**Engagement in a virtual learning environment predicts academic achievement in research methods modules: A longitudinal study combining behavioural and self-reported data**

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# Engagement in a virtual learning environment predicts academic achievement in research methods modules: A longitudinal study combining behavioural and self-reported data

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**Abstract:**

The use of virtual learning environments (VLE) has grown exponentially in the past years. Research indicates that students' online learning behaviour predicts their academic performance, and that students' academic emotions can play a key role in this process. However, few studies have attempted to investigate the effectiveness of VLE activities in learning achievement within psychology education. In this longitudinal study, we analysed the relationship between students' activity in a VLE, their attendance, academic emotions and module grades at a face-to face based university in the United Kingdom. Data were collected over one year across two research methods modules, each of which is compulsory for a psychology degree. VLE and attendance data from 210 students were gathered for the first-year module, with 152 students continuing to the second year. The data were cross-referenced with students' module grades, alongside self-reported emotion data for a subset of students. The results showed that overall VLE activity and the use of specific online tools such as optional online tests and lecture recording were important predictors of academic achievement. Whilst some significant relationships between emotions and students learning behaviour and achievement were found, these correlations were relatively small and not consistent throughout the year. These findings have potential implications for curriculum design, particularly by making psychology educators aware of the usefulness of VLE activities and tools from the onset of students' research methods learning journey.

*Key Words: Virtual Learning Environment, Academic Performance, Research methods, Emotions, Longitudinal study*

## Introduction:

Technology-mediated online learning experiences are becoming increasingly popular. The past two decades have seen a rise in various forms of “flexible” education, ranging from purely distant online learning to blended learning, involving a mix of online and face-to-face teaching (Oliver & Trigwell, 2005). This rise in technology-mediated learning has been accelerated further by the challenges posed by the COVID-19 pandemic, with educational institutions switching from face-to-face teaching to online and blended learning and increasingly relying on Virtual Learning Environments (VLE).

VLEs are defined as online learning technologies for the creation, management and delivery of course material (Turnbull et al., 2020). These include software such as Blackboard Learn, Moodle and Canvas. VLEs provide students with convenient access to different online tools such as peer discussion forums, lecture recordings and online quizzes, as well as access to teaching materials and assessment information. The rise of use in these online systems has led to the emerging of a new field of research called “Learning analytics”, which involves the analysis of data about learners and their activities to inform teaching and learning practices (Long & Siemens, 2011). By using VLE data, researchers can gain an in-depth understanding of what, when and how students engage in their learning. For example learning analytics studies have used data generated from learner activities, such as the number of clicks (Kuzilek et al., 2015), learner participation in discussion forums (Macfadyen & Dawson, 2010) and the viewing of lecture recordings (Gardner, 2020) to explore students engagement and learning. Previous studies have also established relations between attendance (Credé et al., 2010), VLE engagement (Cerezo et al., 2016; Macfadyen & Dawson, 2010) and academic success.

For example, in an early study, Morris et al. (2005) examined student engagement in several online courses using student access computer logs. The results showed significant differences in online participation between students who withdrew and students who completed their studies and between successful and non-successful completers, with 31% of the variability in achievement accounted for by the students' online behaviour. More recent research has also established similar correlations between engagement in online learning activities and academic performance, with VLE activity accounting for a significant amount of variance in module grades in online and blended learning courses (Agudo-Peregrina et al., 2014; Kuzilek et al, 2015; Macfadyen & Dawson, 2010). However, less research has found these connections in traditional face-to face based universities where VLEs are used as a supplement to teaching.

In a face-to-face-based learning university (Boulton et al., 2018), the relationship between students' VLE activity and module grades was explored for students in 38 different modules. The findings showed that high VLE activity was associated with high grades, but low activity was not associated with low grades. More specifically, the majority of students interacted very little with the VLE and still got good marks. The overall correlation between VLE activity and module results was relatively small ($r_s$=0.262). However, when students were grouped into high and low performances, there was a stronger correlation between VLE usage and module results in students with grades below 40% ($r_s$=□0.497) compared to students with grades above 40% ($r_s$=□0.298). These findings indicated that VLE usage can help predict performance but that students' engagement with learning at a face to face dominant university is in general hard to determine by VLE usage alone due to the predominance of other on-campus learning activities. These results are consistent with the findings of Agudo-Peregrina et al. (2014), who compared the role of VLE in academic achievement between online courses and traditional university courses with face-to-face teaching supported by VLE.  For the online courses, the study yielded several significant interactions between VLE activity and academic achievement; however, for face-to-face teaching, no such correlations could be found.  Thus, it seems that VLE data can help with understanding student learning performance in some settings, such as within online modules. However, the evidence of the effectiveness of VLE in traditional campus-based settings are mixed, with student engagement seen as a complex and multi-dimensional construct. A way of further understanding the effectiveness and influence of VLE tools is by combining the behavioural data from the VLE with students' self-reported data from other factors important for learning, such as emotions.

The importance of emotions in learning has been recognised in several ways, such as emotional experiences being directly related to students' subjective well-being (Diener, 2000), emotions impacting the quality of learning by affecting motivation, self-regulated learning and learning strategies (Pekrun et al., 2011). Positive emotions are generally correlated with higher academic performance, whereas negative emotions are often correlated with lower academic performance (Pekrun et al., 2002;Pkeunr et al., 2011). Emotions can also facilitate students' learning behaviour and are important facilitators of successful studying and learning (Linnenbrink-Garcia et al., 2016).

The current study uses the control-value theory of achievement emotions framework (Pekrun et al., 2006) to assess the influence of emotions on the effectiveness of online tools for learning. The theory offers an integrative framework that explores different types of emotions experienced in situations involving learning and achievement and the individual and contextual factors that influence these. Pekrun's (2006) control-value theory posits that achievement emotions are determined by an individual's cognitive appraisal of control and value of learning activities. Based on this theory, achievement emotions affect learning and achievement, mediated by attention, self-regulation, and motivation. Achievement emotions can be classified according to valence (positive vs negative), degree of activation (activating vs deactivating) and object focus (activity, outcome). The theory posits that particularly for activating emotions, both positive and negative emotions may be central in terms of engagement (Pekrun & Linnenbrink-Garcia, 2012). Deactivating negative emotions instead foster disengagement from learning activities. Thus, by differentiating academic emotions by their activation dimension, the theory offers a more nuanced understanding of how students' emotions influence educational behaviour and outcomes.

The influence of achievement emotions in learning has been established both in traditional on-campus universities (Pekrun et al., 2002; Pekrun et al., 2011), and in online learning (Artino & Jones, 2012; Stephan et al., 2019) with emotional experiences in technology-mediated learning environments shown to differ from those in traditional on-campus courses.  For example, a study revealed that graduate students in online-modules reported significantly higher levels of technology-related anger, anxiety and helplessness compared to on-campus students (Butz et al., 2015). Similarly, Stephan et al. (2019) found that students who attended online courses reported higher levels of negative emotions but less enjoyment than students attending on-campus modules. However, when it comes to learning analytic studies, the emotional aspect of learning experiences is often ignored, with only a few studies exploring the influence of emotions in combination with VLE data.

Tempelaar et al. (2015a) explored the learning of 922 Economic and Business school undergraduate students on an introductory quantitative methods module delivered through blended learning. The researchers used a dynamic, longitudinal perspective to predict students' performance and captured both VLE data and emotional disposition.  The results indicate that scores on computer-assisted formative maths and statistics tutorials were the best predictors for detecting underperforming students and academic performance, while basic VLE data such as the number of clicks per week only explained 4% of the variance. Similar results were found in a follow-up study with two-cohorts of business and economic students (Tempelaar et al., 2015).

Although these studies by Tempelaar et al. take into account both emotional components and VLE activity, the studies were conducted in a blended-learning setting where attendance was mandatory, and thus attendance was not included in these predictor models. Furthermore, these findings might not be entirely comparable to psychology students' learning of research methods, as previous research indicates that psychology students often see research methods modules as the most challenging part of their degree (Barry, 2012). Furthermore, unlike business and economic courses, where the prevalence of statistics might be expected, psychology students often fail to see the relevance of statistics for their degree (Murtonen et al., 2008; Ruggeri et al., 2008), with statistics anxiety widely spread among students (Onwuegbuzie & Wilson, 2003). It is also this part of research methods learning that has received the most attention with a wealth of literature exploring the influence of statistic anxiety (Bourne, 2018; Onwuegbuzie & Wilson, 2003; Ruggeri et al., 2008), and less research focused on the influence of other emotions.

The current study, therefore, brings together separate lines of learning analytics and emotional research and aims to examine psychology students' academic attainment in research methods modules at a campus-based university. Drawing on both behavioural VLE data and self-reported data from the same experience of learning, this study aimed to examine the associations between emotions, VLE activity and tools on research methods learning achievement. The study offers a novel perspective by coupling this interactive approach with a longitudinal perspective, following students through first- and second-year research methods modules in order to gain a more holistic understanding of students learning behaviour. To the best of our knowledge, this is the first study within psychology education investigating the combined effect of VLE activity and attendance data longitudinally. These objectives resulted in the following set of research questions: 1) What contributions does the use of VLE materials and tools make to learning achievement? 2) To what extent do these influences remain stable from year 1 to year 2? Furthermore, based on the control-value theory framework, it was also hypothesised that 3) achievement emotions would have significant relationships with students' educational behaviour, as measured by VLE activity and academic achievement.

## Method:

### Participants and Procedure

This research employed a longitudinal design examining a cohort of psychology undergraduate students enrolled at a university in London, UK. The study was set across two modules, following students from the Psychology BSc and the Psychology and Counselling BSc course from first year into second year (i.e. between January 2019 and January 2020). Accessible records of students' educational behaviour and grades from the first- and second-year research methods modules were obtained from the university's VLE and attendance monitoring systems. The modules ran for 11 teaching weeks and consisted of lectures and practical sessions, with all teaching being face-to-face and campus-based. Students were encouraged to attend teaching sessions; however, this was not a mandatory requirement. No teaching sessions were delivered online. However, both administrative and teaching materials were made available on the University's VLE platform Blackboard to supplement teaching.

In total, data from 210 students was compiled for the first-year module. 152 students continued to the second-year module indicating a progression rate of 72%. Attrition was attributable to student withdrawal/exclusion from the course as well as failure to gain sufficient credits to progress. This drop-out rate is typical for the university and course. Data were not collected on participants demographic information. However, demographic information gathered from the entry cohort indicates that approximately 92% of the cohort was female, and 65% were between 18-19 years old at the start of the study. This gender imbalance is considered typical of undergraduate Psychology cohorts in the UK. The ethnicity distribution of the cohort was 42.5% Asian students, 30% White students, 15 % Black students, and 12.5 % other ethnicities.  The mean number of “UCAS” points for this cohort was 111, which is consistent with entrants achieving the grades BBC at GCE A-level.

The behavioural data from the VLE were analysed together with self-reported survey data regarding students’ academic emotions. Self-reported emotions data were collected online using the Qualtrics survey platform. The data were collected after the students’ first research methods lecture and seminar and kept open for 4 weeks and during the first four weeks of the second-year module.  This part of the study was entirely voluntary, with the study being advertised to the students during teaching sessions, as well as via the university’s research participation scheme and email.  Self-reported survey data from 60 participants were collected and cross-referenced with their VLE and attendance activity for the first time point. The second point of survey data collection took place 8- months later in the Autumn term of the academic year 2019/2020. Recruitment was kept open for all the second-year students in order to encourage more of the cohort to take part. This resulted in a dynamic sample of students, with some starting the survey study in the first point of measurement and some in the second, with data for 65 participants collected and cross-referenced for time-point 2. 47 had taken part in the previous survey resulting in a 78% retention rate. See Figure 1 for a flow diagram of the sample. The study was approved by the psychology ethics committee of our university.

[Insert Figure 1 here]

**Materials & Measures**

Accessible records of all of the 2018/2019 cohort of psychology students' educational behaviours and grades were obtained from the university's VLE and attendance monitoring system for the two research methods modules. The behavioural data that was obtained included: Attendance, Grades and VLE activity and tool use. For the self-reported surveys, students completed a voluntary online questionnaire twice during an eight-month period.

***Attendance (%)***

Students' attendance was estimated via the university's digital Student Engagement and Attendance systems (SEAtS), which records attendance to all learning sessions. Students are required to tap their ID card against a reader at the beginning of every teaching sessions.

***Online Tools (Blackboard Learn activity)***

Blackboard activity logs retrieved for the first-year research methods module included the number of times students had accessed: Coursework Information, Module Information, Study Materials and the total number of hours spent on the module Blackboard page. The number of weekly online progress tests completed by students was also measured. These tests were voluntary and intended as a tool for students to test their knowledge of the materials covered each week. There were ten tests in total, each consisting of 20 questions, with students receiving scores at the end and unlimited retakes allowed. The current study measured how many of the weekly tests students had attempted at least once, with scores ranging from 0-10. Blackboard activity retrieved for the second-year research methods module included the number of times students had accessed: Study Materials, Module Handbook, Assessment details, as well as the number of hours spent on the Blackboard. Students' use of lecture recordings was assessed via lecture capture log files (Panopto video analytics), with the total number of times students had accessed recordings measured.

***Achievement (%)***

Students' achievement was measured through their grades on the first- and second-year modules. The assessments on the first-year module consisted of a formative research report (feedback from module leader), summative report (50% weighting), in-class SPSS test (open-book, 20% weighting) and a one-hour exam consisting of short and multiple-choice questions (30% weighting). The second-year assessment consisted of a Learning Journal course work (40% weighting) and a 2-hour exam (60% weighting). Students overall percentage grade mark for each module was calculated from the assessments marks and chosen as the outcome measures for this study.

***Achievement emotions (AEQ)***

Students' emotions were measured using the Achievement Emotions Questionnaire (AEQ) (Pekrun & Perry, 2005), which is a multi-dimensional self-report instrument designed to assess students' emotions. There are three sections to the AEQ, containing the class-related, learning-related, and test-related emotion scales. In this study, only the class-related emotions scale was used in a shortened form because we were only interested in the emotions students experienced during the specific research methods modules. The scale consists of 51-items with the following eight emotions: enjoyment, hope, pride, anger, anxiety, shame, hopelessness, and boredom. The emotions were measured on a five-point Likert scale from "strongly disagree" (1) to "strongly agree" (5), with mean scores drawn for each emotion. The emotions were then categorised into Positive-activating (enjoyment, hope, pride), Negative-activating (anxiety, anger, shame) and Negative-deactivating( boredom, anger) as theorised by the control-value theory, with the scales summed and a mean score drawn. The internal consistency coefficients for the current study ranged between $\alpha$ =.75- .93.

## Results

Records of students' educational behaviour were retrieved, cross-referenced and anonymised for both the year 1 and year 2 modules. Table 1 presents means, standard deviations, and zero-order correlations for all behavioural data, including attendance, Blackboard activity and students' overall grade for the year 1 module and the year 2 module [1].

[Insert Table 1 here]

The mean overall grade for the Y1 year module ($N$ = 210) was 51.55 ($SD$ = 13.39). The mean grade for the year 2 module ($N$ = 152) was 57.26 ($SD$ = 12.01), and there was a medium positive correlation between the grades, $r$ (150) = .559, $p < .001$. Furthermore, learning behaviour was correlated with academic grades in both the first and second year. More specifically, attendance (%) on the first-year module was significantly correlated with the module grade, $r$(208) = .370, $p < .001$, as was the number of hours spent on Blackboard, $rs$(208) = .511, $p < .001$. Online tools and Blackboard activity that was significantly correlated with overall grade included: number of weekly online statistics tests, number of times students had accessed "Study Materials", and to a lesser degree, the number of times students had accessed "Module information" and "Coursework information".

Multiple regression analyses were run using SPSS 26 to predict performance on the first-year module, with the assumptions of multivariate normality, homoscedasticity, and multicollinearity met, and no influential cases present (Cooks distance <.05). The behavioural variables with significant correlations to module grade were inputted into a multiple regression model summarised in Table 2, with no significant variance inflation factors (VIF) presents. The results showed that the behavioural variables explained 30% of the variance in the module grade, $F(6, 203) = 15.716$, $p < .001$, with attendance, numbers of hours spent on

[1] For VLE data Non-parametric Spearman's correlations were run as data were not normally distributed.

Blackboard and the number of weekly online tests conducted being significant predictors. A second regression (Model B) was run including only the three significant predictors $F(3, 206) = 28.907$, $p < .001$. This model explained 29% of the variance in the grades, with all three variables adding significantly to the model $p<.05$. To see the unique variance explained by each predictor, the *relaimpo* package and *lmg* metric on the software R version 4.02 were used to calculate decomposed $R^2$-values for each predictor, with the number of hours on Blackboard being the most important predictor (see Table 2 for coefficients and $R^2$values).

[Insert Table 2 here]

Similar results were found for the second-year module, with attendance, $r(150) = .432$, $p < .001$, and the number of hours spent on Blackboard, $r_s(150) = .477$, $p < .001$, significantly correlated with module mark. The specific Blackboard activity that was significantly correlated with the module grade was the number of times students had accessed "*Study Materials*", $r_s(150) = .341$, $p < .001$ and “*Assessment Details*”, $r_s(150) = .176$, $p =.030$. The number of lecture recordings views was also a significant predictor $r_s(150) = .218$, $p =.007$, with 69% ($n$=105) of the students viewing lecture recordings at least once during the term. A multiple regression (Table 2) showed that these variables explained 35% of the variance in the second-year module grade, $F(5, 146) = 16.799$, $p < .001$ adj $R^2$=.346, with attendance, Blackboard activity hours and the number of lecture recording views being significant predictors of module grade. To further explore this, a new model was run, including only the significant predictors as well as the first-year research methods grade. The new model explained 49% of the variance in the second-year module grades, $F(4, 147) = 37.086$, $p < .001$, adj $R^2$=.498, indicating that previous attainment was the best predictor of students grades followed by Blackboard activity (see Table 2 for coefficients and $R^2$ values).

***Cross- Lagged Models***

To assess the longitudinal reciprocal associations between Grades and VLE activity, we next conducted comparisons between a series of nested cross-lagged models. Module grades and total Blackboard activity hours for both year 1 and year 2 were included in the models. The models were analysed using maximum likelihood estimation in the *Lavaan* package (version 0.6) on the software R version 4.02.

Firstly, the autoregressive model (M1) was conducted, which estimates the stability of the constructs over time. The comparative fit index CFI (.95) showed a good fit to the data, whereas RMSEA (.18) and Chi-square ($\chi 2$ (2) = 11.56, $p$ <.05) and showed poor fit. The results indicating that both Blackboard Activity (standardized coefficients $\beta$ = 0.54, $p$ < .001) and Grade (standardized coefficients $\beta$ = .54, $p$ < 0.001) exhibited significant stability effects from Time 1 to Time 2. In the second model (M2), the cross-lagged pathway was added from Blackboard Activity Y1 to Y2 Grade. The model (M2) showed appropriate fit to the data ($\chi$ *2* (1) = .52, $p$=.424: RMSEA = .00, CFI = 1). All parameter estimates in the model were significant ($p$ < .05). For the third model (M3), the path leading from Y1 Grade Blackboard activity at Y2 was specified. The model (M3) showed partially appropriate fit ($\chi$ *2* (1) = 11.40, $p$ < .05; CFI = .94, RMSEA = .262). All parameter estimates in the model were significant (p < .001), except for the cross-lagged path from Grade at Time 1 to BB at Time 2, which was not significant (standardised coefficients $\beta$ = 0.08, $p$=. 269)

Finally, M4 (see Figure 2) shows the fully cross-lagged model, which included the autoregressive paths linking the same constructs across time points and the cross-lagged paths between Grades and Blackboard Activity (See Fig. 1.) As expected, the saturated model showed excellent fit to the data (RMSEA = 0.00, CFI = 1.0). Furthermore, while controlling the stability effects, the path from Blackboard Activity at Year 1 to Module grade at Year 2 was significant (standardised coefficients $\beta$ = 0.240 $p$ = .001); however, the path from year 1 grade to Blackboard activity at year 2 was non-significant (standardised coefficients $\beta$ = .05, $p$ = .576). The findings provide overall support for VLE Activity being an important predictor of module grades.

[Insert figure 2]

***Emotions and Academic Achievement***

In order to explore the final research question concerning the influence of emotions on students' learning behaviour and attainment, the self-reported survey answers were cross-referenced with the data from the VLE. In accordance with the control-value theory, the emotions were grouped into three categories Positive Activating emotions, Negative Activating emotions and Negative Deactivating emotions. Due to the relatively low sample size for the self-reported surveys, these could not be included in the previous regression analysis.

Correlational analyses (Table 4) showed that positive activating emotions at the beginning of Year 1 (time-point 1) were positively correlated with the number of weekly tests students conducted in the first-year module, $r_s(58) = .272$, $p = .035$, whereas negative deactivating emotions were negatively correlated with the number of weekly tests, $r_s(58) = -.280$, $p = .026$. Furthermore, negative deactivating emotions at the beginning of the second year (time-point 2) were negatively correlated with the second-year module grade, $r(63) = -.30$, $p = .016$, and positive emotions were positively correlated with second-year module grade $r(63)=.268$, $p=.032$. No significant correlations with activating negative emotions were found.

[Insert Table 3 here]

## Discussion

The aim of the present study was to explore the influence of VLE tools and activity on research methods learning through first year and second year, and whether academic emotions have significant relations to students learning behaviour and achievement. The results showed that the number of hours spent on the VLE positively predicted students' academic achievement in both first year and second year. These results persisted when attendance was included in the regression models, with VLE activity being a higher predictor than attendance in both years. Overall behavioural data explained between 29% and 35% of the variances in grades, indicating that these effects were stable across the first and second year. The results from the cross-lagged model reinforce these findings, with VLE activity being a significant predictor of academic achievement across years. Several specific online tools also emerged as significant predictors of academic achievement, namely "Online self-tests" and "Lecture recording viewings". For the academic emotions, some significant relationships between both module grades and VLE activity were found for negative deactivating emotions and positive activating emotions.

In line with previous research findings, the current study found attendance (Credé et al., 2010), to be one of the highest predictors of module grade. Importantly, the present study demonstrates that VLE activity was just as important for academic achievement as face-to-face attendance during research methods modules. The finding that VLE activity was an important predictor of academic achievement is consistent with previous work conducted in online and distance learning environments (Agudo-Peregrina et al., 2014). However, previous campus-based studies of VLE activity have generally found either small correlations between VLE activity and academic achievement (Boulton et al., 2018) or no correlations at all (Agudo-Peregrina et al., 2014). In contrast, the current study found moderate correlations between the number of hours spent on Blackboard and module grades.

Thus, the present study extends these earlier findings by demonstrating that the effectiveness of VLE activities and tools can also be established with face-to face based modules even for cross-lagged structural equation models and when the influence of attendance is taken into consideration. The longitudinal perspective of the current study indicates the importance of students' online engagement early on in their degree, as the results show that VLE activity in the first year has a potential causal link with attainment in the second year, although experimental control—which was not included in the present study—would have further strengthened assumptions about causality. These results are consistent with the recent findings of Summers et al. (2020), who found that early VLE engagement was a significant predictor of end of year results at a campus-based UK university.

A possible explanation for these finding could be due to the unique advantages offered by VLEs. With the help of VLEs, students can access learning materials at any time and place of their choosing, making VLEs both more accessible and flexible for students with other commitments outside of their studies, such as part-time jobs, children or caring responsibilities.

When looking at the predictiveness of VLE activity on academic achievement, it was the online tools "Online self-test" for first-year and "Lecture recording views" for the second year that were the most predictive of module grades outside of total hours spent on Blackboard, attendance and previous module grade. These findings are consistent with previous work (Tempelaar et al., 2015a, 2015b; Gardner, 2020). Tempelaar found that scores on computer-assisted formative maths and statistics tutorials were the best predictors for detecting underperforming students and academic performance. Our findings extend these results by establishing the effectiveness of voluntary online test in the specific context of psychological research methods modules.

These weekly online tests were intended as formative feedback tools, giving students a way to test their knowledge and gain feedback on their learning progress. Research has clearly shown that feedback promotes learning and achievement, with feedback being one of the most powerful factors in enhancing learning experiences (Wisniewski et al., 2020). Moreover, previous research also indicates that online formative assessment has certain advantages over traditional classroom assessment, such as students being able to take the assessment at any time, repeatedly and getting instant feedback on their progress (Bull, 1999). Thus, the use of online tests could address some of the potential challenges students encounter when studying research methods, such as statistics anxiety, given that previous research has indicated that students' anxiety can be reduced by formative assessments (Cassady & Gridley, 2005).

"Online self-tests" can also be seen to reflect more active learning tools and might be a better measure of engagement within courses than more passive tasks such as number of hours on blackboard pages. As such, these results also complement the findings of Agudo-Peregrina et al. (2014), who found that interactions involving active participation were the best predictor of academic achievement by demonstrating that active participation in other specific VLE activities can also improve learning and achievement. Given that previous research has shown that active learning activities have been associated with promoting higher-order thinking skills as well as deep learning (Prince, 2004), and better attainment in research methods (Ball & Pelco, 2006), the present study provides further evidence for employing such tools.

In terms of lecture capture, evidence of its effectiveness on attainment is less clear. While some researchers have found positive relationships between lecture capture and attainment (Cramer et al., 2007; Gardner, 2020), with evidence of lecture capture supplementing learning from-face to face lectures (Bos et al., 2016; Nordmann et al., 2019), others have argued that the impact of these might be at the expense of an overall reduction in attendance (Edwards & Clinton, 2019). The current study provides support for lecture capture being a significant predictor during research methods modules even when the influence of other engagement factors such as attendance and overall VLE activity is taken into consideration. Therefore, these findings appear to support the idea of lecture capture providing a supplement to face-to-face teaching; however, more research needs to be carried out in order to fully establish the role of lecture capture in research methods learning.

The findings of the current study also add to the literature by providing potential insight into the usefulness of academic emotion in the exploration of VLE tools in research methods learning. The results of the study indicate that both positive activating (enjoyment, hope & pride) and negative deactivating emotions (boredom & hopelessness) at the beginning of term correlated with the number of weekly online tests conducted by students in the first year. Positive and Deactivating negative emotions at the beginning of the second year were also correlated with the second-year module grade. These findings partly support the control-value theory's predictions and previous research findings (Pekrun et al., 2002; Pekrun et al., 2011).

A possible reason why first-year emotions were only correlated to the weekly online self-test and not directly to the module grade could be due to the perceived control and value of these activities. Some students might see less value in participating in these online tests, as they do not contribute to their grades, whereas others might hold more favourable feelings as they feel more in control of the learning activity than, for example, the exam or research reports. Thus, the present results offer some support for the control-value theory and emotions being useful in evaluating the influence of VLE tools and academic achievement. However, more research needs to be conducted. These results are based only on correlational research, with small to moderate r values (<0.3) and several non-significant correlations, with the voluntary nature of the self-reports making them susceptible to bias. A possible area for future research would be to incorporate achievement emotions into the regression models to see the predictive value of these for academic achievement. However, due to a relatively low sample size for the self-reported surveys, this was not possible for the current study.

Another limitation that should be acknowledged is that these results are mainly based on behavioural data gathered from the module-specific BlackBoard pages. The design and availability of information on Blackboard are not standardised, with each module containing different tools making the findings context-specific. As such, these results are hard to compare across modules and other institutions. In the current study, we were limited to testing the VLE tools (Online self-test and Lecture recordings) at the module level and could not estimate any longitudinal implications of these separately. Furthermore, although this study attempts to combine both self-reported emotion data and behavioural data, there are other forms of learning engagement that could confound these results. Future research would benefit from investigating a wider variety of sources, combining not just VLE usage and attendance data but also students use of support services and other learning networks such as friends and parents, as well as the amount of studying done “offline”, in order to more fully estimate the contributions VLE tools make for learning achievement.

In conclusion, the current study demonstrates that VLE activity and tools are useful predictors of academic achievement in research methods modules at a campus-based university and that self-reported emotional data can offer insight in evaluating the effectiveness of these. Recent trends suggest that online learning will continue to be an important part of higher education; as such, this study provides suggestions for the design of the future curriculum. Firstly, the usefulness of VLEs as a learning tool has been highlighted with early measures of online engagement, predictive of both future behaviour and future outcomes. Psychology educators should design their introductory research methods modules with this in mind, encouraging students to make use of all the VLE material available to them. A second recommendation for the curriculum is to implement more active online learning tools, as our results found these to be the best VLE predictors for achievement. Lastly, the results suggest that online engagement is just as important a predictor for academic success as attendance in research methods modules, which offers an optimistic outlook for the capacity of higher education to adapt to the challenges of pandemics.

## References:

Agudo-Peregrina, Á. F., Iglesias-Pradas, S., Conde-González, M. Á., & Hernández-García, Á. (2014). Can we predict success from log data in VLEs? Classification of interactions for learning analytics and their relation with performance in VLE-supported F2F and online learning. *Computers in Human Behavior, 31*(1), 542–550. https://doi.org/10.1016/j.chb.2013.05.031

Artino, A. R., & Jones, K. D. (2012). Exploring the complex relations between achievement emotions and self-regulated learning behaviours in online learning. *The Internet and Higher Education*, *15*(3), 170–175. https://doi.org/10.1016/j.iheduc.2012.01.006

Ball, C. T., & Pelco, L. E. (2006). Teaching research methods to undergraduate psychology students using an active cooperative learning approach. *International Journal of Teaching and Learning in Higher Education*, *17(2)*, 147–154.

Barry, J. A. (2012). Do students who get low grades only in research methods need the same help as students who get low grades in all topics in psychology? *Psychology Teaching Review, 18(2)*, 116-125

Bos, N., Groeneveld, C., van Bruggen, J., & Brand-Gruwel, S. (2016). The use of recorded lectures in education and the impact on lecture attendance and exam performance. *British Journal of Educational Technology*, *47*(5), 906–917. https://doi.org/10.1111/bjet.12300

Boulton, C. A., Kent, C., & Williams, H. T. P. (2018). Virtual learning environment engagement and learning outcomes at a 'bricks-and-mortar' university. *Computers and Education*, *126*, 129–142. https://doi.org/10.1016/j.compedu.2018.06.031

Bourne, V. J. (2018). Exploring statistics anxiety: Contrasting mathematical, academic performance and trait psychological predictors. *Psychology Teaching Review*, 24(1).

Bull, J. (1999.). Computer-Assisted Assessment: Impact on Higher Education Institutions. *Educational Technology & Society*, 2(3).

Butz, N. T., Stupnisky, R. H., & Pekrun, R. (2015). Students' emotions for achievement and technology use in synchronous hybrid graduate programmes: A control-value approach. *Research in Learning Technology*, *23*. https://doi.org/10.3402/rlt.v23.26097

Cassady, J. C., & Gridley, B. E. (2005). The Effects of Online Formative and Summative Assessment on Test Anxiety and Performance. *The Journal of Technology, Learning, and Assessment*, 4(1).

Cerezo, R., Sánchez-Santillán, M., Paule-Ruiz, M. P., & Núñez, J. C. (2016). Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. *Computers and Education*, *96*, 42–54.https://doi.org/10.1016/j.compedu.2016.02.006

Cramer, K. M., Collins, K. R., Snider, D., & Fawcett, G. (2007). The virtual lecture hall: utilisation, effectiveness and student perceptions. *British Journal of Educational Technology*, *38*(1), 106–115. https://doi.org/10.1111/j.1467-8535.2006.00598.x

Credé, M., Roch, S. G., & Kieszczynka, U. M. (2010). Class attendance in college: A meta-analytic review of the relationship of class attendance with grades and student characteristics. *Review of Educational Research*, 80 (2), 272–295. https://doi.org/10.3102/0034654310362998

Diener, E. (2000). Subjective well-being: The science of happiness and a proposal for a national index. *American Psychologist*, *55*(1), 34–43. https://doi.org/10.1037/0003-066X.55.1.34

Edwards, M. R., & Clinton, M. E. (2019). A study exploring the impact of lecture capture availability and lecture capture usage on student attendance and attainment. *Higher Education*, *77*(3), 403–421. https://doi.org/10.1007/s10734-018-0275-9

Gardner, M. R. (2020). Lecture capture adds value to attending psychological research methods lectures. *Scholarship of Teaching and Learning in Psychology*. https://doi.org/10.1037/stl0000212

Kuzilek, J., Hlosta, M., Herrmannova, D., Zdráhal, Z., & Wolff, A. (2015). OU Analyse: analysing at-risk students at The Open University. *Learning Analytics Review*, 1–16.

Linnenbrink-Garcia, L., Patall, E. A., & Pekrun, R. (2016). Adaptive Motivation and Emotion in Education. *Policy Insights from the Behavioral and Brain Sciences, 3*(2), 228–236. https://doi.org/10.1177/2372732216644450

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an “early warning system” for educators: A proof of concept. *Computers & Education*, *54*(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Morris, L. V., Finnegan, C., & Wu, S. S. (2005). Tracking student behavior, persistence, and achievement in online courses. *Internet and Higher Education*, *8*(3), 221–231. https://doi.org/10.1016/j.iheduc.2005.06.009

Murtonen, M., Olkinuora, E., Päivi, A., Ae, T., & Lehtinen, E. (2008). “Do I need research skills in working life?”: University students’ motivation and difficulties in quantitative methods courses. *Higher Education, 56(5), 599-612.* https://doi.org/10.1007/s10734-008-9113-9

Nordmann, E., Calder, C., Bishop, P., Irwin, A., & Comber, D. (2019). Turn up, tune in, don’t drop out: the relationship between lecture attendance, use of lecture recordings, and achievement at different levels of study. *Higher Education*, *77*(6), 1065–1084. https://doi.org/10.1007/s10734-018-0320-8

Oliver, M., & Trigwell, K. (2005). Can ‘blended learning’ be redeemed?. *E-learning and Digital Media,2(1),17-26.*

Onwuegbuzie, A. J., & Wilson, V. A. (2003). Statistics Anxiety: Nature, etiology, antecedents, effects, and treatments--a comprehensive review of the literature. *Teaching in Higher Education*, *8*(2), 195–209. https://doi.org/10.1080/1356251032000052447

Pekrun, R., Elliot, A. J., & Maier, M. A. (2006). Achievement goals and discrete achievement emotions: A theoretical model and prospective test. *Journal of Educational Psychology*, *98*(3), 583–597. https://doi.org/10.1037/0022-0663.98.3.583

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students’ learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology*, *36*(1), 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Pekrun, R., Goetz, T., & Perry, R. P. (2005). A*chievement Emotions Questionnaire (AEQ) - User’s manual.* Munich, Germany: University Of Munich, Department of Psychology.

Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic Emotions in Students’ Self-Regulated Learning and Achievement: A Program of Qualitative and Quantitative Research. *Educational Psychologist*, *37*(2), 91–105. https://doi.org/10.1207/S15326985EP3702_4

Pekrun, R., & Linnenbrink-Garcia, L. (2012). Academic emotions and student engagement. In *Handbook of Research on Student Engagement* (pp. 259–282). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_12

Phil Long, B., & Siemens, G. (2011). Penetrating the Fog: Analytics in Learning and Education. EDUCAUSE review,46(5),30.

Prince, M. (2004). Does Active Learning Work? A Review of the Research. *Journal of Engineering Education*, *93*(3), 223–231. https://doi.org/10.1002/j.2168-9830.2004.tb00809.x

Ruggeri, K., Dempster, M., Hanna, D., & Cleary, C. (2008). Experiences and expectations: the real reason nobody likes stats. *Psychology Teaching Review*, *14*, 75–83.

Stephan, M., Markus, S., & Gläser-Zikuda, M. (2019). Students' Achievement Emotions and Online Learning in Teacher Education. *Frontiers in Education*, *4*, 109. https://doi.org/10.3389/feduc.2019.00109

Summers, R. J., Higson, H. E., & Moores, E. (2020). Measures of engagement in the first three weeks of higher education predict subsequent activity and attainment in first year undergraduate students: a UK case study. *Assessment & Evaluation in Higher Education*, 1–16. https://doi.org/10.1080/02602938.2020.1822282

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015a). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior*, *47*, 157–167. https://doi.org/10.1016/j.chb.2014.05.038

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015b). Stability and sensitivity of Learning Analytics based prediction models. P*roceedings of 7th International conference on Computer Supported Education, 23-25, May 2015*, Lisbon, Portugal

Turnbull, D., Chugh, R., & Luck, J. (2020). Learning management systems: a review of the research methodology literature in Australia and China. *International Journal of Research & Method in Education*, 1-15. https://doi.org/10.1080/1743727X.2020.1737002

Wisniewski, B., Zierer, K., & Hattie, J. (2020). The Power of Feedback Revisited: A Meta-Analysis of Educational Feedback Research. *Frontiers in Psychology*, *10*, 3087. https://doi.org/10.3389/fpsyg.2019.03087

**Table 1**

*Means, standard deviations, and zero-order correlations for all behavioural data including attendance, Blackboard activity and students' overall grade for year 1 module and the year 2 module.*

| | Descriptive Statistics | | | Zero Order Correlations | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year 1: | N | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 1. Grade | 210 | 51.55 | 13.39 | - | | | | | | | | | | | | |
| 2. Attendance % | 210 | 40.61 | 22.16 | **.37$^{***}$** | - | | | | | | | | | | | |
| 3. Blackboard Hours | 210 | 30.26 | 21.32 | .51$^{***}$ | .37$^{***}$ | - | | | | | | | | | | |
| 4. Coursework info Clicks | 210 | 12.25 | 7.47 | .26$^{***}$ | .13 | .47$^{***}$ | - | | | | | | | | | |
| 5. Module Info Clicks | 210 | 5.98 | 4.70 | .26$^{***}$ | .08 | .31$^{***}$ | .40$^{***}$ | - | | | | | | | | |
| 6. Study Material Clicks | 210 | 32.12 | 20.36 | .42$^{***}$ | .38$^{***}$ | .66$^{***}$ | .56$^{***}$ | .47$^{***}$ | - | | | | | | | |
| 7. No of Weekly Tests | 210 | 2.70 | 3.50 | .40$^{***}$ | .22$^{**}$ | .59$^{***}$ | .40$^{***}$ | .28$^{***}$ | .45$^{***}$ | - | | | | | | |
| Year 2: | | | | | | | | | | | | | | | | |
| 8. Grade | 152 | 57.26 | 12.01 | **.56$^{***}$** | **.36$^{***}$** | .40$^{***}$ | .19$^{*}$ | .06 | .28$^{***}$ | .33$^{***}$ | - | | | | | |
| 9. Attendance % | 152 | 36.24 | 22.55 | **.27$^{**}$** | **.67$^{***}$** | .37$^{***}$ | .22$^{*}$ | .04 | .33$^{***}$ | .33$^{***}$ | **.43$^{***}$** | - | | | | |
| 10.Blackboard Hours | 152 | 31.62 | 19.00 | .26$^{**}$ | .26$^{**}$ | .58$^{***}$ | .40$^{***}$ | .21$^{**}$ | .36$^{***}$ | .37$^{***}$ | .48$^{***}$ | .35$^{***}$ | - | | | |
| 11.Lecture recording Views | 152 | 7.80 | 10.61 | .17$^{*}$ | .01 | .29$^{***}$ | .17$^{*}$ | .15 | .19$^{*}$ | .18$^{*}$ | .22$^{**}$ | .01 | .38$^{***}$ | - | | |
| 12.Module Handbook Clicks | 152 | 4.36 | 3.95 | -.02 | -.13 | .14 | .22$^{**}$ | .39$^{***}$ | -.01 | .04 | .10 | -.05 | .31$^{***}$ | .28$^{**}$ | - | |
| 13.Study Material Clicks | 152 | 54.18 | 31.69 | .16$^{*}$ | .21$^{**}$ | .43$^{***}$ | .50$^{***}$ | .26$^{**}$ | .25$^{**}$ | .27$^{***}$ | .34$^{***}$ | .27$^{**}$ | .62$^{***}$ | .44$^{***}$ | .41$^{***}$ | - |
| 14.Assessment Detail Clicks | 152 | 17.60 | 9.51 | .04 | .05 | .18$^{*}$ | .40$^{***}$ | .28$^{***}$ | .17$^{*}$ | .20$^{*}$ | .18$^{*}$ | .17$^{*}$ | .46$^{***}$ | .20$^{*}$ | .35$^{***}$ | .57$^{***}$ |

**p*<.05, ***p*<.01, ***p*<.001, Note: Bold indicates Pearson's correlation coefficients; all others are non-parametric (Spearman's Rank) correlations

**Table 2**

*Summary of Multiple Regression Analyses for Variables Predicting Year 1 (N=210) and Year 2 module grade (N=152)*

| | Model A | | | | | | Model B | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | B | SE B | β | t | $R^2$ | *p* | B | SE B | β | t | $R^2$ | *p* |
| Year 1: | | | | | | | | | | | | |
| Blackboard Hours | .129 | .053 | .206 | 2.42 | **.091** | .016 | .173 | .050 | .275 | 3.49 | **.126** | .001 |
| Attendance % | .125 | .039 | .206 | 3.22 | **.069** | .001 | .136 | .038 | .225 | 3.59 | **.081** | <.001 |
| No of Weekly Tests | .660 | .290 | .173 | 2.28 | **.069** | .024 | .736 | .289 | .193 | 2.55 | **.089** | .011 |
| Study Materials Clicks | .097 | .052 | .173 | 2.28 | .058 | .062 | | | | | | |
| Module Info Clicks | .177 | .190 | .062 | .931 | .020 | .353 | | | | | | |
| Coursework Info Clicks | -.042 | .133 | -.024 | -.33 | .015 | .746 | | | | | | |
| Year 2: | | | | | | | | | | | | |
| Blackboard Hours | .182 | .055 | .287 | 3.318 | **.125** | .001 | .125 | .034 | .234 | 3.950 | **.132** | <.001 |
| Attendance % | .167 | .037 | .313 | 4.453 | **.122** | <.001 | .165 | .041 | .261 | 4.001 | **.106** | <.001 |
| Lecture recordings Views | .198 | .081 | .174 | 3.318 | **.046** | .015 | .181 | .069 | .161 | 2.641 | **.049** | .009 |
| Study Materials Clicks | .044 | .032 | .116 | 1.369 | .058 | .173 | | | | | | |
| Assessment Details Clicks | -.039 | .099 | -.031 | -.395 | .014 | .694 | | | | | | |
| Year 1 Research Methods Grade | | | | | | | .464 | .071 | .405 | 6.549 | **.215** | <.001 |

Note: Bold indicates significant predictors

**Table 3**

*Means, standard deviations, and zero-order correlations for VLE data for year 1 and year 2, and emotions for time-point 1 and Time-point 2*

| | Descriptive Statistics | | | Zero Order Correlations | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year 1: | N | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 1.Positive Activating T1 | 60 | 3.39 | .59 | - | | | | | | | | | | | | |
| 2.Negative Deactivating T1 | 60 | 2.29 | .79 | **-.53**$^{***}$ | - | | | | | | | | | | | |
| 3.Negative Activating T1 | 60 | 2.10 | .77 | **-.39**$^{**}$ | **.68**$^{***}$ | - | | | | | | | | | | |
| 4.Grade | 210 | 51.55 | 13.39 | **.01** | **-.12** | **-.05** | - | | | | | | | | | |
| 5.Blackboard Hours | 210 | 30.26 | 21.32 | .03 | -.08 | -.07 | .51$^{***}$ | - | | | | | | | | |
| 6.Attendance % | 210 | 40.61 | 22.16 | **-.12** | **-.11** | **.002** | **.37**$^{***}$ | .37$^{***}$ | - | | | | | | | |
| 7.No of Weekly Tests | 210 | 2.70 | 3.50 | .27$^{*}$ | .28$^{*}$ | -.09 | .40$^{***}$ | .59$^{***}$ | .22$^{**}$ | - | | | | | | |
| Year 2: | | | | | | | | | | | | | | | | |
| 8.Positive Activating T2 | 65 | 5.10 | .93 | **.60**$^{***}$ | **-.44**$^{**}$ | **-.39**$^{*}$ | **.15** | -.05 | **-.04** | .001 | - | | | | | |
| 9.Negative Deactivating T2 | 65 | 2.32 | .77 | **-.36**$^{*}$ | **.60**$^{***}$ | **.54**$^{***}$ | **-.31**$^{*}$ | -.11 | **-.19** | -.18 | **-.59**$^{***}$ | - | | | | |
| 10.Negative Activating | 65 | 2.31 | .78 | **-.25** | **.43**$^{**}$ | **.53**$^{**}$ | **-.11** | .03 | **-.12** | -.02 | **-.56**$^{***}$ | **.84**$^{***}$ | - | | | |
| 11.Grade | 152 | 57.26 | 12.01 | **.13** | **-.25** | **-.21** | **.56**$^{***}$ | .40$^{***}$ | **.36**$^{***}$ | .33$^{***}$ | **.27**$^{*}$ | **-.30**$^{*}$ | **-.16** | - | | |
| 12.Blackboard Hours | 152 | 31.62 | 19.00 | -.04 | -.04 | .12 | .26$^{**}$ | .58$^{***}$ | .26$^{***}$ | .37$^{***}$ | -.16 | .14 | .20 | .48$^{***}$ | - | |
| 13.Attendance % | 152 | 36.24 | 22.55 | **.02** | **-.22** | **-.08** | **.27**$^{**}$ | .37$^{***}$ | **.67**$^{***}$ | .33$^{***}$ | **.07** | **-.16** | **.01** | **.43**$^{***}$ | .35$^{***}$ | - |
| 14.Lecture Recording Views | 152 | 7.80 | 10.61 | .08 | -.01 | .22 | .17$^{*}$ | .29$^{***}$ | .01 | .18$^{*}$ | .09 | -.20 | -.08 | .22$^{**}$ | .38$^{**}$ | .01 |

$^{*}p<.05$, $^{**}p<.01$$^{***}p<.001$, Note: Bold indicates Pearson's correlation coefficients; all others are non-parametric (Spearman's Rank) correlations.

**Figure 1**

*Flow diagram of sample consisting of behavioural data for year 1 and 2 & Self-reported survey data for T1 & T2*

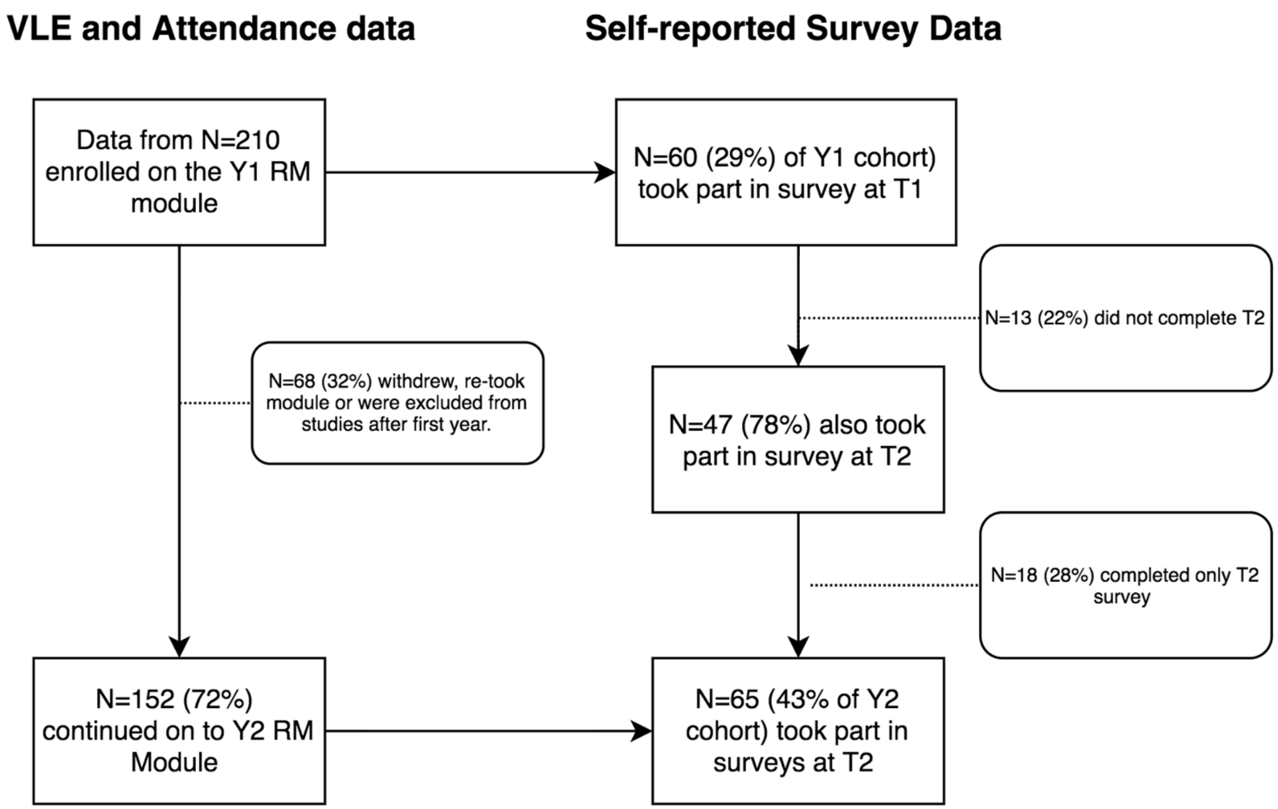
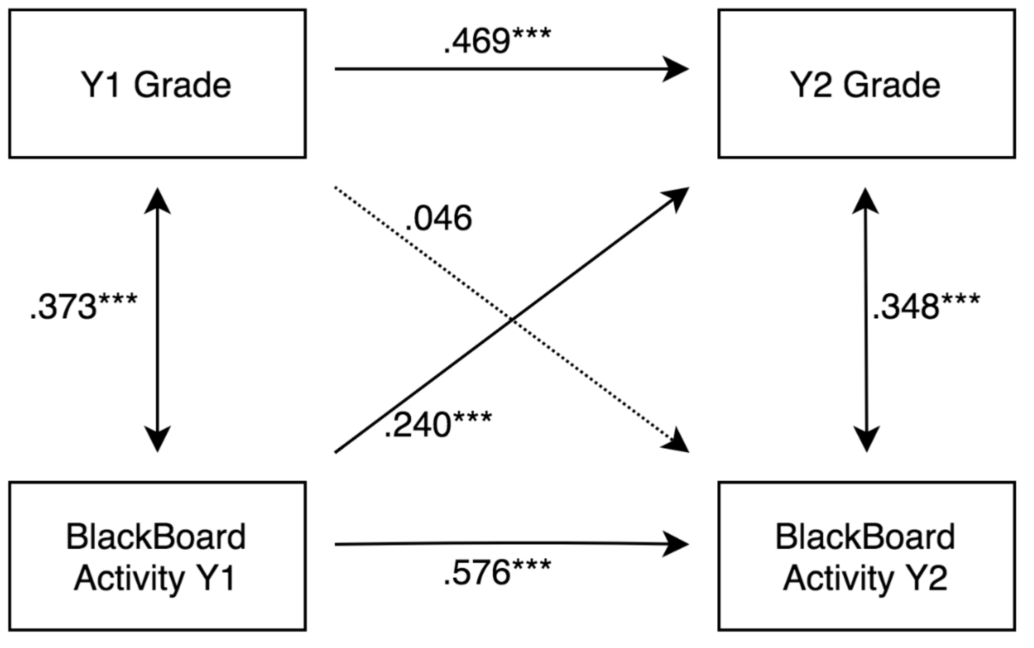


**Figure 2**

*M4- Autoregressive cross-lagged final model. Note: Solid lines represent significant pathways, dotted lines represent non-significant pathways*




****p<.001*