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Critical factors for assessing building deconstructability: Exploratory and confirmatory factor analysis

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A B S T R A C T

In various cities/other urban settlements, buildings are replaced with newer stocks, ending many buildings' lives. Unfortunately, these buildings nearing or at end-of-useful lives are mostly not deconstructed; instead, they get demolished, resulting in waste generation and pollution, among other environmental concerns. Deconstruction supports closing the material loop in construction, facilitating reuse at end-of-life of the building; however, it is not always easy to assess the feasibility of deconstruction for existing buildings – deconstructability. For this purpose, this paper investigated critical factors that needed to be checked to make informed decisions about the deconstructability of buildings. These factors cover economic, social, environmental, legal, and technical dimensions. Based on the exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), 31 significant drivers were identified. These drivers were classed into seven factors. The findings in this paper contribute to the practice of deconstruction, mainly supporting deconstructability decision-making and are helpful for deconstruction/demolition auditors, waste-management consultants and/or other stakeholders with waste minimisation goals, particularly for buildings nearing or at the end-of-useful lives.

1. Background

In the United Kingdom (UK), the architectural, engineering, and construction (AEC) sector employs around 2.4 million people, representing 10% of total employment, and contributes over 6% to the country's economic output, equivalent to £117 billion in 2018 (Rhodes, 2019). Similar substantial economic impacts are observed globally, including in China, the United States of America, and India (Alaloul et al., 2022). Furthermore, the industry promotes social development by improving well-being and advancing healthier communities (Altomonte et al., 2020), (Chadwick, 2020), (Younger et al., 2008). The sector is noteworthy in a nation's socioeconomic development and growth.

Despite the undeniably positive impacts of the AEC industry on the economy and people's well-being, growing arguments highlight its detrimental effects on the socio-physical environment. The sector generates significant waste, primarily from construction, demolition, and excavation activities collectively called CDEW. Among these activities, an end-of-life process, demolition is mainly responsible for producing the most significant volume of waste compared to other construction activities (Balogun et al., 2022a). This is primarily attributed to the fact that demolition renders more than 90% of the building components as waste and renders the waste irrecoverable (Del Río Merino et al., 2010). According to a report by the Department for Environment, Food, and Rural Affairs (DEFRA), demolition activities account for approximately 62% of UK waste (DEFRA, 2020). Like the UK, demolition contributes significantly to the waste stream in other countries, such as China and the USA (Aslam et al., 2020), (Huang et al., 2018).

The urgent need to address most of the identified concerns at building end-of-life has prompted the adoption of deconstruction as an alternative to demolition. Deconstruction has gained popularity as a sustainable building strategy in recent years due to its ability to decrease waste and enhance resource efficiency. Deconstruction, in contrast to demolition, is the deliberate and non-destructive dismantling of a building to reuse the materials and components (Rios et al., 2015a) rather than disposing of them in a landfill.

Despite the benefits of deconstruction, the decision-making process regarding selecting between demolition and deconstruction when a building has reached or nears its useful end-of-life remains complex and intricate, owing to a wide range of factors (Balogun et al., 2022a) herein, this paper aims to investigate the critical drivers/factors for assessing deconstructability for building nearing or at the end-of-useful lives.

1.1. Terms and their definitions

Thomson et al. (Thomsen et al., 2011) defined *demolition* as completely removing all building parts. Furthermore, Zahir et al. (2016)

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referred to demolition as an intentionally engineered process to knock down buildings, mainly resulting in debris. *Deconstruction*, however, is carefully knocking down a building into its components to rescue its materials for recycling, reuse, and reconstruction reasons (Rios et al., 2015b). Deconstruction is a means to an end; it exists for the appropriate recovery of building elements, components, sub-components, and materials for either reuse or recycling in the most cost-effective manner (Bradley Guy, 2004). Meanwhile, *deconstructability* is a concept that evaluates the feasibility and practicality of deconstructing buildings (Akinadé et al., 2015), (Kim and Kim, 2022), (Guy, 2001), (Guy and Ohlsen, 2003). It extends beyond the physical aspects and considers broader implications, including structural, environmental, social, and economic factors. Through systematically examining these facets, deconstructability aims to determine whether deconstructing a building offers advantages over conventional demolition.

2. Drivers influencing deconstructability

Balogun et al. (2022a) established that studies have explored and used various deconstructability influencing drivers. Still, they predominantly considered these drivers and deconstructability from specific dimensions, such as technical (e.g., (Rakhshan et al., 2021a), (Akinade et al., 2015), (Àkànbí et al., 2019), (Basta et al., 2020a)) or economic (Guy, 2001), (Rakhshan et al., 2021b). For instance, focusing on economic rewards, Guy (2001) proposed a tool to predict the deconstructability of wooden building structures, mainly considering drivers that could contribute to revenue and reduce costs from the deconstruction. The study considered drivers like building age, damages, grade of the materials, and disposal cost. Similarly, Rakshan et al. (Rakhshan et al., 2021b) proposed using drivers like labour cost, purchasing price, and insurance cost, among others, to assess the deconstructability of load-bearing components. The study highlights the joint effects of labour cost, financial risk, and procurement process on load-bearing reusability.

In another study focused on the deconstructability of a building from a design and technical point of view, the authors developed a deconstructability assessment score (DAS) (Akinadea et al., 2015). Akinade et al. (Akinadea et al., 2015) proposed DAS and considered drivers like connection type, materials, and secondary finishes. Also, Basta et al. (2020b) extended DAS to assess the deconstructability of a steel-framed building. Aside from this study, others like (Àkànbí et al., 2019) and (Akinade and Oyedele, 2019) have adopted DAS in different settings.

Using a machine learning model, Rakshan et al. (Rakhshan et al., 2021a) assess the deconstructability of load-bearing building components. This study considered technical and design-related drivers, like the presence of hazardous or banned materials, among others. As per the findings of this study, the foremost factor impacting the reusability of a building component from a design perspective is the compatibility of the reclaimed materials.

However, assessing deconstructability while looking at it from a single dimension, as mostly done in literature, arguably fails to provide a holistic overview of the perspectives necessary for a realistic deconstructability assessment of buildings. Some studies emphasised expanding beyond technical criteria when assessing building deconstructability (Akinadé et al., 2017) (Balogun et al., 2022b) (Balogun et al., 2024). These studies advocate for a broader evaluation and consideration of a more comprehensive array of drivers from various dimensions beyond mere technical or economic. As a result, in a 2023 study, (Balogun et al., 2022a) adopted a systematic literature review to unveil the drivers influencing deconstructability at the building end of life. This comprehensive review identified 42 drivers from distinct dimensions. While the study arguably established a more comprehensive dimension and drivers influencing deconstructability, it has failed to investigate the critical drivers/factors that deconstruction stakeholders need to be aware of to decide on the deconstructability of a building; as such, there is a need for empirical investigation. Following this, we aimed to investigate critical drivers/factors influencing deconstructability for buildings nearing or at the end of life using exploratory and confirmatory factor analysis. The remaining part of the paper is structured as follows: research methodology (Section 3), analysis and result (Section 4), discussion and conclusions (Section 5).

3. Methodology

3.1. Study setting and design

The research study adopted the established drivers (Balogun et al., 2022a). These drivers cover diverse dimensions: economic, technical, legal, social, schedule and environmental. Subsequently, the chosen drivers were transformed and operationalised into 42 explanatory variables. These variables constituted the core elements employed in collecting data. Fig. 1 presents the overview of the methodology.

3.2. Data collection

A survey tool was initially developed based on the established variables to collect data. A pilot survey was conducted among construction/civil engineering academicians, including research fellows and students, to ensure the utmost clarity and appropriateness of the survey questions. The valuable feedback garnered from this pilot was analysed and judiciously incorporated to refine and enhance the quality of the questions.

Following this, a purposive random sampling strategy was employed to recruit participants possessing requisite expertise in the field of deconstruction, given the specialised knowledge required to respond effectively to the survey questions.

The electronically distributed survey questionnaires targeted a diverse cohort of recognised deconstruction experts and professionals, representing a rich tapestry of disciplines, including architects, quantity surveyors, project managers, deconstruction engineers and managers, and demolition engineers and managers. Identifying these professionals was achieved by carefully exploring various sources, such as reputable professional bodies, groups, and forums, as well as renowned companies operating within and beyond the geographic boundaries of the United Kingdom (UK). Prominent organisations and entities, including the Institute of Demolition Engineers (IDE), the Chartered Institute of Builders (CIOB), and the Royal Institute of British Architects (RIBA), among numerous others, were actively engaged and contacted to ensure the broadest possible reach. Furthermore, academicians possessing a profound understanding and expertise in the realm of deconstruction were also thoughtfully approached, both from within and beyond the authors' institution.

A panoply of communication channels, including but not limited to widely recognised professional networking platforms like LinkedIn, were adroitly harnessed to establish fruitful and meaningful connections with these esteemed professionals following studies such as (Kayam and Hirsch, 2012), (Koranteng and Wiafe, 2019). Additionally, conventional means of communication, such as emails, were effectively utilised to reach these highly regarded experts. The data collection phase spanned an extended period from November 2021 to June 2022, allowing for a thorough gathering of vital information.

The survey questionnaire was carefully crafted, featuring a series of close-ended questions divided into five sections. The inaugural section, aptly designated as the "Opening Section," embarked on the inquiry into the professional's deconstruction expertise, specifically probing their involvement in leading or participating in previous deconstruction projects. In the event of a negative response, the subsequent questions were rendered redundant, effectively terminating the respondent's participation in the survey. Conversely, an affirmative response would prompt the professionals to provide additional insights into their roles, including their job titles and the number of years of experience amassed in the field of deconstruction. This strategic addition of supplementary details was conceived with the overarching objective of augmenting the

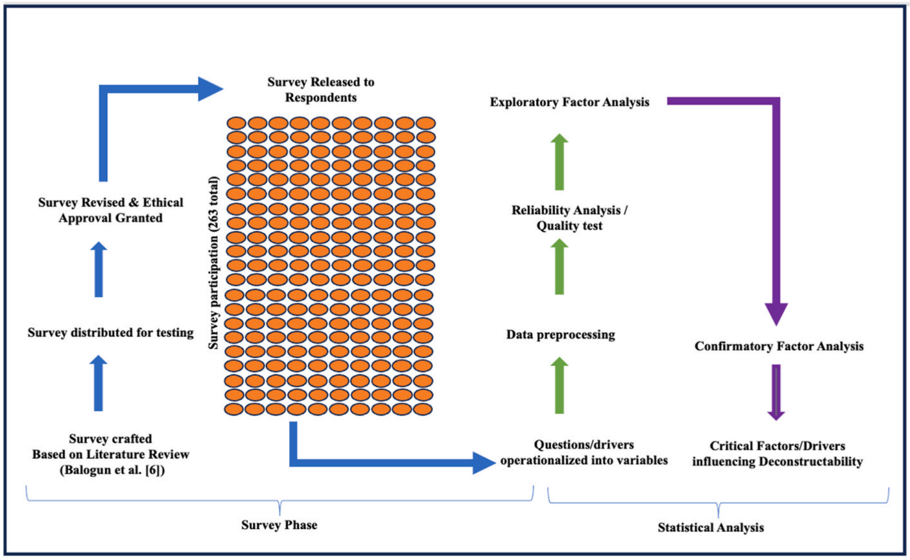

Fig. 1. Overview of the methodology.

quality and depth of the collected data.

Furthermore, respondents were instructed to confine their responses to a single deconstruction project they had previously worked on, instilling a sense of coherence and focused analysis within the collected dataset. Moreover, respondents were asked to assess the deconstructability of the building based on their first-hand experience. They provided scores indicating the degree of deconstructability, with higher percentages indicating deconstructible for most of the building components and elements and a lower percentage suggesting non-deconstructible (denoted as q1 in the paper).

3.3. Ethical issues

Ethical approval was obtained from the University ethics committee before conducting this research. Supporting statements and approval reference numbers were included as part of the introductory session of the survey. Participants were informed of the nature of the study and provided their informed consent for the survey.

3.4. Data description

A total of 2831 prospective deconstruction professionals were contacted. After several back-and-forth reminders, 301 responded. Two hundred sixty-three professionals were confirmed to have previously worked on deconstruction projects, representing the valid data retrieved – indicating 263 deconstruction projects.

Data were downloaded from the survey platform in CSV format and then exported to JASP 0.18.1 for detailed analysis. Descriptive data analysis was used to check for missing values. Data pre-processing was done accordingly. Outliers were checked, and the response rates of all items were also checked (Obaid et al., 2019).

To evaluate the validity and reliability of the data, Cronbach's alpha coefficient, standardised lambda coefficient and squared multiple correlation coefficient (R^2) were employed following exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

3.5. Exploratory Factor Analysis (EFA)

EFA was adopted to investigate latent variables. Basic steps were tried, including evaluating suitability and probing the sample size and correlations using measures like Kaiser Meyer Olkin (KMO) adequacy and Bartlett's correlation test. Additionally, steps including factor extraction, determining retained factors, and eventually applying rotation methods were agreed upon as part of EFA (Taherdoost et al., 2014). KMO value falls within a range of [0, 1]; it will be deemed adequate if the value is > 0.5 (Hair et al., 2014), (Tabachnick et al., 2013) or even better if it is > 0.6 (Lloret et al., 2017), (Burton and Mazerolle, 2011). Bartlett's test of sphericity was also used to measure the overall significance of correlations among variables. It tells whether the matrix is an identity matrix: a significant p-value <0.05 indicates that the data is appropriate for factor analysis (Hair et al., 2014), (Burton and Mazerolle, 2011), (Hair et al., 2021).

In EFA, various methods can be employed to retain factors, such as principal axis factoring (PAF), image factoring (IF), maximum likelihood (ML), and principal component analysis (PCA), among others (Tabachnick et al., 2013). Notably, PCA is a default option in many analytical software. Arguably, PCA is the most utilised in EFA studies (Tabachnick et al., 2013). The choice between PCA and PAF is debated among analysts despite often having negligible practical differences (Burton and Mazerolle, 2011). Considering these, this study will adopt PCA.

Additionally, the number of retainable variables is obtained using the variable loading. A variable loading >0.3 is acceptable (Tabachnick et al., 2013), while Burton and Stephanie (Burton and Mazerolle, 2011) emphasised a threshold$\geq$0.50 as a practical guideline. In this paper, we decided to set a variable loading threshold of$\geq$0.5 as this is one of the commonest acceptable thresholds among construction research studies (Xu et al., 2019), (Liu et al., 2020), (Yang et al., 2022), (Mohammed et al., 2021), (Mardani et al., 2020).

3.6. Confirmatory Factor Analysis (CFA)

Conversely, CFA is a hypothesis-testing technique that appraises the fit of a predetermined model. Consequently, utilising CFA to investigate a model derived from EFA is a valid methodology for developing theory and its analysis (Taherdoost et al., 2014), (Hair et al., 2021), (Kline, 2023), (Rodrigues et al., 2019). Usually, Structural Equation Modelling (SEM) is chosen for conducting CFA, as CFA is seen as a specialised use of SEM. Within SEM, CFA is termed the "measurement model", focusing on revealing how latent variables are reflected by their underlying observed variables, using measures: parameter estimates and fit indices. Different model fit indices assessed the overall model fit. We adopted $\chi 2/df$, comparative fit index (CFI), Tucker Lewis's index (TLI), parsimony normed fit index (PNFI), goodness of fit index (GFI), where comparative fit index (CFI) and Tucker Lewis Index (TLI) values > 0.9 indicated an acceptable model fit. $\chi 2/df < 3.0$, PNFI and PGFI >0.5 were considered good and acceptable (Hair et al., 2014), (Rodrigues et al., 2019). Additionally, root mean square error of approximation (RMSEA) was adopted, where values between 0.05 and 0.08 were considered an adequate model fit (Liu et al., 2020), (Yang et al., 2022), (Mohammed et al., 2021), (Mardani et al., 2020), (Ajayi and Oyedele, 2018), (Jiang et al., 2020), (Naji et al., 2022).

3.7. Reliability and validity tests

The reliability and validity were tested after assessing the model's overall fit. Reliability relates to the internal consistency of observed variables, while validity relates to the underlying cause of the variable's covariation. The reliability herein was estimated via Cronbach's alpha coefficient. Cronbach's alpha coefficient ranges between 0 and 1, with higher values indicating better reliability. The Cronbach alpha >0.7 is considered acceptable (Nunnally, 1994), (Cortina, 1993).

The validity of each path in the CFA model was evaluated using a standardised lambda coefficient. In contrast, reliability was assessed using a squared multiple correlation coefficient (R^2)—both the validity coefficient and R^2 value range from 0 to 1. As the validity coefficient approaches 1, the indicator reveals a higher level in representing the construct of interest. Similarly, as the R^2 value approaches 1, the greater the variability in each indicator accounted for by the unobserved variable.

4. Analysis and results

4.1. Exploratory factor analysis

To ensure that the survey tool was suitable for EFA, statistical tests such as KMO, Bartlett's test of sphericity, and communalities were applied. Sampling adequacy tested by KMO was reported at 0.739, indicating that items were sampled adequately. Bartlett's test of sphericity was reported at a p-value of 0.001, which is less than the significance level of 0.05 and indicates a robust concomitant probability among samples. These tests confirm that the collected data is wholly fit for analysis using the EFA method.

Principal component analysis with varimax rotation was conducted on 42 variables influencing deconstructability. As illustrated in Table 1, the presence of seven factors was revealed, which are labelled as Technical (F1), Building characteristics (F2), Time (F3), Policy (F4), Safety & recoverability (F5), Market (F6) and Region (F7). These seven factors explain 60.99% of the total variance satisfying requirements (Hair et al., 2012), (Egwim et al., 2021).

Table 1
Results of the exploratory factor analysis.

Description	Loadings							
	Code	F1	F2	F3	F4	F5	F6	F7
Project Location	q2	0.425	0.373	0.186	0.043	0.075	0.047	0.055
Neighbourhood Type	q3	0.023	0.330	0.051	0.213	0.056	0.193	**0.553**
Structure Type	q4	0.086	0.268	0.088	0.093	**0.549**	0.075	**0.542**
Social acceptance	q5	0.151	0.037	0.075	0.101	0.027	0.373	**0.601**
Building age	q6	0.134	**0.691**	0.099	0.011	0.182	0.134	0.151
Size	q7	**0.510**	0.100	**0.543**	0.177	0.170	0.099	0.165
Floor area (average)	q8	0.074	0.154	**0.576**	0.361	0.422	0.076	0.212
Frame	q9	0.219	**0.692**	0.036	0.263	0.159	0.095	0.007
HVAC	q10	0.052	0.191	0.112	0.103	0.164	**0.541**	0.143
Interior finishes	q11	0.131	0.357	0.129	0.183	0.212	**0.535**	0.271
External/Government policies	q12	0.025	0.098	0.089	**0.911**	0.026	0.164	0.008
Ill-defined benefits	q13	0.078	0.404	0.040	0.024	0.175	0.214	0.289
Incentives	q14	0.021	0.019	0.106	0.478	0.014	0.078	0.460
Damages	q15	0.228	**0.582**	0.052	0.199	0.054	0.103	0.188
Road network/Accessibility	q16	0.207	0.375	0.280	0.001	**0.526**	0.076	0.272
Standard quality/grading	q17	0.366	**0.757**	0.085	0.044	0.124	0.083	0.039
Skills/Experience	q18	**0.672**	0.135	0.061	0.080	0.138	0.168	0.070
Landfill/tipping tax	q19	**0.515**	0.059	0.208	0.343	0.191	0.260	0.069
Permit cost/time	q20	0.159	0.344	0.077	0.199	0.035	0.280	0.464
Equipment/resources	q21	0.065	0.082	0.041	0.036	0.164	**0.704**	0.021
Specialised labour	q22	**0.776**	0.058	0.018	0.038	0.011	0.010	0.284
Economic value/social	q23	0.371	**0.508**	0.149	0.059	0.322	0.011	0.203
Prefab/traditional	q24	**0.876**	0.130	0.018	0.021	0.106	0.012	0.051
Material demand	q25	0.486	0.283	0.013	0.016	**0.543**	0.082	0.145
Market	q26	0.251	0.104	0.145	0.037	0.110	**0.720**	0.049
Financial aid	q27	0.002	0.290	0.027	0.132	0.048	0.010	**0.738**
Storage	q28	**0.560**	0.358	0.268	0.065	0.092	0.339	0.279
Insurance	q29	0.255	0.020	0.293	**0.536**	0.136	0.282	0.072
Materials Recoverable	q30	0.406	0.084	0.113	0.108	**0.632**	0.220	0.108
Toxic/banned material	q31	0.368	0.155	0.142	0.322	**0.670**	0.250	0.162
Insurance	q32	0.017	0.149	0.206	0.154	0.411	0.053	0.173
Inventory Document	q33	**0.660**	0.001	0.040	0.090	0.271	0.028	0.229
Design and plan document	q34	**0.704**	0.089	0.040	0.203	0.321	0.078	0.235
Composite Material	q35	0.176	0.135	0.022	0.032	**0.597**	0.064	0.118
Accessible connection	q36	0.065	0.029	**0.801**	0.318	0.236	0.001	0.163
Connection types	q37	0.108	**0.628**	**0.648**	0.072	0.025	0.117	0.039
Sorting & Processing duration	q38	0.099	0.253	**0.677**	0.050	0.019	0.453	0.097
project time	q39	0.002	0.056	**0.770**	0.137	0.318	0.138	0.031
Complexity of activities	q40	0.125	0.429	0.315	0.317	0.365	0.253	0.101
Code/regulation	q41	0.005	0.222	0.037	**0.596**	0.194	0.119	0.119
Stakeholders' decision	q42	0.327	0.101	0.424	0.204	0.077	0.486	0.137
inertia	q43	0.335	0.242	0.276	0.036	0.111	0.258	0.373
Loading Cumulative %		15.43	25.98	35.32	43.66	50.91	56.07	60.99

As seen in Table 1, the model retained 38 items that displayed an item loading of 0.5 or higher. At the same time, the findings revealed that a few variables yielded loadings≥0.5; however, they appeared in more than one factor (i.e., seven cross-loadings were discovered). We decided to drop all the cross-loadings following recommendations (Costello and Osborne, 2005), (Dion, 2008), (Bowen and Guo, 2011), and we were left with 31 variables.

4.2. Confirmatory factor analysis

Results from EFA disclosed seven latent factors contributing to the deconstructability of buildings. We employed CFA to check the factorial validity of the different factors influencing deconstructability and to generate evidence regarding the fitness of the proposed model. The result of the CFA shows all variables were significant with $p < 0.05$. At the same time, the overall model fitness was acceptable and satisfactory. Table 2 offers the overall model fitness.

4.3. Reliability and validity tests

After assessing the model's overall fit, its reliability and validity were investigated. Reliability refers to the consistency of a set of observed indicators, while validity relates to the underlying cause of the indicators' covariation. The validity of each path in the CFA model was evaluated using a standardised lambda coefficient. In contrast, reliability was assessed using a squared multiple correlation coefficient (R^2) - both the validity coefficient and R^2 value range from 0 to 1. As the validity coefficient approaches 1, the indicator reveals a higher level in representing the construct of interest.

Similarly, as the R^2 value approaches 1, the greater the variability in each indicator accounted for by the unobserved variable. The lower acceptable limit for the validity coefficient is 0.5. However, there has yet to be a consensus on the lower limit for accepting R^2 (Xu et al., 2019). All the standardised loadings (standardised lambda coefficients) range from 0.076 to 0.927 for the observed variables. This exceeds the minimum threshold. The p-value associated with each latent variable is significant at the 0.05 level, and all the standardised loadings are higher than 0.5, except F5 and F6 loading, which stands at 0.346 and 0.379. While this loading is low, the latent variable of F5 and F6 was retained as it has been argued in previous studies to be a significant dimension determining deconstruction feasibility.

Furthermore, in assessing the reliability, the composite reliability (CR) was calculated (Raykov, 1997). It has been suggested in earlier studies that CR > 0.6 is a satisfactory threshold (Hair et al., 2014). Similarly, the average variance extracted (AVE) > 0.4 is an acceptable threshold (Gebremedhin et al., 2022), (Dilekli and Tezci, 2019). Applying these tests to the data, we discovered that CR and the AVE scores, respectively, for each construct were F1 (0.86, 0.45), F2 (0.81, 0.42), F3 (0.83, 0.45), F4 (0.73, 0.49), F5 (0.76, 0.44), F6 (0.79, 0.41) and F7 (0.7, 0.48). Findings suggested that all seven criteria satisfied the required level. These comprehensive checks proved the proposed model satisfactory, providing the best fit for the collected data. Overall, the proposed model, which contains 31 variables grouped under seven factors/dimensions, offers critical factors/drivers for determining the deconstructability of buildings under consideration for deconstruction.

Table 2
Results of the overall fit test for the confirmatory factor analysis (CFA).

Indices	Model	Standard (Hair et al., 2014), (Liu et al., 2020), (Naji et al., 2022), (S and LO Ajayi, 2018)
χ2/df	1.288	<3.0
CFI	0.986	>0.9
TLI	0.981	>0.9
PNFI	0.707	>0.5
GFI	0.975	>0.5
RSMEA	0.068	<0.08

5. Discussions and conclusion

5.1. Comparisons and evaluation of the criteria

The result revealed that the critical factors/drivers for assessing deconstructability are rooted in various considerations, including economic (e.g., monetary value and demand), social (e.g., cultural and historical values), environmental (e.g., the presence of toxic or banned materials), technical elements (e.g., connection type and construction method), and legal considerations (e.g., regional policy) (Balogun et al., 2022a). This effectively fulfils the need to make well-informed decisions regarding building deconstructability at the end of its life cycle, as seen in Fig. 2.

Moreover, the research revealed that the established factors/drivers encompass broader dimensions. Serving as a decision support, it incorporates both static criteria (e.g., technical elements) and dynamic criteria (e.g., the volume and value of recoverable materials and components), allowing the assessment of deconstructability to address multiple objectives.

5.1.1. Policy

The study highlighted that policy is the most critical factor affecting deconstructability (loadings = 0.933) (see Fig. 3). This is mainly due to the multifaceted impact policies have. Whether devised by professional bodies or the government, policies significantly influence deconstruction. These policies encompass regulations, incentives, and directives that can either facilitate or hinder the dismantling of existing structures.

Setting clear sustainability targets and implementing supportive directives are pivotal in driving deconstruction practices. Regulations are crucial in promoting global sustainability, which is evident in the varying policies encouraging deconstruction. For instance, the UK government introduced a waste prevention program to reduce demolition waste. At the same time, Paris aims for 30% of office space construction to be reversible by 2030 as part of its Paris Climate Action Plan. These initiatives are pivotal in driving more deconstructions.

Moreover, these policies are intricately linked to the region. The regional setting, including geographical location, socio-economic dynamics, and cultural influences, significantly affects deconstruction feasibility. The geographical location can influence cultural values, community perceptions, and acceptance of deconstruction practices. It also plays a role in determining the availability of resources, recycling facilities, and market demands for reclaimed materials.

A critical examination of these factors reveals complexities in policy formulation and regional variations. Policies that support sustainable practices, provide financial incentives, or mandate deconstruction considerations in building can substantially enhance feasibility. Conversely, stringent regulations, a lack of incentives, or inadequate infrastructure may hinder the feasibility of deconstruction. The interplay between policy structures and regional dynamics strongly impacts building deconstruction. This calls for a nuanced grasp of policy development and regional intricacies to optimise deconstruction potential.

5.1.2. State of the building and environment

The factors of building characteristics, which include the physical state of the building, play a more critical role in decision-making regarding deconstructability. This is because buildings in good structural condition with minimal damage or degradation are generally more conducive to deconstruction. Conversely, buildings compromised by structural instability, extensive damage, or hazardous materials may pose safety risks and logistical challenges, thereby impacting deconstructability.

The surrounding environment also plays a pivotal role. Factors such as accessibility, available space for deconstruction activities, and proximity to other structures or infrastructure affect the feasibility. A building in a congested urban area might need help with logistics, space constraints, and disturbance to neighbouring properties during the

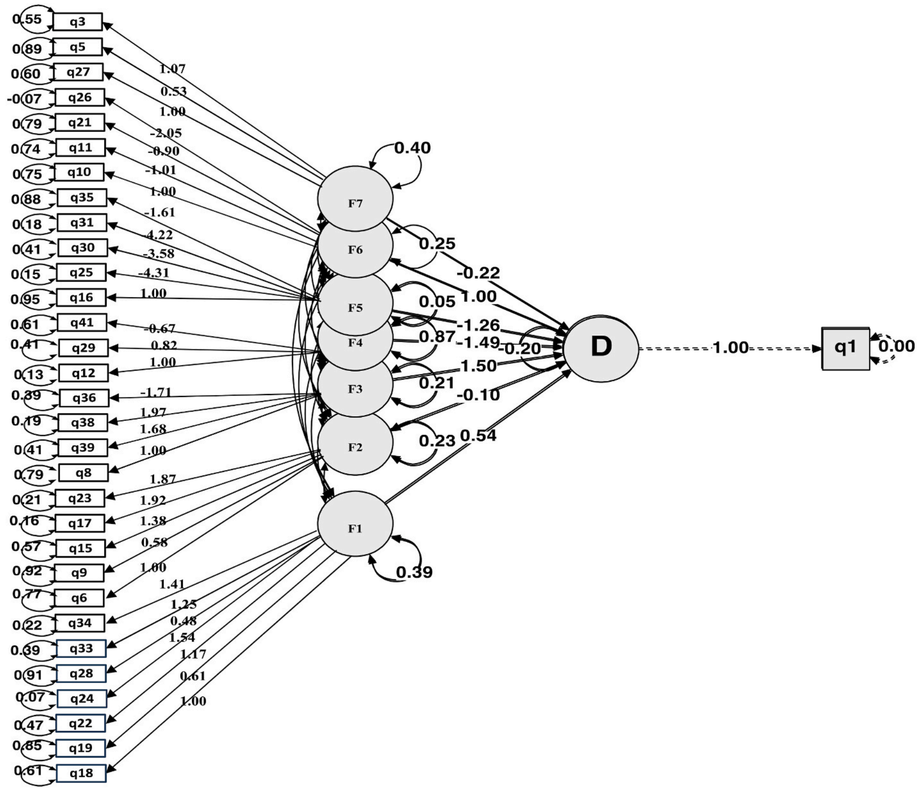

Fig. 2. Model of critical factors influencing deconstructability.

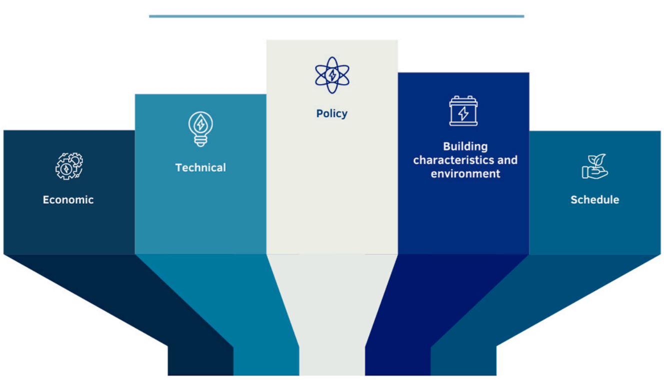

Fig. 3. Significant Criteria influencing the deconstruction feasibility.

deconstruction process, impacting its feasibility.

Another critical aspect is the presence of surrounding utilities or infrastructure. Buildings closely connected to essential services like power lines, water mains, or transportation networks might pose challenges during deconstruction, impacting feasibility due to potential service disruptions or safety concerns.

Community considerations and local perceptions about the building and its surroundings are also crucial. Community sentiments, historical significance, and cultural value attached to the building might influence decisions regarding its deconstruction. Resistance from local communities or stakeholders due to sentimental or heritage reasons can significantly impact the feasibility of deconstruction efforts.

In summary, the state of the building and its environment underscores the need for a comprehensive evaluation that considers structural integrity, environmental factors, logistical challenges, community sentiments, and the broader context to determine the deconstructability effectively.

5.1.3. Economic and technical concerns

The economic and technical criteria are critical determinants in evaluating the feasibility of building deconstruction. From an economic sphere, deconstructability is intricately tied to market dynamics. The potential for resource recovery and material reuse is a key economic variable. Buildings with salvageable materials and components present economic opportunities through material resale, contributing to the cost-effectiveness of deconstruction projects. Additionally, market demand for reclaimed materials, influenced by sustainability trends and construction industry preferences, plays a pivotal role in determining economic feasibility. Labour expertise, while indispensable, poses a double-edged sword: while skilled workers streamline processes, their fair compensation escalates costs, often significantly influencing overall feasibility. Other significant economic variables include storage cost, insurance, and specialised handling of hazardous materials.

Storage costs, an inevitable aspect of salvaged material management, demand scrutiny. While essential, adequate storage incurs additional expenses, potentially straining budgets. The economic burden of storage rentals, maintenance, and security amplifies the complexity of deconstruction feasibility. Similarly, Insurance, regarded as a safety net against potential risks, embodies a necessary yet substantial financial component. Its comprehensive coverage shields projects from liabilities but inherently adds to the inflated cost structures, raising pertinent questions about balancing protection with economic sustainability. Still, the specialised handling of hazardous materials, although imperative for safety and regulatory compliance, introduces substantial economic implications in economics. Costs associated with expert handling, disposal procedures, and safety protocols elevate project expenses, prompting a critical evaluation of the trade-offs between safety and financial feasibility.

From a technical point of view, variables such as construction methods, connection types, accessibility, material type, and building types are critical elements pivotal in assessing the feasibility and intricacies of the process. Buildings constructed using modular or easily disassembled methods, such as timber-framed structures or prefabricated buildings, are often more conducive to deconstruction due to their inherent design for dismantling. Equally, buildings employing reinforced concrete or steel structures pose more significant challenges due to their complex interconnections and integration, potentially impacting deconstruction feasibility. Also, the type of connections utilised within a building's structure is paramount. Buildings relying on bolted or mechanically connected systems facilitate easier disassembly, contributing to higher deconstruction feasibility than structures with welded or chemically bonded connections, which might necessitate more intricate and time-consuming dismantling processes.

Accessibility to connections/integral components further influences deconstruction prospects. Ease of access to building elements, such as foundations, support structures, and mechanical systems, impacts the deconstruction process. Buildings with accessible connections and components typically fare better in terms of feasibility than structures with concealed or inaccessible elements that might require specialised equipment or techniques for dismantling.

Considerations of building materials and their compatibility with recycling or reusability play a vital role. Buildings constructed using materials with higher recyclability rates, such as timber or certain metals, often offer more significant potential for salvage and resale, enhancing their economic feasibility for deconstruction initiatives. In a technical appraisal of building deconstruction, the amalgamation of construction methods, connection types, accessibility to integral components, and material recyclability forms the bedrock of strategic planning. Understanding these technical intricacies aids in devising efficient and cost-effective deconstruction strategies, paving the way for sustainable and resource-efficient building practices.

5.2. Conclusions

The paper identified critical factors/drivers influencing deconstructability. It comprises 31 variables chosen through exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) from a comprehensive literature review. The findings indicate policy, economic, technical, building characteristics and environmental dimensions. Notably, the paper evaluates not only the inherent traits of a specific building but also external factors like neighbourhood features, regional context, and other related aspects.

Using exploratory factor analysis, the paper grouped the 31 identified drivers/variables into seven categories: Technical, Building characteristics, schedules, Policy, Safety & recoverability, Market and Region. Afterwards, confirmatory factor analysis (CFA) was adopted for validity and reliability. From the results of the CFA, the most crucial factors were policy and schedules, with a high loading score of 0.933. This highlights the substantial influence of policies, whether set by professional bodies or councils, in determining the deconstructability of buildings. The estimated time to sort the deconstruction process was highlighted as a significant and crucial factor influencing the deconstructability.

Additionally, the region was significantly impacted (loading = 0.630), signifying their pivotal role in assessing deconstructability. The technical factor (loading = 0.626), market (loading = 0.505), building characteristics (loading = 0.476), schedule (loading = 0.455), and building safety & recoverability (loading = 0.214) were also recognised as significant factors impacting deconstructability.

The findings contribute to deconstruction by providing a realistic guide to decision-making around building deconstructability. The paper only established critical factors influencing the deconstructability of buildings. However, further studies can explore using other advanced techniques to develop essential factors/drivers influencing deconstructability. At the same time, other studies can explore using these factors/drivers to develop predictive techniques/models for deconstructability.

CRediT authorship contribution statement

Habeeb Balogun: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hafiz Alaka:** Writing – review & editing, Supervision, Project administration. **Saheed Ajayi:** Writing – review & editing, Project administration. **Christian Nnaemeka Egwim:** Writing – review & editing, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

APPENDIX. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.639	15.438	15.438	6.639	15.438	15.438	5.264	12.242	12.242
2	4.535	10.546	25.985	4.535	10.546	25.985	4.285	9.966	22.208
3	4.015	9.337	35.321	4.015	9.337	35.321	3.653	8.496	30.704
4	3.586	8.341	43.662	3.586	8.341	43.662	3.579	8.323	39.028
5	3.117	7.250	50.912	3.117	7.250	50.912	3.408	7.925	46.953
6	2.222	5.166	56.078	2.222	5.166	56.078	3.066	7.130	54.083
7	2.116	4.920	60.998	2.116	4.920	60.998	2.974	6.916	60.998
8	1.852	4.308	65.306						
9	1.597	3.714	69.020						
10	1.509	3.509	72.529						
11	1.449	3.369	75.898						
12	1.141	2.653	78.551						
13	1.045	2.430	80.981						
14	0.960	2.233	83.214						
15	0.931	2.164	85.378						
16	0.794	1.847	87.225						
17	0.697	1.621	88.846						
18	0.615	1.429	90.276						
19	0.543	1.263	91.538						

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Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
20	0.462	1.075	92.613						
21	0.439	1.022	93.635						
22	0.390	0.908	94.542						
23	0.343	0.797	95.340						
24	0.315	0.734	96.073						
25	0.274	0.636	96.709						
26	0.228	0.531	97.241						
27	0.186	0.434	97.674						
28	0.186	0.433	98.107						
29	0.152	0.354	98.461						
30	0.133	0.310	98.770						
31	0.117	0.272	99.042						
32	0.088	0.204	99.246						
33	0.080	0.186	99.432						
34	0.069	0.162	99.594						
35	0.046	0.107	99.701						
36	0.043	0.100	99.801						
37	0.033	0.076	99.877						
38	0.021	0.049	99.926						
39	0.020	0.046	99.971						
40	0.007	0.015	99.987						
41	0.004	0.009	99.996						
42	0.002	0.004	100.000						
43	0.000	0.000	100.000						

Extraction Method: Principal Component Analysis.

```
#latent variable Model zero.
F1 = ~q18 + q19 + q22 + q24 + q28 + q33 + q34 + q7.
F2 = ~q6+q9+q15 + q17 + q23 + q37.
F3 = ~q7+q8+q39 + q38 + q36 + q37.
F4 = ~q12 + q29 + q41.
F5 = ~q16 + q25 + q30 + q31 + q35.
F6 = ~q10 + q11 + q21 + q26.
F7 = ~q27 + q5+q3+q4.
D = ~q1.
#regression.
D ~ F1.
D ~ F2.
D ~ F3.
D ~ F4.
D ~ F5.
D ~ F6.
D ~ F7.
```

R-Squared	
	R^2
q18	0.392
q19	0.146
q22	0.532
q24	0.927
q28	0.089
q33	0.612
q34	0.777
q6	0.227
q9	0.076
q15	0.434
q17	0.837
q23	0.791
q8	0.207
q39	0.588
q38	0.805
q36	0.608
q12	0.871
q29	0.587
q41	0.386
q16	0.046
q25	0.852
q30	0.588
q31	0.816
q35	0.119
q10	0.255

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R-Squared	
	R^2
q11	0.258
q21	0.206
q26	
q27	0.396
q5	0.112
q3	0.454
q1	1.000
D	

Parameter estimates.

Factor Loadings

Latent	Indicator	Estimate	Std. Error	z-value	p	95% Confidence Interval		Standardized		
						Lower	Upper	All	LV	Endo
D	q1	1.000	0.000			1.000	1.000	1.000	0.992	1.000
F1	q18	1.000	0.000			1.000	1.000	0.626	0.626	0.626
	q19	0.610	0.100	6.071	<0.001	0.413	0.806	0.382	0.382	0.382
	q22	1.165	0.111	10.496	<0.001	0.948	1.383	0.729	0.729	0.729
	q24	1.538	0.140	11.013	<0.001	1.264	1.812	0.963	0.963	0.963
	q28	0.476	0.087	5.500	<0.001	0.307	0.646	0.298	0.298	0.298
	q33	1.250	0.114	10.959	<0.001	1.027	1.474	0.783	0.783	0.783
	q34	1.409	0.121	11.597	<0.001	1.171	1.647	0.882	0.882	0.882
F2	q6	1.000	0.000			1.000	1.000	0.476	0.476	0.476
	q9	0.578	0.144	4.004	<0.001	0.295	0.861	0.275	0.275	0.275
	q15	1.384	0.212	6.518	<0.001	0.968	1.800	0.659	0.659	0.659
	q17	1.921	0.272	7.064	<0.001	1.388	2.454	0.915	0.915	0.915
	q23	1.867	0.272	6.863	<0.001	1.334	2.401	0.889	0.889	0.889
F3	q8	1.000	0.000			1.000	1.000	0.455	0.455	0.455
	q39	1.684	0.301	5.587	<0.001	1.093	2.275	0.767	0.767	0.767
	q38	1.971	0.351	5.619	<0.001	1.283	2.658	0.897	0.897	0.897
	q36	−1.712	0.319	−5.368	<0.001	−2.337	−1.087	−0.780	−0.780	−0.780
F4	q12	1.000	0.000			1.000	1.000	0.933	0.933	0.933
	q29	0.821	0.091	9.047	<0.001	0.643	0.999	0.766	0.766	0.766
	q41	−0.666	0.079	−8.393	<0.001	−0.822	−0.511	−0.622	−0.622	−0.622
F5	q16	1.000	0.000			1.000	1.000	0.214	0.214	0.214
	q25	−4.315	1.060	−4.070	<0.001	−6.392	−2.237	−0.923	−0.923	−0.923
	q30	−3.584	0.886	−4.046	<0.001	−5.320	−1.848	−0.767	−0.767	−0.767
	q31	−4.224	1.042	−4.052	<0.001	−6.266	−2.181	−0.904	−0.904	−0.904
	q35	−1.614	0.467	−3.459	<0.001	−2.529	−0.700	−0.345	−0.345	−0.345
F6	q10	1.000	0.000			1.000	1.000	0.505	0.505	0.505
	q11	−1.007	0.206	−4.900	<0.001	−1.410	−0.604	−0.508	−0.508	−0.508
	q21	−0.900	0.209	−4.318	<0.001	−1.309	−0.492	−0.454	−0.454	−0.454
	q26	−2.049	0.430	−4.759	<0.001	−2.892	−1.205	−1.034	−1.034	−1.034
F7	q27	1.000	0.000			1.000	1.000	0.630	0.630	0.630
	q5	0.532	0.176	3.016	0.003	0.186	0.877	0.335	0.335	0.335
	q3	1.071	0.276	3.877	<0.001	0.529	1.612	0.674	0.674	0.674

Regression coefficients

Predictor	Outcome	Estimate	Std. Error	z-value	p	95% Confidence Interval		Standardized		
						Lower	Upper	All	LV	Endo
F1	D	0.539	0.717	0.751	0.452	−0.866	1.944	0.340	0.340	0.340
F2	D	−0.097	2.674	−0.036	0.971	−5.337	5.143	−0.047	−0.047	−0.047
F3	D	1.502	1.453	1.034	0.301	−1.345	4.350	0.690	0.690	0.690
F4	D	−1.488	0.648	−2.297	0.022	−2.757	−0.218	−1.399	−1.399	−1.399
F5	D	−1.259	4.546	−0.277	0.782	−10.169	7.652	−0.271	−0.271	−0.271
F6	D	1.004	1.662	0.604	0.546	−2.253	4.262	0.511	0.511	0.511
F7	D	−0.215	1.220	−0.177	0.860	−2.606	2.175	−0.137	−0.137	−0.137

Factor variances

Variable	Estimate	Std. Error	z-value	p	95% Confidence Interval		Standardized		
					Lower	Upper	All	LV	Endo
F1	0.392	0.055	7.086	<0.001	0.283	0.500	1.000	1.000	1.000
F2	0.227	0.057	3.974	<0.001	0.115	0.338	1.000	1.000	1.000
F3	0.207	0.068	3.066	0.002	0.075	0.340	1.000	1.000	1.000
F4	0.871	0.126	6.890	<0.001	0.623	1.118	1.000	1.000	1.000
F5	0.046	0.022	2.085	0.037	0.003	0.089	1.000	1.000	1.000
F6	0.255	0.083	3.085	0.002	0.093	0.416	1.000	1.000	1.000

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Factor variances									
Variable	Estimate	Std. Error	z-value	p	95% Confidence Interval		Standardized		
					Lower	Upper	All	LV	Endo
F7	0.396	0.155	2.551	0.011	0.092	0.701	1.000	1.000	1.000
D	−0.200	0.350	−0.571	0.568	−0.886	0.486	−0.203	−0.203	−0.203
Factor covariances									
Variables	Estimate	Std. Error	z-value	p	95% Confidence Interval		Standardized		
					Lower	Upper	All	LV	Endo
F1 – F2	0.148	0.024	6.081	<0.001	0.101	0.196	0.498	0.498	0.498
F1 – F3	−0.013	0.013	−1.037	0.300	−0.039	0.012	−0.047	−0.047	−0.047
F1 – F4	0.105	0.035	3.021	0.003	0.037	0.173	0.180	0.180	0.180
F1 – F5	−0.094	0.024	−3.938	<0.001	−0.141	−0.047	−0.701	−0.701	−0.701
F1 – F6	−0.076	0.021	−3.593	<0.001	−0.117	−0.034	−0.239	−0.239	−0.239
F1 – F7	0.035	0.030	1.192	0.233	−0.023	0.094	0.090	0.090	0.090
F2 – F3	0.054	0.016	3.341	<0.001	0.022	0.085	0.247	0.247	0.247
F2 – F4	0.055	0.033	1.684	0.092	−0.009	0.119	0.124	0.124	0.124
F2 – F5	−0.058	0.016	−3.549	<0.001	−0.090	−0.026	−0.568	−0.568	−0.568
F2 – F6	0.007	0.015	0.471	0.637	−0.022	0.035	0.029	0.029	0.029
F2 – F7	0.184	0.044	4.218	<0.001	0.099	0.270	0.615	0.615	0.615
F3 – F4	0.168	0.038	4.383	<0.001	0.093	0.243	0.394	0.394	0.394
F3 – F5	−0.024	0.008	−2.916	0.004	−0.041	−0.008	−0.251	−0.251	−0.251
F3 – F6	−0.080	0.023	−3.549	<0.001	−0.124	−0.036	−0.348	−0.348	−0.348
F3 – F7	0.015	0.026	0.555	0.579	−0.037	0.066	0.051	0.051	0.051
F4 – F5	−0.050	0.018	−2.858	0.004	−0.084	−0.016	−0.251	−0.251	−0.251
F4 – F6	0.086	0.043	2.014	0.044	0.002	0.169	0.182	0.182	0.182
F4 – F7	−0.033	0.062	−0.532	0.595	−0.155	0.089	−0.056	−0.056	−0.056
F5 – F6	0.046	0.015	3.064	0.002	0.017	0.075	0.425	0.425	0.425
F5 – F7	−0.001	0.009	−0.121	0.903	−0.020	0.017	−0.009	−0.009	−0.009
F6 – F7	0.024	0.025	0.960	0.337	−0.025	0.073	0.076	0.076	0.076
Residual variances									
Variable	Estimate	Std. Error	z-value	p	95% Confidence Interval		Standardized		
					Lower	Upper	All	LV	Endo
q18	0.608	0.000			0.608	0.608	0.608	0.608	0.608
q19	0.854	0.000			0.854	0.854	0.854	0.854	0.854
q22	0.468	0.000			0.468	0.468	0.468	0.468	0.468
q24	0.073	0.000			0.073	0.073	0.073	0.073	0.073
q28	0.911	0.000			0.911	0.911	0.911	0.911	0.911
q33	0.388	0.000			0.388	0.388	0.388	0.388	0.388
q34	0.223	0.000			0.223	0.223	0.223	0.223	0.223
q6	0.773	0.000			0.773	0.773	0.773	0.773	0.773
q9	0.924	0.000			0.924	0.924	0.924	0.924	0.924
q15	0.566	0.000			0.566	0.566	0.566	0.566	0.566
q17	0.163	0.000			0.163	0.163	0.163	0.163	0.163
q23	0.209	0.000			0.209	0.209	0.209	0.209	0.209
q8	0.793	0.000			0.793	0.793	0.793	0.793	0.793
q39	0.412	0.000			0.412	0.412	0.412	0.412	0.412
q38	0.195	0.000			0.195	0.195	0.195	0.195	0.195
q36	0.392	0.000			0.392	0.392	0.392	0.392	0.392
q12	0.129	0.000			0.129	0.129	0.129	0.129	0.129
q29	0.413	0.000			0.413	0.413	0.413	0.413	0.413
q41	0.614	0.000			0.614	0.614	0.614	0.614	0.614
q16	0.954	0.000			0.954	0.954	0.954	0.954	0.954
q25	0.148	0.000			0.148	0.148	0.148	0.148	0.148
q30	0.412	0.000			0.412	0.412	0.412	0.412	0.412
q31	0.184	0.000			0.184	0.184	0.184	0.184	0.184
q35	0.881	0.000			0.881	0.881	0.881	0.881	0.881
q10	0.745	0.000			0.745	0.745	0.745	0.745	0.745
q11	0.742	0.000			0.742	0.742	0.742	0.742	0.742
q21	0.794	0.000			0.794	0.794	0.794	0.794	0.794
q26	−0.068	0.000			−0.068	−0.068	−0.068	−0.068	−0.068
q27	0.604	0.000			0.604	0.604	0.604	0.604	0.604
q5	0.888	0.000			0.888	0.888	0.888	0.888	0.888
q3	0.546	0.000			0.546	0.546	0.546	0.546	0.546
q1	0.000	0.000			0.000	0.000	0.000	0.000	0.000

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