	6	Input 6	Assess Counselling	**Did you achieve your planned exercise goals today?** (Including any gym classes that you planned to join)	Options:	Related to IPAQ-SF.	1.2. Problem solving 2.2. Feedback on behaviour 2.3. Self-

					o Yes		monitoring of behaviour
					o No	The Garmin device will provide accurate daily steps. Other user reported activities will be used primarily for motivation and encouragement.	
					o Could not exercise (e.g., sick, traveling, etc.)		
					If yes: congratulate!		
					If No: Encouragement, education (tips to include more exercise) and action planning options (Provide a free textbox to brainstorm how to include more exercise into the day)		
	1	Prompt 1	Assign Counselling	**Prepare for a restful sleep. See tips to optimise your sleep.**	Menopause 7 - Tips to improve	N/A. Linked to PSQI.	4.1. Instruction on behaviour 5.1. Information

				 Good night!	sleep (provided by a GP)		about health consequences
EMA (Diet education)	1	Information	Counselling	Diet education (on-demand, and embedded in EMA prompts)	All educational content provided in the EMA app will be developed by a qualified nutritionist and reviewed by a GP.		4.1. Instruction on behaviour 5.1. Information about health consequences 9.1. Credible source
Garmin fitness tracker (used for recording daily steps and sleep)	1	Information	Review Counselling	Viewing daily steps, intensity minutes, hydration.	Ability to self-monitor steps and progression towards set steps goal. The home screen widget on the device will be set to: Daily steps (IG), time of day (CG)		2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour
	2	Prompt	Counselling	Breathing exercise	Relax reminder will be set for (IG). When Garmin detects high stress level, it occasionally	Stress (based on HRV)	2.6. Biofeedback 4.1. Instruction on behaviour 7.1. Prompts/cues

					prompts the user to do a short breathing activity.		
	3	Prompt	Counselling	Earning and receiving badges	Automatically receive badges for completed goals and challenges.		2.2. Feedback on behaviour 7.1. Prompts/cues 10.3. Non-specific reward
	4	Prompt	Assign Counselling	Reducing sedentary time	Reminder to move (after 1hr of sedentary time, and every 15 mins after if no movement). All disabled for the controls		2.2. Feedback on behaviour 4.1. Instruction on behaviour 7.1. Prompts/cues
Garmin Connect (used for PA goal setting, viewing progress, and community support of the study group)	1	Information	Assign Counselling	Participating in the study group community	Reading messages, adding comments, encouraging each other		3.1. Social support (unspecified)
	2	Information	Assign	Signing up for challenges	Joining weekly walking challenges setup by the researcher.		1.1. Goal setting (behaviour) 1.4. Action planning
	3	Information	Counselling	Earning and receiving badges	Automatically receive badges for completed		10.3. Non-specific reward 10.4. Social reward

					goals and challenges.		
	4	Input	Assign	Setting and updating goals for steps, intensity minutes, and hydration.	Setting/updating daily goals for: Steps, hydration. Setting/updating weekly goals for: Intensity minutes		1.1. Goal setting (behaviour) 1.5. Review behaviour goal(s)
	5	Information	Review Assess	Viewing detailed summary of physical activity progress,	Walking (distance, time, pace, average heart rate, calories), heart rate (resting, high), body battery, intensity minutes (weekly progress and goal per week), steps (progress and daily goal), floors (progress and goal), calories, sleep (dee, light, REM, awake times)), stress (Rest, low, med, high)		2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 2.6. Biofeedback

	6	Informatio n	Review Assess	Viewing detailed summary for yesterday	Same as daily with an indication of whether set goals were completed		2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 2.6. Biofeedback
	7	Informatio n	Review Assess	Viewing detailed summary for the last 7 days	Same as daily with totals and averages, as appropriate		2.2. Feedback on behaviour 2.3. Self-monitoring of behaviour 2.6. Biofeedback

Intervention Design If-Then Scenarios

General Use Case Flow

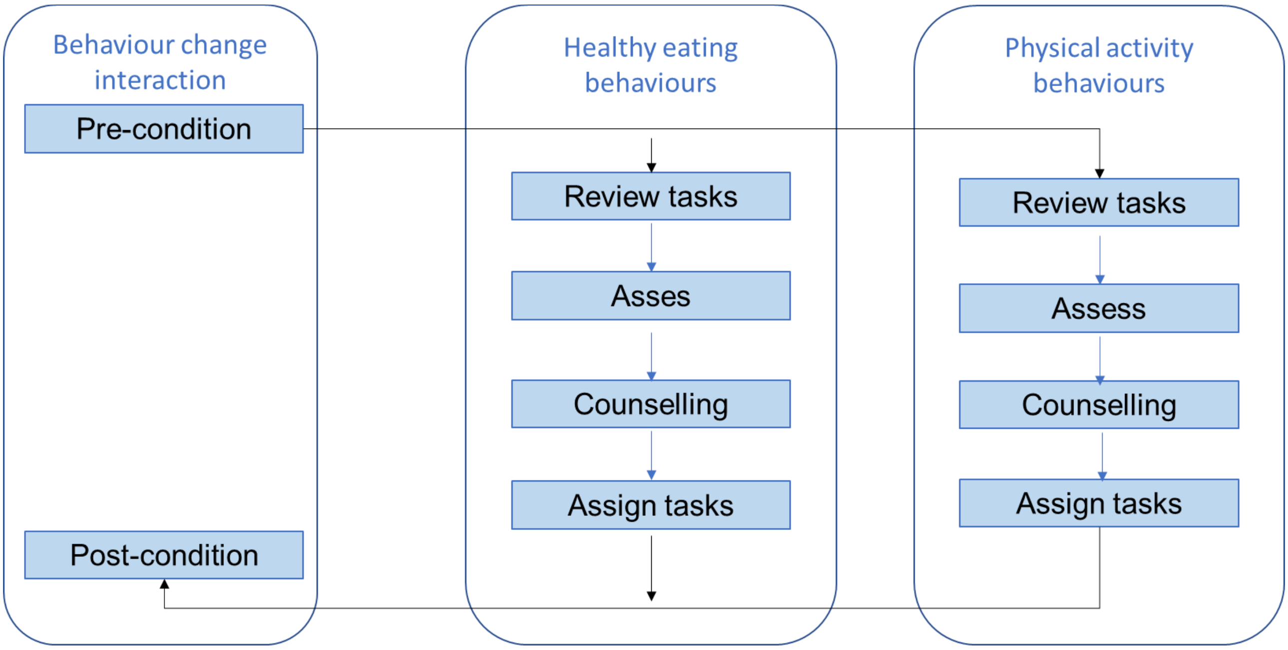


Figure 70: High level use case flow

Late Morning EMA Survey

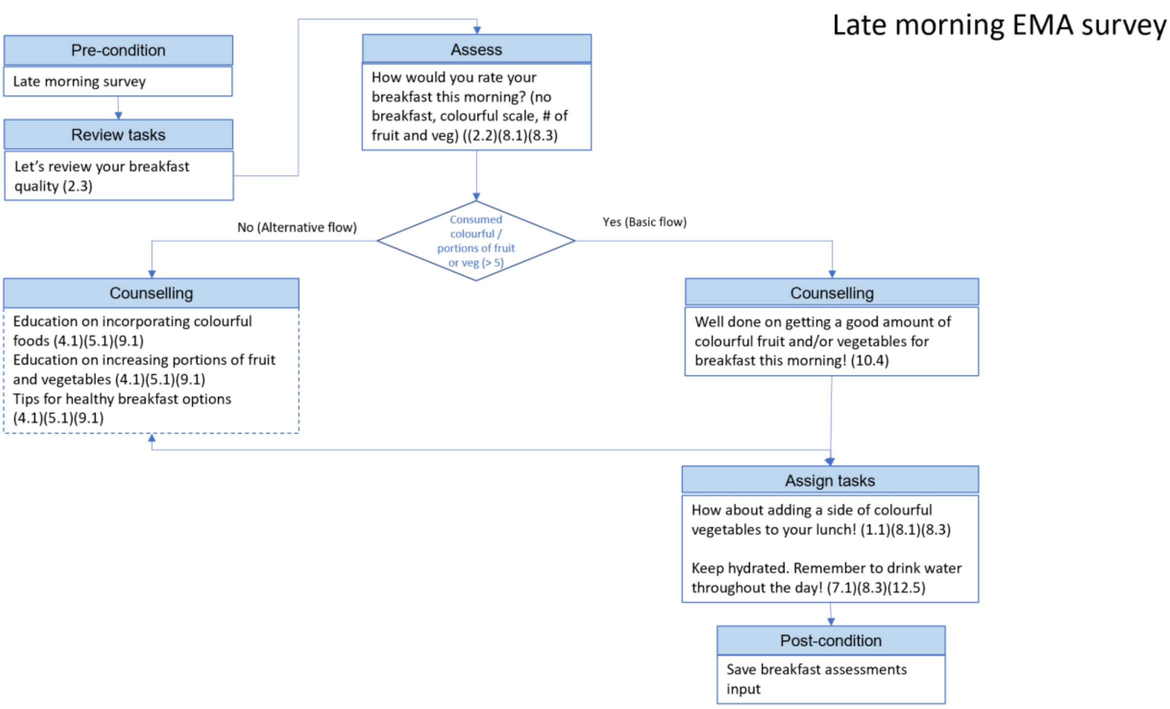


Figure 71: Late morning EMA survey use case flow

Afternoon EMA Survey

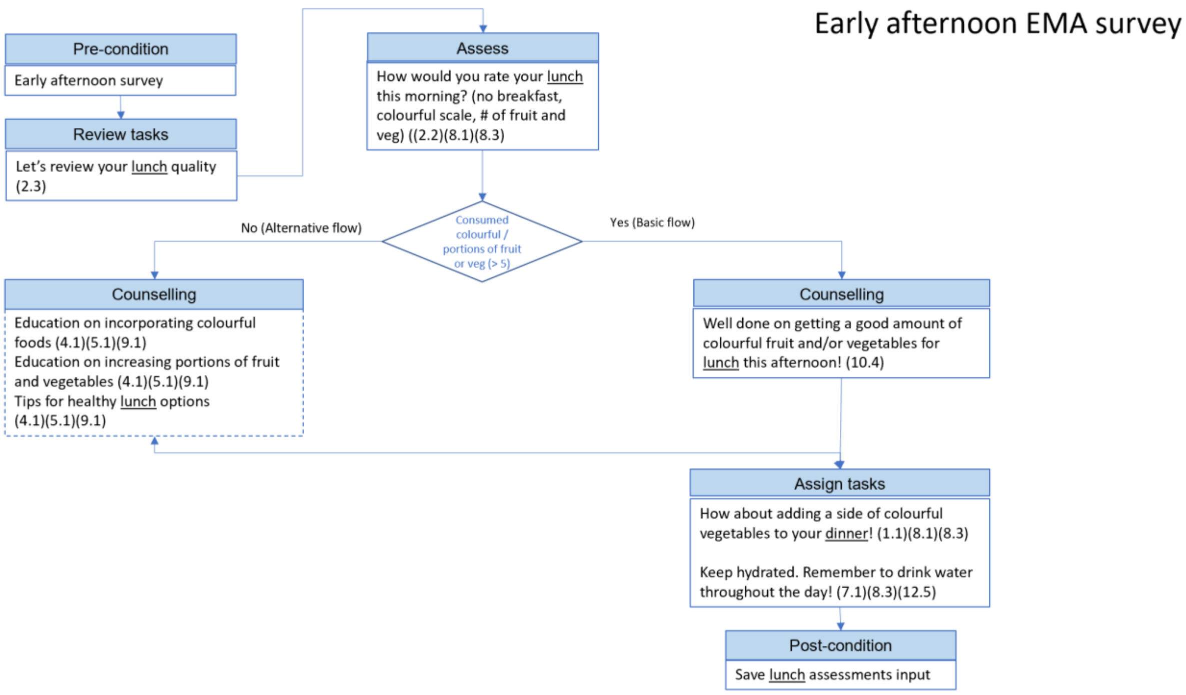


Figure 72: Afternoon EMA survey use case flow

Late Afternoon EMA Survey

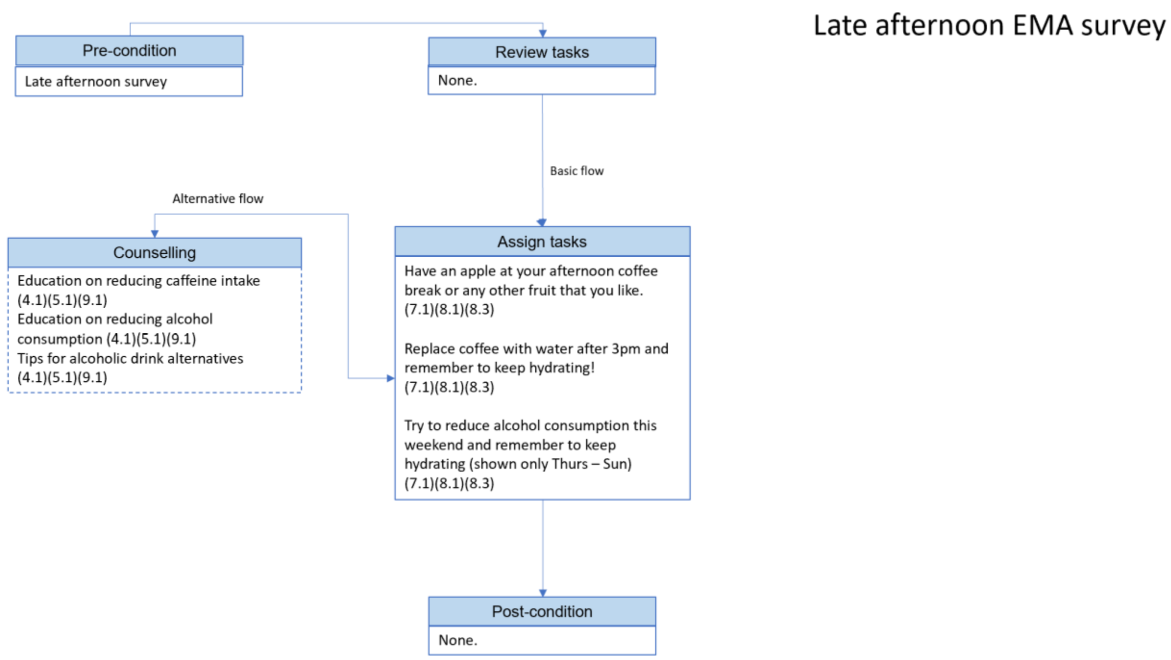


Figure 73: Late afternoon EMA survey use case flow

Evening EMA Survey

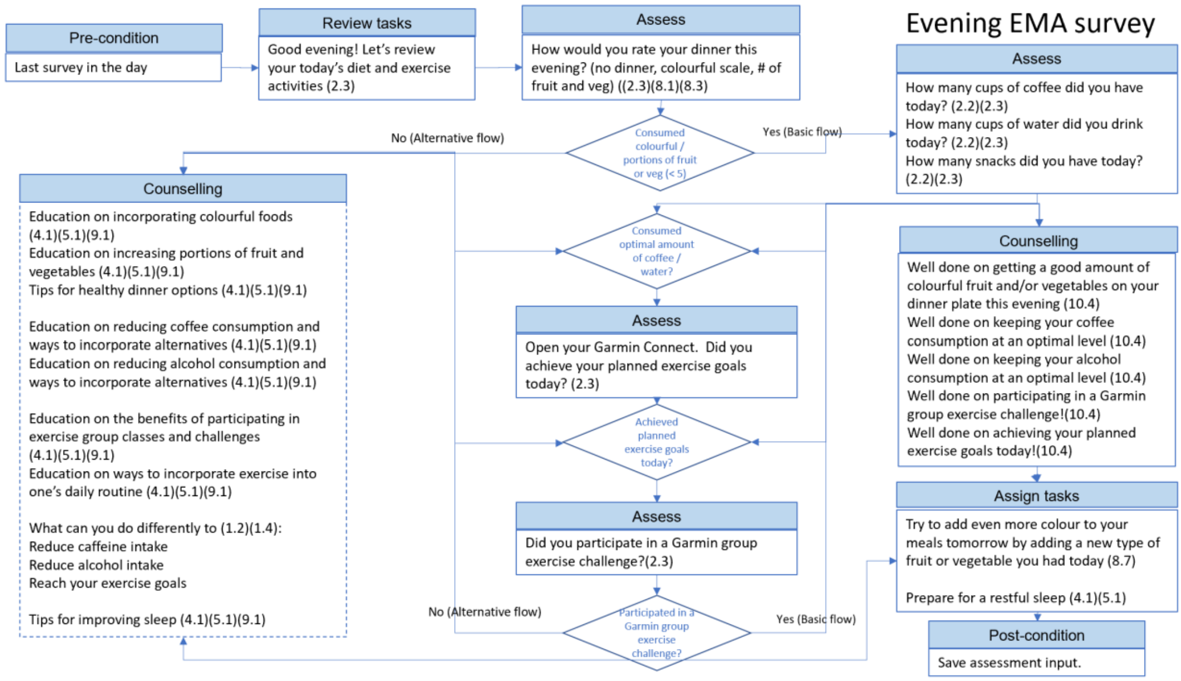


Figure 74: Evening EMA survey use case flow

Methods for Data Preparation

Missing Data Adjustment

Table 62: Required data for a complete record consideration

Variable measured	Morning EMA	Late morning EMA	Early afternoon EMA	Late afternoon EMA	Evening EMA	Garmin (automatically)
Alcohol consumption (previous day)	x					
Portions of fruit (or skipped meal)		x	x		x	
Portions of vegetables (or skipped meal)		x	x		x	
Water (glasses)					x	
Coffee (cups)					x	
Snacks (portions)					x	
Meals (number/day)					x	
Missed entries for all previous EMAs					x	
Steps						x
Sleep (total)						x
Sleep (deep)						x

Additional Intervention Results

Additional Participants Characteristics

Table 63: Health status participants characteristics

Health status:	**N**	**(%)**	**N**	**(%)**
General health:				
Poor	2	(5.41)	1	(4.17)
Fair	4	(10.81)	2	(8.33)
Good	18	(48.65)	13	(54.17)
Very good	12	(32.43)	8	(33.33)
Excellent	1	(2.70)	0	(0.00)
Menarche age:				
12 or younger	15	(40.54)	11	(45.83)
13 to 14	17	(45.95)	10	(41.67)
15 to16	4	(10.81)	3	(12.50)
17 or older	1	(2.7)	0	(0.00)
Lifelong irregular menstrual cycle:				
No	28	(75.68)	16	(66.67)
Yes	8	(21.62)	7	(29.17)
Not applicable	1	(2.70)	1	(4.17)
First pregnancy age:				
25 or younger	2	(5.41)	2	(8.33)
26 - 30	6	(16.22)	3	(12.50)
31 or older	20	(54.05)	12	(50.00)
Not applicable	9	(24.32)	7	(29.17)
Menopause stage:				
Peri-menopause	20	(54.05)	12	(50.00)
Post-menopause	4	(10.81)	2	(8.33)
Pre-menopause	7	(18.92)	6	(25.00)
Surgical menopause	2	(5.41)	2	(8.33)
Unsure	4	(10.81)	2	(8.33)
Post-menopause age:				
< 40	1	(2.70)	4	(16.67)
45 - 49	4	(10.81)	1	(4.17)
50 - 54	3	(8.11)	1	(4.17)
Unsure	3	(8.11)	2	(8.33)
Not applicable	26	(70.27)	16	(66.67)

Table 64: Menopause symptoms participants characteristics

Menopause symptoms management:	**N**	**(%)**	**N**	**(%)**
HRT use:				
Currently	14	(37.84)	7	(29.17)
Never	23	(62.16)	17	(70.83)
Antidepressants use:				
Currently	4	(10.81)	3	(12.50)
In the past	1	(2.70)	0	(0.00)
Never	32	(86.49)	21	(87.50)
CBT use:				
Currently	3	(8.11)	3	(12.50)
In the past	5	(13.51)	3	(12.50)
Never	29	(78.38)	18	(75.00)
Perspective on the menopause:				
Accepting of it	11	(29.73)	8	(33.33)
Have not thought about it	1	(2.70)	1	(4.17)
Looking forward to it	1	(2.70)	0	(0.00)
Neutral	7	(18.92)	5	(20.83)
Not looking forward to it	13	(35.14)	8	(33.33)
Unsure	4	(10.81)	2	(8.33)
Menopause knowledge:				
Not informed at all	1	(2.70)	1	(4.17)
Some knowledge	26	(70.27)	17	(70.83)
Very informed	10	(27.03)	6	(25.00)

Table 65: Lifestyle participants characteristics

Lifestyle:	**N**	**(%)**	**N**	**(%)**
Smoking:				
Never	20	(54.05)	13	(54.17)
Currently or in the past	17	(45.95)	11	(45.83)
Made lifestyle changes (e.g., diet, exercise)				
No	17	(45.95)	10	(41.67)
Yes	19	(51.35)	13	(54.17)
Not applicable	1	(2.70)	1	(4.17)

Sick prior to the intervention:				
No	33	(89.19)	24	(100.00)
Yes	4	(10.81)	0	(0.00)

Table 66: Technology use of the participants

Technology use:	**N**	**(%)**	**N**	**(%)**
Lifestyle technology user:				
No	11	(29.73)	4	(16.67)
Yes	26	(70.27)	20	(83.33)
Type of lifestyle technologies:				
Fitness tracker to track my physical activity	9	(24.32)	7	(29.17)
Fitness tracker to track my physical activity, Apps for running	1	(2.70)	0	(0.00)
Fitness tracker to track my physical activity, Apps to track my eating habits	5	(13.51)	4	(16.67)
Fitness tracker to track my physical activity, Apps to track my eating habits, Apps to track my menopause symptoms, Apps to track my sleep	1	(2.70)	1	(4.17)
Fitness tracker to track my physical activity, Apps to track my eating habits, Apps to track my sleep	3	(8.11)	2	(8.33)
Fitness tracker to track my physical activity, Apps to track my eating habits, Apps to track my sleep, Heart rate monitor	1	(2.70)	1	(4.17)
Fitness tracker to track my physical activity, Apps to track my menopause symptoms, Apps for mindfulness	1	(2.70)	1	(4.17)
Fitness tracker to track my physical activity, Apps to track my menstrual cycle	1	(2.70)	1	(4.17)

Fitness tracker to track my physical activity, Apps to track my sleep	4	(10.81)	3	(12.50)
Not applicable	11	(29.73)	4	(16.67)

Table 67: The menopause specific quality of life questionnaire (MENQOL)

MENQOL	**All participants**		**Participants in data analysis**	
	N	**(%)**	**N**	**(%)**
Hot flushes				
Not experienced	28	(75.68)	16	(66.67)
Not bothered at all 0	1	(2.70)	1	(4.17)
Bothered 1	1	(2.70)	1	(4.17)
Bothered 2	5	(13.51)	4	(16.67)
Bothered 3	0	(0.00)	0	(0.00)
Bothered 4	1	(2.70)	1	(4.17)
Bothered 5	1	(2.70)	1	(4.17)
Extremely bothered 6	0	(0.00)	0	(0.00)
Night sweats				
Not experienced	25	(67.57)	14	(58.33)
Not bothered at all 0	1	(2.70)	1	(4.17)
Bothered 1	1	(2.70)	1	(4.17)
Bothered 2	1	(2.70)	0	(0.00)
Bothered 3	4	(10.81)	4	(16.67)
Bothered 4	3	(8.11)	2	(8.33)
Bothered 5	2	(5.41)	2	(8.33)
Extremely bothered 6	0	(0.00)	0	(0.00)
Sweating				
Not experienced	25	(67.57)	14	(58.33)
Not bothered at all 0	0	(0.00)	0	(0.00)
Bothered 1	2	(5.41)	2	(8.33)
Bothered 2	1	(2.70)	1	(4.17)
Bothered 3	4	(10.81)	2	(8.33)
Bothered 4	3	(8.11)	3	(12.50)
Bothered 5	1	(2.70)	1	(4.17)
Extremely bothered 6	1	(2.70)	1	(4.17)
Dissatisfaction with my personal life				
Not experienced	9	(24.32)	7	(29.17)
Not bothered at all 0	1	(2.70)	1	(4.17)
Bothered 1	3	(8.11)	2	(8.33)
Bothered 2	6	(16.22)	4	(16.67)
Bothered 3	8	(21.62)	4	(16.67)
Bothered 4	3	(8.11)	2	(8.33)

Bothered 5	6	(16.22)	3	(12.50)
Extremely bothered 6	1	(2.70)	1	(4.17)
Feeling anxious or nervous				
Not experienced	4	(10.81)	3	(12.50)
Not bothered at all 0	0	(0.00)	0	(0.00)
Bothered 1	5	(13.51)	4	(16.67)
Bothered 2	2	(5.41)	1	(4.17)
Bothered 3	8	(21.62)	5	(20.83)
Bothered 4	9	(24.32)	5	(20.83)
Bothered 5	8	(21.62)	5	(20.83)
Extremely bothered 6	1	(2.70)	1	(4.17)
Poor memory				
Not experienced	6	(16.22)	5	(20.83)
Not bothered at all 0	1	(2.70)	0	(0.00)
Bothered 1	2	(5.41)	2	(8.33)
Bothered 2	5	(13.51)	4	(16.67)
Bothered 3	9	(24.32)	5	(20.83)
Bothered 4	12	(32.43)	7	(29.17)
Bothered 5	2	(5.41)	1	(4.17)
Extremely bothered 6	0	(0.00)	0	(0.00)
Accomplishing less than I used to				
Not experienced	5	(13.51)	3	(12.50)
Not bothered at all 0	2	(5.41)	1	(4.17)
Bothered 1	3	(8.11)	3	(12.50)
Bothered 2	9	(24.32)	5	(20.83)
Bothered 3	9	(24.32)	7	(29.17)
Bothered 4	6	(16.22)	4	(16.67)
Bothered 5	3	(8.11)	1	(4.17)
Extremely bothered 6	0	(0.00)	0	(0.00)
Feeling depressed, down or blue				
Not experienced	8	(21.62)	4	(16.67)
Not bothered at all 0	4	(10.81)	4	(16.67)
Bothered 1	4	(10.81)	3	(12.50)
Bothered 2	7	(18.92)	4	(16.67)
Bothered 3	5	(13.51)	5	(20.83)
Bothered 4	7	(18.92)	4	(16.67)
Bothered 5	2	(5.41)	0	(0.00)
Extremely bothered 6	0	(0.00)	0	(0.00)
Being impatient with other people				
Not experienced	6	(16.22)	4	(16.67)
Not bothered at all 0	4	(10.81)	3	(12.50)
Bothered 1	5	(13.51)	2	(8.33)
Bothered 2	6	(16.22)	3	(12.50)
Bothered 3	8	(21.62)	7	(29.17)

Bothered 4	2	(5.41)	1	(4.17)
Bothered 5	5	(13.51)	4	(16.67)
Extremely bothered 6	1	(2.70)	0	(0.00)
Feeling or wanting to be alone				
Not experienced	8	(21.62)	5	(20.83)
Not bothered at all 0	3	(8.11)	3	(12.50)
Bothered 1	2	(5.41)	1	(4.17)
Bothered 2	7	(18.92)	4	(16.67)
Bothered 3	5	(13.51)	3	(12.50)
Bothered 4	6	(16.22)	4	(16.67)
Bothered 5	3	(8.11)	1	(4.17)
Extremely bothered 6	2	(5.41)	2	(8.33)
NA	1	(2.70)	1	(4.17)
Flatulence (wind) or gas pains				
Not experienced	10	(27.03)	5	(20.83)
Not bothered at all 0	6	(16.22)	6	(25.00)
Bothered 1	9	(24.32)	6	(25.00)
Bothered 2	1	(2.70)	0	(0.00)
Bothered 3	6	(16.22)	4	(16.67)
Bothered 4	1	(2.70)	1	(4.17)
Bothered 5	1	(2.70)	1	(4.17)
Extremely bothered 6	3	(8.11)	1	(4.17)
Aching in muscles and joints				
Not experienced	7	(18.92)	5	(20.83)
Not bothered at all 0	1	(2.70)	1	(4.17)
Bothered 1	4	(10.81)	4	(16.67)
Bothered 2	5	(13.51)	4	(16.67)
Bothered 3	4	(10.81)	3	(12.50)
Bothered 4	10	(27.03)	5	(20.83)
Bothered 5	6	(16.22)	2	(8.33)
Extremely bothered 6	0	(0.00)	0	(0.00)
Feeling tired and worn out				
Not experienced	0	(0.00)	0	(0.00)
Not bothered at all 0	1	(2.70)	0	(0.00)
Bothered 1	3	(8.10)	3	(12.50)
Bothered 2	3	(8.10)	2	(8.33)
Bothered 3	11	(29.70)	9	(37.50)
Bothered 4	6	(16.20)	3	(12.50)
Bothered 5	11	(29.70)	5	(20.83)
Extremely bothered 6	2	(5.40)	2	(8.33)
Difficulty sleeping				
Not experienced	4	(10.81)	3	(12.50)
Not bothered at all 0	2	(5.41)	2	(8.33)

Bothered 1	5	(13.51)	3	(12.50)
Bothered 2	4	(10.81)	3	(12.50)
Bothered 3	9	(24.32)	6	(25.00)
Bothered 4	5	(13.51)	2	(8.33)
Bothered 5	6	(16.22)	5	(20.83)
Extremely bothered 6	2	(5.41)	0	(0.00)
Aches in back of head or neck				
Not experienced	10	(27.03)	6	(25.00)
Not bothered at all 0	4	(10.81)	3	(12.50)
Bothered 1	3	(8.11)	2	(8.33)
Bothered 2	6	(16.22)	4	(16.67)
Bothered 3	4	(10.81)	2	(8.33)
Bothered 4	7	(18.92)	6	(25.00)
Bothered 5	2	(5.41)	1	(4.17)
Extremely bothered 6	1	(2.70)	0	(0.00)
Decrease in physical strength				
Not experienced	5	(13.51)	5	(20.83)
Not bothered at all 0	2	(5.41)	2	(8.33)
Bothered 1	7	(18.92)	5	(20.83)
Bothered 2	5	(13.51)	2	(8.33)
Bothered 3	10	(27.03)	6	(25.00)
Bothered 4	6	(16.22)	4	(16.67)
Bothered 5	2	(5.41)	0	(0.00)
Extremely bothered 6	0	(0.00)	0	(0.00)
Decrease in stamina				
Not experienced	6	(16.22)	6	(25.00)
Not bothered at all 0	2	(5.41)	2	(8.33)
Bothered 1	5	(13.51)	3	(12.50)
Bothered 2	5	(13.51)	3	(12.50)
Bothered 3	7	(18.92)	2	(8.33)
Bothered 4	9	(24.32)	7	(29.17)
Bothered 5	2	(5.41)	0	(0.00)
Extremely bothered 6	0	(0.00)	0	(0.00)
NA	1	(2.70)	1	(4.17)
Lack of energy				
Not experienced	5	(13.51)	4	(16.67)
Not bothered at all 0	0	(0.00)	0	(0.00)
Bothered 1	2	(5.41)	2	(8.33)
Bothered 2	7	(18.92)	5	(20.83)
Bothered 3	9	(24.32)	6	(25.00)
Bothered 4	6	(16.22)	4	(16.67)
Bothered 5	7	(18.92)	3	(12.50)
Extremely bothered 6	1	(2.70)	0	(0.00)
Dry skin				

Not experienced	10	(27.03)	9	(37.50)
Not bothered at all 0	3	(8.11)	1	(4.17)
Bothered 1	4	(10.81)	2	(8.33)
Bothered 2	4	(10.81)	2	(8.33)
Bothered 3	10	(27.03)	7	(29.17)
Bothered 4	1	(2.70)	1	(4.17)
Bothered 5	5	(13.51)	2	(8.33)
Extremely bothered 6	0	(0.00)	0	(0.00)
Weight gain				
Not experienced	9	(24.32)	6	(25.00)
Not bothered at all 0	2	(5.41)	1	(4.17)
Bothered 1	2	(5.41)	1	(4.17)
Bothered 2	5	(13.51)	4	(16.67)
Bothered 3	6	(16.22)	6	(25.00)
Bothered 4	7	(18.92)	4	(16.67)
Bothered 5	2	(5.41)	0	(0.00)
Extremely bothered 6	4	(10.81)	2	(8.33)
Increased facial hair				
Not experienced	21	(56.76)	15	(62.50)
Not bothered at all 0	1	(2.70)	1	(4.17)
Bothered 1	4	(10.81)	1	(4.17)
Bothered 2	3	(8.11)	3	(12.50)
Bothered 3	3	(8.11)	2	(8.33)
Bothered 4	3	(8.11)	2	(8.33)
Bothered 5	2	(5.41)	0	(0.00)
Extremely bothered 6	0	(0.00)	0	(0.00)
Not experienced	12	(32.43)	9	(37.50)
Not bothered at all 0	2	(5.41)	1	(4.17)
Bothered 1	4	(10.81)	3	(12.50)
Bothered 2	4	(10.81)	2	(8.33)
Bothered 3	7	(18.92)	3	(12.50)
Bothered 4	6	(16.22)	5	(20.83)
Bothered 5	1	(2.70)	0	(0.00)
Extremely bothered 6	1	(2.70)	1	(4.17)
Feeling bloated				
Not experienced	11	(29.73)	9	(37.50)
Not bothered at all 0	2	(5.41)	1	(4.17)
Bothered 1	4	(10.81)	2	(8.33)
Bothered 2	5	(13.51)	3	(12.50)
Bothered 3	5	(13.51)	4	(16.67)
Bothered 4	6	(16.22)	5	(20.83)
Bothered 5	3	(8.11)	0	(0.00)
Extremely bothered 6	1	(2.70)	0	(0.00)
Low backache				

Not experienced	12	(32.43)	8	(33.33)
Not bothered at all 0	3	(8.11)	2	(8.33)
Bothered 1	3	(8.11)	1	(4.17)
Bothered 2	4	(10.81)	1	(4.17)
Bothered 3	4	(10.81)	4	(16.67)
Bothered 4	4	(10.81)	3	(12.50)
Bothered 5	5	(13.51)	4	(16.67)
Extremely bothered 6	2	(5.41)	1	(4.17)
Frequent urination				
Not experienced	12	(32.43)	8	(33.33)
Not bothered at all 0	5	(13.51)	3	(12.50)
Bothered 1	5	(13.51)	4	(16.67)
Bothered 2	0	(0.00)	0	(0.00)
Bothered 3	6	(16.22)	4	(16.67)
Bothered 4	2	(5.41)	1	(4.17)
Bothered 5	6	(16.22)	4	(16.67)
Extremely bothered 6	1	(2.70)	0	(0.00)
Not experienced	13	(35.14)	7	(29.17)
Not bothered at all 0	4	(10.81)	3	(12.50)
Bothered 1	2	(5.41)	1	(4.17)
Bothered 2	2	(5.41)	1	(4.17)
Bothered 3	6	(16.22)	6	(25.00)
Bothered 4	4	(10.81)	3	(12.50)
Bothered 5	3	(8.11)	2	(8.33)
Extremely bothered 6	2	(5.41)	0	(0.00)
NA	1	(2.70)	1	(4.17)
Decrease in sexual desire				
Not experienced	9	(24.32)	7	(29.17)
Not bothered at all 0	2	(5.41)	2	(8.33)
Bothered 1	3	(8.11)	2	(8.33)
Bothered 2	3	(8.11)	2	(8.33)
Bothered 3	5	(13.51)	2	(8.33)
Bothered 4	6	(16.22)	4	(16.67)
Bothered 5	5	(13.51)	3	(12.50)
Extremely bothered 6	4	(10.81)	2	(8.33)
Vaginal dryness				
Not experienced	17	(45.95)	12	(50.00)
Not bothered at all 0	3	(8.11)	2	(8.33)
Bothered 1	1	(2.70)	0	(0.00)
Bothered 2	5	(13.51)	4	(16.67)
Bothered 3	3	(8.11)	2	(8.33)
Bothered 4	5	(13.51)	2	(8.33)
Bothered 5	1	(2.70)	1	(4.17)
Extremely bothered 6	2	(5.41)	1	(4.17)

Avoiding intimacy				
Not experienced	14	(37.84)	10	(41.67)
Not bothered at all 0	3	(8.11)	3	(12.50)
Bothered 1	1	(2.70)	0	(0.00)
Bothered 2	1	(2.70)	1	(4.17)
Bothered 3	7	(18.92)	4	(16.67)
Bothered 4	4	(10.81)	1	(4.17)
Bothered 5	4	(10.81)	3	(12.50)
Extremely bothered 6	3	(8.11)	2	(8.33)

Additional Intervention Results for Changes in Outcomes

Total Sleep Minutes: Descriptive Statistics

The baseline (wave 0) sleep value for all participant consisted of an average of their daily total sleep minutes during their 7-day baseline phase. Sleep data was recorded on average on 6 days during the 7-day baseline (median = 6; range 5 – 7 days) and 50% (12/24) of the participants recorded their sleep on 6 days of the baseline phase. The average total sleep (minutes) per day at baseline (wave 0) was 437.59 minutes (SD 70.24). This increased in the intervention period (wave 1 – 14), with an average of 411.50 (SD 94.45). A breakdown of total sleep at each wave of the intervention shows maximum increase halfway through the intervention (wave 7), with 450.62 minutes (7.51 hours), (SD 40.57) (**Table 68**).

Table 68: Descriptive statistics for daily total sleep minutes

Wave	Count	Mean	Var	SD	Median	IQR
0	24	437.59	4932.97	70.24	438.18	74.81
1	17	417.18	9465.90	97.29	385.00	141.00
2	17	416.59	7104.13	84.29	444.00	93.00
3	14	422.36	8975.17	94.74	433.00	81.75
4	17	439.71	5207.72	72.16	433.00	76.00
5	8	386.38	9819.70	99.09	417.00	92.00
6	7	400.29	23915.24	154.65	422.00	146.00
7	8	450.62	1645.98	40.57	455.00	54.00
8	10	369.70	10863.57	104.23	428.00	168.00
9	11	417.45	8039.87	89.67	425.00	66.00
10	11	421.18	9772.36	98.86	447.00	98.00
11	6	403.83	14756.57	121.48	425.50	112.75
12	6	379.83	12153.37	110.24	412.00	170.25
13	9	428.22	7792.69	88.28	443.00	146.00
14	6	324.50	6636.70	81.47	309.00	106.25

Deep Sleep Minutes: Descriptive Statistics

The average deep sleep (minutes) per day at baseline (wave 0) was 128.97 minutes (SD 48.03). This increased in the intervention period (wave 1 – 14), with an average of 135.9 (SD 75.33). A breakdown of deep sleep at each wave of the intervention shows maximum increase halfway through the intervention (wave 7), with 174.00 minutes (2.9 hours), (SD 63.58) (**Table 69**).

Table 69: Descriptive statistics for daily deep sleep minutes

Wave	Count	Mean	Var	SD	Median	IQR
0	24	128.97	2306.93	48.03	129.75	74.12
1	17	149.41	2662.13	51.60	153.00	65.00
2	17	151.59	9129.63	95.55	141.00	107.00
3	14	149.79	8063.41	89.80	136.00	115.25
4	17	135.18	5698.40	75.49	141.00	130.00
5	8	140.75	4811.07	69.36	167.00	56.50
6	7	169.57	8641.95	92.96	169.00	100.00
7	8	174.00	4042.00	63.58	192.50	62.25
8	10	116.10	3059.43	55.31	119.00	80.25
9	11	138.91	10155.89	100.78	123.00	89.00
10	11	95.00	2841.60	53.31	72.00	58.50
11	6	81.17	2852.17	53.41	53.00	75.75
12	6	118.00	4431.20	66.57	104.00	33.50
13	9	120.11	3992.11	63.18	128.00	40.00
14	6	125.50	5850.70	76.49	133.50	75.00

Water Intake: Descriptive Statistics

The average water intake per day at baseline (wave 0) was 4.15 glasses (SD 2.30). This increased in the intervention period (wave 1 – 14), with an average of 7.33 (SD 2.04). A breakdown of fruit portions intake at each wave of the intervention shows maximum increase in the later phase of the intervention (wave 10), with 8.64 glasses (SD 1.86) (**Table 70**).

Table 70: Descriptive statistics for glasses of water per wave

Wave	Count	Mean	Var	SD	Median	IQR
0	24	4.15	5.29	2.30	4.00	2.50
1	17	6.00	5.00	2.24	5.00	2.00
2	17	7.00	3.75	1.94	7.00	2.00
3	14	6.21	4.03	2.01	6.00	2.00
4	17	7.24	2.69	1.64	7.00	2.00
5	8	7.50	4.57	2.14	7.00	2.25
6	7	7.86	3.48	1.86	8.00	1.50

7	8	8.50	0.57	0.76	9.00	1.00
8	10	7.80	3.51	1.87	9.00	2.75
9	11	7.00	3.60	1.90	7.00	1.50
10	11	8.64	3.45	1.86	9.00	1.00
11	6	8.17	6.97	2.64	8.00	3.00
12	6	7.50	5.50	2.35	7.50	3.25
13	9	7.67	5.25	2.29	7.00	2.00
14	6	8.50	1.50	1.22	9.00	1.50

Coffee Intake: Descriptive Statistics

The average caffeine intake per day at baseline (wave 0) was 2.50 cups (SD 2.40). This decreased in the intervention period (wave 1 – 14), with an average of 2.69 (SD 1.15). A breakdown of coffee intake at each wave of the intervention shows maximum decrease in the later phase of the intervention (wave 14), with 1.50 cups (SD 0.55) (**Table 71**).

Table 71: Descriptive statistics for cups of coffee per wave

Wave	Count	Mean	Var	SD	Median	IQR
0	24	2.50	5.74	2.40	2.00	2.25
1	17	3.12	1.36	1.17	3.00	2.00
2	17	3.12	2.24	1.50	3.00	2.00
3	14	2.93	1.30	1.14	3.00	2.00
4	17	2.88	1.86	1.36	3.00	1.00
5	8	3.00	1.71	1.31	3.00	2.00
6	7	3.00	1.00	1.00	3.00	0.50
7	8	2.38	0.55	0.74	2.50	1.00
8	10	2.70	0.90	0.95	3.00	1.00
9	11	2.64	1.25	1.12	3.00	1.00
10	11	2.18	0.56	0.75	2.00	1.00
11	6	2.50	0.30	0.55	2.50	1.00
12	6	2.00	1.20	1.10	2.00	0.75
13	9	2.22	0.69	0.83	2.00	1.00
14	6	1.50	0.30	0.55	1.50	1.00

Alcoholic Beverages Consumed: Descriptive Statistics

The average alcoholic beverages intake per day at baseline (wave 0) was 1.42 units (SD 1.87). This decreased in the intervention period (wave 1 – 14), with an average of 0.93 (SD 1.84). A breakdown of alcoholic beverages intake at each wave of the intervention shows maximum decrease in the later phase of the intervention (wave 11 and 12), with 0 units of alcohol (**Table 72**).

Table 72: Descriptive statistics for units of alcohol per wave

Wave	Count	Mean	Var	SD	Median	IQR
0	24	1.42	3.49	1.87	0.71	2.00
1	17	1.53	3.76	1.94	0.00	3.00
2	17	0.82	2.65	1.63	0.00	0.00
3	14	1.36	5.94	2.44	0.00	2.25
4	17	0.82	2.90	1.70	0.00	0.00
5	8	1.50	10.29	3.21	0.00	0.75
6	7	2.43	3.62	1.90	3.00	2.50
7	8	0.62	1.41	1.19	0.00	0.50
8	10	0.70	4.90	2.21	0.00	0.00
9	11	0.18	0.36	0.60	0.00	0.00
10	11	0.36	0.65	0.81	0.00	0.00
11	6	0.00	0.00	0.00	0.00	0.00
12	6	0.00	0.00	0.00	0.00	0.00
13	9	1.22	5.94	2.44	0.00	0.00
14	6	1.00	2.80	1.67	0.00	1.50

Snacks Consumed: Descriptive Statistics

The average portions of snacks consumed per day at baseline (wave 0) was 1.92 portions (SD 1.25). This increased in the intervention period (wave 1 – 14), with an average of 2.44 (SD 1.17). A breakdown of snacks intake at each wave of the intervention shows maximum increase in the later phase of the intervention (wave 7), with 3.25 snacks (SD 2.19) (**Table 73**).

Table 73: Descriptive statistics for number of snacks per wave

Wave	Count	Mean	Var	SD	Median	IQR
0	24	1.92	1.56	1.25	2.00	2.00
1	17	2.18	1.03	1.01	2.00	0.00
2	17	2.06	0.93	0.97	2.00	1.00
3	14	2.50	0.88	0.94	2.50	1.00
4	17	2.59	1.38	1.18	2.00	1.00
5	8	1.75	0.50	0.71	2.00	1.00

6	7	2.71	1.24	1.11	3.00	1.50
7	8	3.25	4.79	2.19	3.00	2.00
8	10	2.50	1.39	1.18	2.00	1.75
9	11	2.64	0.45	0.67	3.00	1.00
10	11	2.27	1.02	1.01	2.00	1.50
11	6	2.50	0.70	0.84	2.00	0.75
12	6	2.83	2.97	1.72	2.50	1.00
13	9	2.33	2.25	1.50	2.00	2.00
14	6	2.83	2.17	1.47	2.50	1.75

Meals Consumed: Descriptive Statistics

The data included in the analysis consisted of both, the participants having and not having a meal. This means that if the participants answered an EMA that asked about rating their meal and they confirmed not having a meal, the portions of fruit and vegetables for that meal were set to 0. On the other hand, those having a meal, were included only if they provided both, portions of fruit, vegetables, and additional diet metrics requested in the evening EMAs. For example, during the intervention (wave 1 – 14), 7 participants were reporting as not having breakfast, on 2.71 days on average (range 1 – 8 days). At lunch, 7 participants reported not having lunch, on 2.29 days on average (range 1 – 6 days). At dinner, 8 participants reported not having dinner, on 1.25 days on average (range 1 – 2 days). The average meals per day at baseline (wave 0) was 2.75 meals (SD 0.44). This fluctuated and eventually decreased in the intervention period (wave 1 – 14), with an average of 2.68 (SD 0.54). A breakdown of meals at each wave of the intervention shows maximum decrease in the later phase of the intervention (wave 14), with 2.50 meals (SD 0.84) (see **Table 74**).

Table 74: Descriptive statistics for number of meals per wave

Wave	Count	Mean	Var	SD	Median	IQR
0	24	2.75	0.20	0.44	3.00	0.25
1	17	2.65	0.37	0.61	3.00	1.00
2	17	2.65	0.24	0.49	3.00	1.00
3	14	2.50	0.58	0.76	3.00	1.00
4	17	2.65	0.37	0.61	3.00	1.00
5	8	2.62	0.27	0.52	3.00	1.00
6	7	3.00	0.00	0.00	3.00	0.00
7	8	2.62	0.27	0.52	3.00	1.00
8	10	2.70	0.23	0.48	3.00	0.75
9	11	2.91	0.09	0.30	3.00	0.00
10	11	2.55	0.27	0.52	3.00	1.00
11	6	3.00	0.00	0.00	3.00	0.00
12	6	2.67	0.27	0.52	3.00	0.75
13	9	2.78	0.19	0.44	3.00	0.00
14	6	2.50	0.70	0.84	3.00	0.75

Appendix D: Chapter 8

Additional Design Mappings

Selected Time-Constant Predictors Used in RFE Predictions

Table 75: Time-constant features selected for best-fit model identification

Features	Values (examples)
County of residence	9 UK counties (e.g., Southwest England, London, Wales)
Ethnicity	Black African, Chinese, Indian, Latin American, Other white background, White and Black Caribbean, White British, White Irish
Perspective on the menopause	Accepting of it, have not thought about it, neutral, not looking forward to it, unsure
Participated in group exercises in the past	Yes/No
Age group	40-44, 45-49, 50-54, 55-59, 60-64, 65+
General health status	Poor, fair, good, very good, excellent
Household income level	< £18,000, £18,00 to £30,999, £31,000 to £51,999, £52,000 to £100,000, > £100,000
Marital status	Divorced, separated, widowed, Married, living as married, Never married, Prefer not to say
Menopause stage	Peri-menopause, post-menopause, pre-menopause, surgical menopause, unsure
Generation British	Native, 1st generation, 2nd generation, 3rd or more
Antidepressants use to manage menopause symptoms	In the past, never, currently
HRT use	In the past, never, currently
Knowledge about menopause	Not informed at all, some knowledge, very informed
Number of children	0, 1-2, 3 or more
CBT use to manage menopause symptoms	In the past, never, currently
Education level	College or university, lower secondary, postgraduate
Employment capacity	Full-time, part-time, not working
Smoking	In the past, never, currently
Children (18+ y/o) living at home	Yes/No
Lifestyle technology use in the past	Yes/No

Additional Results for each Target Behaviour

Optimised Set of BCTs for Total Sleep

From the intervention design's 34 BCTs, the FS RFE algorithm identified 6 time-varying predictors (from a set of 24 predictors) relevant to total sleep outcome. These 6 predictors were linked to groups of BCTs and with some of the BCTs repeating for different features, there are 17 unique BCTs used in predicting total sleep (see **Table 76**), representing 50% (17/34) of intervention BCTs. Therefore, these 17 BCTs theoretically represent optimised set of BCTs for increasing total sleep.

Table 76: Optimised set of BCTs for total sleep based on FS time-varying predictors

BCTs	**Time-varying predictors**
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-evening
1.1 Goal setting, 1.9 Commitment	Setting goals-fruit consumption
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (more colourful = more fruit and vegetables)

Time-Varying Predictors for Total Sleep Using Correlation Matrix

The CM produced 6 statistically significant ($p<0.05$) time-varying predictors with medium correlation with total sleep outcome. The selected predictors reveal that for example, receiving EMA education (counselling), rating meals for colourfulness, and attending group exercises, all significantly contributed to prediction for total sleep minutes (sleep quantity) (**Table 77**).

Table 77: Time-varying predictors for total sleep with Correlation Matrix

Predictors	r_s	**p-value**
Accessing education library	-0.3882	0.0281
Rating meal colourfulness-breakfast	-0.5433	0.0013
Rating meal colourfulness-breakfast (yes/no)	-0.5084	0.0030
Rating meal colourfulness-lunch	-0.4905	0.0044
Rating meal colourfulness-dinner	-0.4476	0.0102
Joined group exercise	-0.3673	0.0386

Optimised Set of BCTs for Deep Sleep

From the intervention design's 34 BCTs, the FS RFE algorithm identified 7 time-varying predictors (from a set of 24 predictors) relevant to deep sleep outcome. These 7 predictors were linked to groups of BCTs and with some of the BCTs repeating for different features, there are 19 unique BCTs used in predicting deep sleep (**Table 78**), representing 56% (19/34) of intervention BCTs. Therefore, these 19 BCTs theoretically represent optimised set of BCTs for increasing deep sleep.

Table 78: Optimised set of BCTs for deep sleep based on FS time-varying predictors

BCTs	Time-varying predictors
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (yes/no)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-afternoon

Time-Varying Predictors for Deep Sleep Using Correlation Matrix

The CM produced 7 statistically significant ($p<0.05$) time-varying predictors with medium correlation with deep sleep outcome. The selected predictors reveal that for example, answering EMA surveys, receiving EMA education (counselling), accessing education library, setting goals for fruit consumption, rating meals for colourfulness, and alcohol consumption previous day, all significantly contributed to prediction for deep sleep minutes (sleep quality) (**Table 79**).

Table 79: Time-varying predictors for deep sleep with Correlation Matrix

Predictors	r_s	p-value
Total EMA surveys answered	0.4223	0.0161
EMA education received (counselling)	0.5506	0.0011
Accessing education library	-0.3552	0.0460
Setting goals-fruit consumption	-0.4688	0.0068
Rating meal colourfulness-breakfast	-0.3966	0.0246
Rating meal colourfulness-breakfast (yes/no)	-0.4916	0.0043
Alcohol consumed last night	0.4241	0.0156

Optimised Set of BCTs for Water Intake

From the intervention design's 34 BCTs, the FS RFE algorithm identified 17 time-varying predictors (from a set of 24 predictors) relevant to water intake outcome. These 17 predictors were linked to groups of BCTs and with some of the BCTs repeating for different features, there are 22 unique BCTs used in predicting water intake (see **Table 80**), representing 65% (22/34) of intervention BCTs. Therefore, these 22 BCTs theoretically represent optimised set of BCTs for increasing water intake.

Table 80: Optimised set of BCTs for water intake based on FS time-varying predictors

BCTs	Time-varying predictors
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning

1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-evening
1.1 Goal setting, 1.9 Commitment	Setting goals-fruit consumption
2.3 Self-monitoring, 3.3 Social support (emotional)	Joined group exercise
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (yes/no)
2.3 Self-monitoring	Alcohol consumed last night
1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring, 8.7 Graded tasks	Setting goals-steps (yes/no)
4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 9.1 Credible sources, 12.1 Restructuring the physical environment	Accessing education library

5.1 Information about health consequences	Accessing education library (yes/no)
2.2 Feedback on behaviour, 2.3 Self-monitoring, 8.3 Habit formation	Total EMA surveys answered
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (more colourful = more fruit and vegetables)
1.6 Discrepancy between current behaviour and goal, 2.3 Self-monitoring, 15.1 Verbal persuasion about capability, 15.3 Focus on past success	Achieved planned exercise (self-reported)

Time-Varying Predictors for Water Intake Using Correlation Matrix

The CM produced 6 statistically significant ($p<0.05$) time-varying predictors with medium correlation with water intake outcome. The selected predictors reveal that for example, receiving EMA education (counselling), rating meals for colourfulness, setting goals for vegetables and fruit consumption, and attending group exercises, all significantly contributed to prediction for water intake (**Table 81**).

Table 81: Time-varying predictors for water intake with Correlation Matrix

Predictors	r_s	**p-value**
EMA education received (counselling)	-0.4820	0.0052
Setting goals-vegetables consumption	0.6078	0.0002
Setting goals-fruit consumption	0.5535	0.0010
Rating meal colourfulness-lunch (yes/no)	0.5550	0.0010
Achieved planned exercise (self-reported)	0.5220	0.0022
Joined group exercise	0.4853	0.0049

Optimised Set of BCTs for Coffee Intake

From the intervention design's 34 BCTs, the FS RFE algorithm identified 10 time-varying predictors (from a set of 24 predictors) relevant to coffee intake outcome. These 10 predictors were linked to groups of BCTs and with some of the BCTs repeating for different features, there are 19 unique BCTs used in predicting coffee intake (**Table 82**), representing 56% (19/34) of intervention BCTs. Therefore, these 19 BCTs theoretically represent optimised set of BCTs for decreasing coffee intake.

Table 82: Optimised set of BCTs for coffee intake based on FS time-varying predictors

BCTs	**Time-varying predictors**
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning
1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
1.1 Goal setting, 1.9 Commitment	Setting goals-fruit consumption
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (yes/no)
2.3 Self-monitoring	Alcohol consumed last night

2.2 Feedback on behaviour, 2.3 Self-monitoring, 8.3 Habit formation	Total EMA surveys answered

Time-Varying Predictors for Coffee Intake Using Correlation Matrix

The CM produced 6 statistically significant ($p<0.05$) time-varying predictors with medium correlation with coffee intake outcome. The selected predictors reveal that for example, receiving EMA surveys, receiving EMA education (counselling), rating meals for colourfulness, and setting steps goals, all significantly contributed to prediction for coffee intake (**Table 83**).

Table 83: Time-varying predictors for coffee intake with Correlation Matrix

Predictor	r_s	**p-value**
Total EMA surveys answered	0.5194	0.0023
Accessing education library	-0.5924	0.0004
Rating meal colourfulness-breakfast (yes/no)	-0.5883	0.0004
Rating meal colourfulness-lunch	-0.5876	0.0004
Rating meal colourfulness-lunch (yes/no)	-0.5059	0.0031
Setting goals-steps	0.3526	0.0478

Optimised Set of BCTs for Alcohol Consumption

From the intervention design's 34 BCTs, the FS RFE algorithm identified 21 time-varying predictors (from a set of 24 predictors) relevant to alcohol consumption outcome. These 21 predictors were linked to groups of BCTs and with some of the BCTs repeating for different features, there are 24 unique BCTs used in predicting alcohol consumption (**Table 84**), representing 71% (24/34) of intervention BCTs. Therefore, these 24 BCTs theoretically represent optimised set of BCTs for reducing alcohol consumption.

Table 84: Optimised set of BCTs for alcohol consumption based on FS time-varying predictors

BCTs	**Time-varying predictors**
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption

1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning
1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-evening
1.1 Goal setting, 1.9 Commitment	Setting goals-fruit consumption
2.3 Self-monitoring, 3.3 Social support (emotional)	Joined group exercise
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (yes/no)
2.3 Self-monitoring	Alcohol consumed last night
1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring, 8.7 Graded tasks	Setting goals-steps (yes/no)
4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 9.1 Credible sources, 12.1 Restructuring the physical environment	Accessing education library

5.1 Information about health consequences	Accessing education library (yes/no)
2.2 Feedback on behaviour, 2.3 Self-monitoring, 8.3 Habit formation	Total EMA surveys answered
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (yes/no)
1.6 Discrepancy between current behaviour and goal, 2.3 Self-monitoring, 15.1 Verbal persuasion about capability, 15.3 Focus on past success	Achieved planned exercise (self-reported)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-afternoon
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (yes/no)
2.2 Feedback on behaviour, 3.2 Social support (practical), 3.3 Social Support(emotional), 15.1 Verbal persuasion about capability, 15.3 Focus on past success	Human coach interaction (once weekly communication from the researcher, prior to the start of each phase)

Time-Varying Predictors for Alcohol Consumption Using Correlation Matrix

The CM produced 7 statistically significant ($p<0.05$) time-varying predictors with medium correlation with units of alcoholic beverages outcome. The selected predictors reveal that for example, accessing education library, rating dinner for colourfulness, achieving planned exercise, attending group exercises, and human-coach interaction, all significantly contributed to prediction for alcoholic beverages consumption (**Table 85**).

Table 85: Time-varying predictors for units of alcoholic beverages with Correlation Matrix

Predictors	**r_s**	**p-value**
Accessing education library (yes/no)	0.3787	0.0326
Rating meal colourfulness-dinner (yes/no)	0.4234	0.0158
Achieved planned exercise (self-reported)	0.4549	0.0089
Joined group exercise	0.4274	0.0147
Setting goals-exercise-morning	0.3585	0.0439
Setting goals-exercise-evening	-0.3746	0.0346
Human coach interaction	0.4227	0.0160

Optimised Set of BCTs for Snacks Consumed

From the intervention design's 34 BCTs, the FS RFE algorithm identified 18 time-varying predictors (from a set of 24 predictors) relevant to snacks consumed outcome. These 18 predictors were linked to groups of BCTs and with some of the BCTs repeating for different features, there are 23 unique BCTs used in predicting snacks consumption (**Table 86**), representing 71% 68% (23/34) of intervention BCTs. Therefore, these 23 BCTs theoretically represent optimised set of BCTs for snacks consumption.

Table 86: Optimised set of BCTs for snacks consumption based on FS time-varying predictors

BCTs	**Time-varying predictors**
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning

1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-evening
1.1 Goal setting, 1.9 Commitment	Setting goals-fruit consumption
2.3 Self-monitoring, 3.3 Social support (emotional)	Joined group exercise
2.3 Self-monitoring	Alcohol consumed last night
1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring, 8.7 Graded tasks	Setting goals-steps (yes/no)
4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 9.1 Credible sources, 12.1 Restructuring the physical environment	Accessing education library
5.1 Information about health consequences	Accessing education library (yes/no)
2.2 Feedback on behaviour, 2.3 Self-monitoring, 8.3 Habit formation	Total EMA surveys answered

1.6 Discrepancy between current behaviour and goal, 2.3 Self-monitoring, 15.1 Verbal persuasion about capability, 15.3 Focus on past success	Achieved planned exercise (self-reported)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-afternoon
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (yes/no)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Sleep quality (self-reported)

Time-Varying Predictors for Snacks Consumed Using Correlation Matrix

The CM produced 7 statistically significant ($p<0.05$) time-varying predictors with medium correlation with number of snacks outcome. The selected predictors reveal that for example, rating meals for colourfulness, having alcohol the day prior, achieving planned exercise, and sleep quality, all significantly contributed to prediction for number of snacks (**Table 87**).

Table 87: Time-varying predictors for number of snacks with Correlation Matrix

Predictors	r_s	**p-value**
Rating meal colourfulness-lunch (yes/no)	-0.3541	0.0468
Rating meal colourfulness-dinner (yes/no)	-0.4117	0.0192
Alcohol consumed last night	-0.4380	0.0122
Achieved planned exercise (self-reported)	-0.5700	0.0007
Joined group exercise	-0.4575	0.0085
Setting goals-exercise-evening	0.3977	0.0242
Sleep quality (self-reported)	-0.3710	0.0366

Optimised Set of BCTs for Meals Consumed

From the intervention design's 34 BCTs, the FS RFE algorithm identified 18 time-varying predictors (from a set of 24 predictors) relevant to snacks consumed outcome. These 18 predictors were linked to groups of BCTs and with some of the BCTs repeating for different features, there are 16 unique BCTs used in predicting meals consumption (**Table 88**), representing 47% (16/34) of intervention BCTs. Therefore, these 16 BCTs theoretically represent optimised set of BCTs for meals consumption.

Table 88: Optimised set of BCTs for meals consumption based on FS time-varying predictors

BCTs	Time-varying predictors
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-evening
2.3 Self-monitoring, 3.3 Social support (emotional)	Joined group exercise
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (yes/no)
2.3 Self-monitoring	Alcohol consumed last night
1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring, 8.7 Graded tasks	Setting goals-steps (yes/no)
4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 9.1 Credible sources, 12.1 Restructuring the physical environment	Accessing education library
5.1 Information about health consequences	Accessing education library (yes/no)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (more colourful = more fruit and vegetables)

2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-dinner (yes/no)
1.6 Discrepancy between current behaviour and goal, 2.3 Self-monitoring, 15.1 Verbal persuasion about capability, 15.3 Focus on past success	Achieved planned exercise (self-reported)
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-afternoon
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (yes/no)
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Sleep quality (self-reported)

Time-Varying Predictors for Meals Consumed Using Correlation Matrix

The CM produced 9 statistically significant ($p<0.05$) time-varying predictors with medium correlation with number of meals outcome. The selected predictors reveal that for example, receiving EMA education (counselling), accessing education library, setting goals for fruit consumption, rating meals for colourfulness, having alcohol the day prior, and achieving planned exercise, all significantly contributed to prediction for number of meals (**Table 89**).

Table 89: Time-varying predictors for number of meals with Correlation Matrix

Predictors	r_s	**p-value**
Accessing education library	0.5348	0.0016
Accessing education library (yes/no)	0.4637	0.0075
Setting goals-fruit consumption	0.4098	0.0198
Rating meal colourfulness-breakfast	0.6239	0.0001
Alcohol consumed last night	0.3849	0.0296
Achieved planned exercise (self-reported)	0.4710	0.0065
Joined group exercise	0.5946	0.0003
Setting goals-exercise-morning	0.4256	0.0152
Setting goals-exercise-evening	-0.3966	0.0246

Summary Results

Summary of Time-Varying Predictors for Each Target Behaviour

Table 90: Summary of time-varying predictors mapped to BCTs

BCTs	Predictors	Steps count	Total sleep minutes	Deep sleep minutes	Portions of vegetables	Portions of fruit	Glasses of water	Cups of coffee	Units of alcohol	Number of snacks	Number of meals	Frequency of predictors used
1.1 Goal setting, 1.9 Commitment, 8.7 Graded tasks	Setting goals-steps	x	x	x	x	x	x	x	x	x	x	10
1.1 Goal setting, 1.9 Commitment	Setting goals-vegetables consumption	x	x	x	x	x	x	x	x	x	x	10
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-morning	x			x	x	x	x	x	x	x	8

1.2 Problem solving, 1.4 Action planning, 2.2 Feedback on behaviour, 4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 7.1 Prompts/cues, 8.1 Behavioural practice/rehearsal, 8.4 Habit reversal, 9.1 Credible sources, 10.4 Social reward, 10.10 Reward (outcome), 12.1 Restructuring the physical environment, 12.5 Adding objects to the environment	EMA education received (counselling)		x	x	x	x	x	x	x	x		8
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (more colourful = more fruit and vegetables)			x	x	x	x	x	x	x	x	8

2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (more colourful = more fruit and vegetables)			x	x	x	x	x	x	x	x	8
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-evening		x		x		x		x	x	x	6
1.1 Goal setting, 1.9 Commitment	Setting goals-fruit consumption		x			x	x	x	x	x		6
2.3 Self-monitoring, 3.3 Social support (emotional)	Joined group exercise	x				x	x		x	x	x	6
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-lunch (yes/no)				x	x	x	x	x		x	6
2.3 Self-monitoring	Alcohol consumed last night					x	x	x	x	x	x	6
1.1 Goal setting, 1.9 Commitment, 2.3 Self-monitoring, 8.7 Graded tasks	Setting goals-steps (yes/no)	x				x	x		x	x	x	6

4.1 Instructions on how to perform the behaviour, 4.4 Behavioural experiments, 5.1 Information about health consequences, 9.1 Credible sources, 12.1 Restructuring the physical environment	Accessing education library					x	x		x	x	x	5
5.1 Information about health consequences	Accessing education library (yes/no)					x	x		x	x	x	5
2.2 Feedback on behaviour, 2.3 Self-monitoring, 8.3 Habit formation	Total EMA surveys answered					x	x	x	x	x		5
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness- dinner (more colourful = more fruit and vegetables)		x		x		x		x		x	5
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness- dinner (yes/no)			x	x	x			x		x	5

1.6 Discrepancy between current behaviour and goal, 2.3 Self-monitoring, 15.1 Verbal persuasion about capability, 15.3 Focus on past success	Achieved planned exercise (self-reported)	x					x		x	x	x	5
1.4 Action Planning, 2.3 Self-monitoring	Setting goals-exercise-afternoon			x					x	x	x	4
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Rating meal colourfulness-breakfast (yes/no)					x			x	x	x	4
2.3. Self-monitoring of behaviour 8.1. Behavioural practice/rehearsal 8.3. Habit formation	Sleep quality (self-reported)									x	x	2
2.2 Feedback on behaviour, 3.2 Social support (practical), 3.3 Social Support(emotional), 15.1 Verbal persuasion about capability, 15.3	Human coach interaction (once weekly communication from the researcher, prior to the start of each phase)								x			1

Focus on past success												
	Predictors, n	6	6	7	10	16	17	10	21	18	18	
	Sig predictors (p < 0.05), n	3	1	1	6	3	6	5	4	2	3	
	Ratio sig predictors to all predictors, %	50.00 %	16.67 %	14.29 %	60.00%	18.75 %	35.29 %	50.00 %	19.05 %	11.11 %	16.67 %	
	Adj. R-squared, %	50.50 %	56.00 %	43.00 %	55.50%	44.90 %	33.80 %	49.40 %	83.40 %	67.00 %	83.09 %	

Summary of Optimised Sets of BCTs Selected for Each Intervention Outcome

Table 91: Summary of optimised sets of BCTs linked to time-varying predictors

BCT categories and BCTs	All BCTs used in the intervention, n	Steps count, n	Total sleep minutes, n	Deep sleep minutes, n	Portions of vegetables, n	Portions of fruit, n	Glasses of water, n	Cups of coffee, n	Units of alcohol, n	Number of snacks, n	Number of meals, n
1.Goals and planning, n	8	4	4	4	4	4	5	4	5	5	4
BCTs from all possible BCTs (9 BCTS), %	89%	44%	44%	44%	44%	44%	56%	44%	56%	56%	44%
1.1. Goal setting (behaviour)	x	x	x	x	x	x	x	x	x	x	x
1.2. Problem solving	x		x	x	x	x	x	x	x	x	
1.3. Goal setting (outcome)											
1.4. Action planning	x	x	x	x	x	x	x	x	x	x	x
1.5. Review behaviour goal(s)	x										
1.6. Discrepancy between current behaviour and goal	x	x					x		x	x	x
1.7. Review outcome goal(s)	x										
1.8. Behavioural contract	x										
1.9. Commitment	x	x	x	x	x	x	x	x	x	x	x
2.Feedback and monitoring, n	4	1	1	2	2	2	2	2	2	2	1
BCTs from all possible BCTs (7 BCTs), %	57%	14%	14%	29%	29%	29%	29%	29%	29%	29%	14%
2.1. Monitoring of behaviour by others without feedback											

2.2. Feedback on behaviour	x		x	x	x	x	x	x	x	x	
2.3. Self-monitoring of behaviour	x	x		x	x	x	x	x	x	x	x
2.4. Self-monitoring of outcome(s) of behaviour											
2.5. Monitoring of outcome(s) of behaviour without feedback											
2.6. Biofeedback	x										
2.7. Feedback on outcome(s) of behaviour	x										
3. Social support, n	3	1	0	0	1	1	0	0	2	1	1
BCTs from all possible BCTs (3 BCTs), %	100%	33%	0%	0%	33%	33%	0%	0%	67%	33%	33%
3.1. Social support (unspecified)	x										
3.2. Social support (practical)	x								x		
3.3. Social support (emotional)	x	x			x	x			x	x	x
4. Shaping knowledge	3	0	2	2	2	2	2	2	2	2	2
BCTs from all possible BCTs (4 BCTs), %	75%	0%	50%	50%	50%	50%	50%	50%	50%	50%	50%
4.1. Instruction on behaviour	x		x	x	x	x	x	x	x	x	x
4.2. Information about Antecedents	x										
4.3. Re-attribution											
4.4. Behavioural experiments	x		x	x	x	x	x	x	x	x	x
5.Natural consequences, n	2	0	1	1	1	1	1	1	1	1	1
BCTs from all possible BCTs (6 BCTs), %	67%	0%	33%	33%	33%	33%	33%	33%	33%	33%	33%
5.1. Information about health consequences	x		x	x	x	x	x	x	x	x	x
5.2. Salience of consequences											

5.3. Information about social and environmental consequences	x										
5.4. Monitoring of emotional consequences											
5.5. Anticipated regret											
5.6. Information about emotional consequences											
6.Comparison of behaviour, n	1	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (3 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
6.1. Demonstration of the behaviour	x										
6.2. Social comparison											
6.3. Information about others' approval											
7.Associations, n	1	0	1	1	1	1	1	1	1	1	1
BCTs from all possible BCTs (8 BCTs), %	13%	0%	13%	13%	13%	13%	13%	13%	13%	13%	13%
7.1. Prompts/cues	x		x	x	x	x	x	x	x	x	
7.2. Cue signalling reward											
7.3. Reduce prompts/cues											
7.4. Remove access to the reward											
7.5. Remove aversive stimulus											
7.6. Satiation											
7.7. Exposure											
7.8. Associative learning											
8.Repetition and substitution, n	5	1	3	4	4	4	4	4	4	4	3
BCTs from all possible BCTs (7 BCTs), %	71%	14%	43%	57%	57%	57%	57%	57%	57%	57%	43%

8.1. Behavioural practice/rehearsal	x		x	x	x	x	x	x	x	x	x
8.2. Behaviour substitution	x										
8.3. Habit formation	x			x	x	x	x	x	x	x	x
8.4. Habit reversal	x		x	x	x	x	x	x	x	x	
8.5. Overcorrection											
8.6. Generalisation of target behaviour											
8.7. Graded tasks	x	x	x	x	x	x	x	x	x	x	x
9.Comparison of outcomes, n	1	0	1	1	1	1	1	1	1	1	1
BCTs from all possible BCTs (3 BCTs), %	33%	0%	33%	33%	33%	33%	33%	33%	33%	33%	33%
9.1. Credible source	x		x	x	x	x	x	x	x	x	x
9.2. Pros and cons											
9.3. Comparative imagining of future outcomes											
10.Reward and threat, n	2	0	2	2	2	2	2	2	2	2	0
BCTs from all possible BCTs (11 BCTs), %	18%	0%	18%	18%	18%	18%	18%	18%	18%	18%	0%
10.1. Material incentive (behaviour)											
10.2. Material reward (behaviour)											
10.3. Non-specific reward											
10.4. Social reward	x		x	x	x	x	x	x	x	x	
10.5. Social incentive											
10.6. Non-specific incentive											
10.7. Self-incentive											
10.8. Incentive (outcome)											
10.9. Self-reward											
10.10. Reward (outcome)	x		x	x	x	x	x	x	x	x	
10.11. Future punishment											

11.Regulation, n	0	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (4 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
11.1. Pharmacological support											
11.2. Reduce negative emotions											
11.3. Conserving mental resources											
11.4. Paradoxical instructions											
12.Antecedents, n	2	0	2	2	2	2	2	2	2	2	1
BCTs from all possible BCTs (6 BCTs), %	33%	0%	33%	33%	33%	33%	33%	33%	33%	33%	17%
12.1. Restructuring the physical environment	x		x	x	x	x	x	x	x	x	x
12.2. Restructuring the social environment											
12.3. Avoidance/reducing exposure to cues for the behaviour											
12.4. Distraction											
12.5. Adding objects to the environment	x		x	x	x	x	x	x	x	x	
12.6. Body changes											
13. Identity, n	0	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (5 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
13.1. Identification of self as role model											
13.2. Framing/reframing											
13.3. Incompatible beliefs											
13.4. Valued self-identify											
13.5. Identity associated with changed behaviour											

14. Scheduled consequences, n	0	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (10 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
14.1. Behavior cost											
14.2. Punishment											
14.3. Remove reward											
14.4. Reward approximation											
14.5. Rewarding completion											
14.6. Situation-specific reward											
14.7. Reward incompatible behaviour											
14.8. Reward alternative behaviour											
14.9. Reduce reward frequency											
14.10. Remove punishment											
15.Self-belief, n	2	2	0	0	0	0	2	0	2	2	2
BCTs from all possible BCTs (4 BCTs), %	50%	50%	0%	0%	0%	0%	50%	0%	50%	50%	50%
15.1. Verbal persuasion capability	x	x					x		x	x	x
15.2. Mental rehearsal of successful performance											
15.3. Focus on past success	x	x					x		x	x	x
15.4. Self-talk											
16. Covert learning, n	0	0	0	0	0	0	0	0	0	0	0
BCTs from all possible BCTs (3 BCTs), %	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
16.1. Imaginary punishment											
16.2. Imaginary reward											
16.3. Vicarious consequences											

BCTs per use case, n	34	9	17	19	20	20	22	19	24	23	16
BCTs from all possible BCTs (intervention), %	100%	26%	50%	56%	59%	59%	65%	56%	71%	68%	47%

Summary of Time-Constant Predictors for Each Target Behaviour

Table 92: Summary of time-constant predictors

Time-constant Predictors	Values (examples)	Steps count	Total sleep minutes	Deep sleep minutes	Portions of vegetables	Portions of fruit	Glasses of water	Cups of coffee	Units of alcohol	Number of snacks	Number of meals	Frequency of predictors used
County of residence	9 UK counties (e.g., Southwest England, London, Wales)	x	x	x	x	x	x	x	x	x	x	10
Ethnicity	Black African, Chinese, Indian, Latin American, Other white background, White and Black Caribbean, White British, White Irish	x	x	x	x			x	x	x		7
Perspective on the menopause	Accepting of it, have not thought about it, neutral, not looking forward to it, unsure	x	x		x		x	x			x	6
Participated in group exercises in the past	Yes/No	x			x	x	x				x	5
Age group	40-44, 45-49, 50-54, 55-59, 60-64, 65+	x				x			x		x	4
General health status	Poor, fair, good, very good, excellent	x						x		x	x	4
Household income level	< £18,000, £18,00 to £30,999, £31,000 to	x	x							x	x	4

	£51,999, £52,000 to £100,000, > £100,000											
Marital status	Divorced, separated, widowed, Married, living as married, Never married, Prefer not to say	x				x				x	x	4
Menopause stage	Peri-menopause, post-menopause, pre-menopause, surgical menopause, unsure	x			x		x	x				4
Generation British	Native, 1st generation, 2nd generation, 3rd or more	x			x						x	3
Antidepressants use to manage menopause symptoms	In the past, never, currently	x							x			2
HRT use	In the past, never, currently	x							x			2
Knowledge about menopause	Not informed at all, some knowledge, very informed	x			x							2
Number of children	0, 1-2, 3 or more	x			x							2
CBT use to manage menopause symptoms	In the past, never, currently	x										1
Education level	College or university, lower secondary, postgraduate	x										1

Employment capacity	Full-time, part-time, not working		x									1
Smoking	In the past, never, currently	x										1
Children (18+ y/o) living at home	Yes/No											0
Lifestyle technology use in the past	Yes/No											0
	Predictors, n	17	5	2	8	4	4	5	5	5	8	
	Sig predictors, n	4	2	2	3	3	2	3	3	3	2	
	Ratio: sig predictors to all predictors, %	23.53%	40.00%	100.00%	37.50%	75.00%	50.00%	60.00%	60.00%	60.00%	25.00%	
	Adj R-squared	45.00%	40.00%	26.28%	37.50%	19.90%	29.70%	54.00%	38.85%	38.90%	33.54%	

Appendix E: Chapter 9

Behaviour Change Intervention Ontologies

Recent advancements in behavioural science also include development of ontologies, which are standardised frameworks that provide controlled vocabularies to assist in unifying and connecting scientific fields (Wright et al., 2020). More specifically, ontologies are classification systems specifying entities, definitions, and inter-relationships for a given domain (Norris et al., 2019). A scoping review identified 15 ontologies in the domain of cognition, mental health and emotions, although no ontology represented the breadth and detail of human behaviour change to support advancement in behavioural science (Norris et al., 2019). Therefore, the Behaviour Change Intervention Ontology (BCIO) was recently developed, a compositive of interrelated component ontologies (sub-ontologies). BCIO is part of the Human behaviour change project (HBCP) (Michie et al., 2017a), a programme of work that uses AI/ML-based knowledge system to find research reports in a given area of behavioural science, extract key information using an ontology of BCIs, and predict intervention outcomes in novel scenarios (Michie et al., 2017a). The Ontology-based modelling system (OBMS) (Hale et al., 2020) identified 76 theories that were included in the HBCP. Furthermore, the BCIO provides means to transform printed reports to computer-readable research reports, thus making published reports of BCIs not only readable by humans but readable by computers (Michie, Thomas, et al., 2020). This requires standardising of scientific language (entities and relationships) to overcome heterogeneity in the way reports are currently written and published (Michie, Thomas, et al., 2020). BCIO consists of upper level ontology (Michie, West, et al., 2020), intervention content ontology (e.g., behaviour change techniques ontology (BCTO) (Marques et al., 2023), and dose ontology (not yet published)), intervention delivery ontologies (e.g., mode of delivery (Marques et al., 2020), intervention source ontology (Norris et al., 2021), schedule of delivery options (not yet published), style of delivery ontology (not yet published)), behaviour ontology (e.g., human behaviour ontology (not yet published)), mechanism of action ontology (Schenk et al., 2023), population ontology (not yet published), setting ontology (Norris et al., 2020), engagement ontology, and fidelity ontology (not yet published). The BCIO also provides prototype templates (Norris et al., 2024) to enable researchers to extract contents of their reports and upload these to the HBCP repository. Currently, the HBCP Prediction tool includes only smoking cessation interventions that can be queried using filters for several intervention components (e.g., BCTs included, mode of delivery, characteristics of the participants). A protocol has been developed for mental health ontology (Schenk, Hastings and Michie, 2024), which will also involve stakeholder involvement, including domain experts and co-production with people with lived experiences. Future studies should incorporate ontologies in the description of the intervention designs so that future studies can be incorporated into the growing body of empirical evidence.

Updates to the BCT Taxonomy

This thesis used the current version of the BCT taxonomy (BCTTv1) (Michie et al., 2013) consisting of 93 BCTs grouped into 16 clusters. An updated version of the taxonomy consists of the Behaviour Change Technique Ontology (BCTO) (Marques et al., 2023), providing a standard terminology and comprehensive classification system for the content of BCIs, that can be used to describe these interventions (Marques et al., 2023). The BCTO consists of 281 BCTs organised into 20 higher-level groups over five hierarchical levels (Marques et al., 2023). The BCTO provides an open-access, computer readable description of the content of BCIs. Therefore, future studies should annotate their intervention components using the new version of BCTO which provides a standard terminology and comprehensive classification system for the content of BCIs that can be reliably used to describe interventions (Marques et al., 2023).

Barriers to Adopting Digital Health

It is important to note that one third of the global population (i.e., 2.6 billion people) are still offline without Internet (ITU, 2023) and therefore unable to use DHIs that are currently available to the two thirds of the connected world. Sustainable efforts behind the UN Sustainable Development Goals are needed to achieve universal connectivity which is currently the lowest in low-income countries (ITU, 2023). There are however additional inequalities that require addressing. The gender digital divide persists with 70% of men globally using the Internet, compared with 65% of women (ITU, 2023). The urban-rural divide remains with 81% of urban dwellers using the Internet, which is 1.6 times as high as the percentage of Internet users in rural areas (ITU, 2023). Additionally, although technology use has become more common in recent times, and digital technologies provide the ability to reach specific populations that would be extremely hard to reach others otherwise (e.g., geographically dispersed), improve health outcomes, and increase access to health services, not all populations have equal access to these tools (Singh et al., 2023). This means, that introducing additional technologies, such as AI chatbots can further exacerbate existing health disparities, particularly for marginalised individuals who may lack access to technology or digital literacy, such as individuals experiencing homelessness or elderly individuals with limited digital literacy (Singh et al., 2023). More efforts are needed to develop the necessary infrastructure and affordability to reduce inequalities and therefore the ability to provide access to digital health services. Additionally, to ensure that digital tools are accessible and beneficial for everyone, it is crucial to include diverse populations in future studies. Although this thesis is in its preliminary phase of research, and it is designing a DHBCI for a population that resides in a developed country (i.e., UK) and has access to these technologies, it is critical for future DHBCIs to address inequalities and availability of lifestyle health interventions to everyone.

A systematic review of DHIs for ethnic minority and historically underserved populations in developed countries (Armaou, Araviaki and Musikanski, 2020) revealed that there is growing evidence of the effectiveness of DHIs for these populations and further efforts need to be made to culturally tailor and personalise DHIs to ensure equitable and equal access and delivery of the interventions to minority and historically underserved populations. Some of the identified strategies to minimise the influence of social health inequalities while maximising the effectiveness of DHIs includes involving the target audience in the research and development process (co-production) and making sure the community's underserved populations are adequately represented in any sampling and implementation procedures (Armaou, Araviaki and Musikanski, 2020). Another recent scoping review of DHIs for minoritised social groups (migrants, ethnic and cultural minorities) (Radu et al., 2023) revealed that while about half of the included interventions (k=57) did not involve the target population in development and only a minority involved them consistently, the outcomes of the review suggests that the increased involvement of the target population in the development of DHIs leads to a greater acceptance of their use (Radu et al., 2023). Similarly, a review of digital mental health interventions (DMHIs) (Schueller et al., 2019) indicates that DMHIs provide opportunities to alleviate mental health disparities among marginalised populations by overcoming traditional barriers to care and suggest tailoring DMHIs to fit the needs of the target population is needed, as well as collaborating with stakeholders to deliver DMHIs to these underserved populations in need. Future studies exploring the effectiveness of DHIs for ethnic minority and historically underserved populations should strive to provide guidance to policymakers, industry professionals and academics towards delivery community-wide interventions. Adopting a theory-driven, person-centred approaches and following co-design processes can be beneficial in developing relevant and feasible DHIs (Yardley et al., 2015). Developing scalable, sustainable, accessible, and cost-effective strategies to address disparities in healthcare access, utilisation, and outcomes among economically and socially marginalised groups is needed (Zhang et al., 2022). Utilising the APEASE criteria as part of the BCW framework (see **Chapter 3**) can be beneficial to support this objective.

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