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Technology Enhanced Learning in Higher Education; motivations, engagement and academic achievement

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Abstract

Technology Enhanced Learning (TEL) has become a common feature of Higher Education. However, research has been hindered by a lack of differentiation between usage and engagement and not recognising the heterogeneity of TEL applications. The current study aimed to assess the impact of emotional, cognitive and behavioural engagement with TEL on students' grades and to also look at how motivation levels differentially predict engagement across different types of TEL. In a sample of 524 undergraduate students, we measured engagement and usage of TEL, student learning motivations and self-report student grades. Our results indicate that intrinsic motivations predict engagement, whilst extrinsic motivations predict usage. Importantly, engagement was predictive of grades whereas usage was not. Furthermore, when TEL was broken down by type, the use of social media groups was a significant predictor of grade, whereas reviewing lecture slides/ recordings, reading additional content and using course blogs/ discussion boards were not. We conclude that a sole focus on usage of TEL is misleading. Implications for researchers and educators are discussed.

Keywords; academic achievement; improving classroom teaching; interactive learning environments; student engagement; technology enhanced learning.

1. Introduction

Over the last decade, the use of Technology Enhanced Learning (TEL) has increased exponentially in Universities across the UK, partly due to Government incentives and also to meet students' expectations (UCISA, 2016). TEL can be considered as any form of e-learning and can be used to refer to technology enhanced classrooms and learning with technology (HEA, 2019). Alongside this, an emerging literature has begun to discuss the pedagogical value of TEL (Kirkwood & Price, 2014). At least conceptually, there are clear reasons to believe that TEL confers some pedagogical benefits (Beetham & Sharpe, 2013). For example, researchers have argued that TEL can allow students to explore educational content both in line with their own interests and at their own pace (de Jong & van Joolingen, 1998), that TEL can place the students themselves in charge of their learning, rather than learning being purely teacher led (Saye & Brush, 2007) and even that TEL can be used as a means of closing the attainment gap in education (Becker et al., 2017). In terms of whether TEL promotes better learning outcomes, researchers have often conflated positive student appraisals with academic benefits (Henderson et al., 2015; Heflin, Shewmaker, & Nguyen, 2017). The literature explicitly focusing on whether TEL confers academic advantages appears to be mixed, with some studies showing evidence of gains (e.g., Fonseca et al., 2014) and others showing evidence of negative outcomes (e.g., Jacobsen & Forste, 2011). Rather than reflecting some fundamental issue about TEL, we argue here that this better reflects several issues within the literature. These issues, which the current paper aims to address include (i) the operationalising of engagement with TEL, (ii) disentangling the effects of motivation from those of TEL, and (iii) recognising and accounting for the heterogeneity of TEL itself.

1.1. Measuring Engagement With TEL

A common feature of previous studies has been a focus on whether, and/or how long for, such technologies are being used. Frequently, this is measured in terms of usage of TEL, in terms of number of times students access materials, click on a hyperlink, or time spent on web pages/ apps (e.g., Fikes et al., 2018). However, research has shown that such indicators are best conceptualised as behavioural engagement; simply one component of engagement, which is understood as comprising three separate, but related components; emotional, cognitive and behavioural (Fredricks, Blumenfeld, & Paris, 2004).

The role of behavioural engagement as a component of engagement more generally has a long history in the educational literature (e.g., Wu & Huang, 2007). In the 1980s and 1990s, engagement in education was defined narrowly, in terms of "time and effort" (Australian Council for Educational Research, 2010), which was viewed purely mechanistically and was captured via the amount of time spent in the classroom, looking at the front of the class and frequency of attendance (Capie & Tobin, 1981). More recently, this has come to be accepted as insufficient (Kahu, 2013). The current prevalent view in the educational literature is that such behavioural activities comprise only one component of learning engagement, alongside cognitive and emotional components. Put simply, the cognitive component refers to the extent to which students feel challenged by the content and emotional engagement refers to the amount that the student is invested in what they are learning about and their positive emotions towards the subject(s) (Fredericks et al., 2004). This model of engagement has been validated extensively in the literature and has been found to reliably predict academic achievement in the wider academic literature (e.g., Wang & Eccles, 2012). Despite this, most research has focused on usage of TEL (e.g., data on number of unique visits and length of time spent logged in), rather than engagement more generally (Becker et al., 2017). Consequently, whilst usage can sometimes be referred to as engagement, such a definition is at odds with modern educational literature (Kahu, 2013). Measuring engagement with TEL is made more problematic due to there currently being no existing studies which look at engagement with TEL specifically. To address this gap, Havens (2014) published a list of questions, based upon the conceptual work of Fredricks and colleagues (2004) which focus on behavioural, emotional and cognitive engagement. These questions were published with the aim of helping researchers investigate engagement in the context of TEL, but this scale has so far not been operationalised in the literature. The current study expands upon this by utilising these items and empirically assessing their psychometric properties.

1.2. Motivation and Engagement

Research suggests that TEL in the UK is, for the most part, considered to be a vessel for “additional learning”. In other words, TEL is placed alongside traditional lectures and seminars and functions to compliment “core” learning. Consequently, students are free to choose to engage, or not. Research shows that students tend to hold positive views towards TEL (Kennedy & Dunn, 2018; Pechenkina & Aeschliman, 2017) and expect to see it as part of their studies (Margaryan et al., 2011). Despite this, research has shown that when students are afforded greater agency over their learning via TEL, they invest less in the task and can perform worse as a consequence (e.g., Flowerday & Schraw, 2003; Heflin, et al., 2017). More generally, a pattern of lower than expected usage has been observed across the higher education sector (UCISA, 2016).

In the education literature more broadly, research has consistently shown that engagement arises from student’s motivation (e.g., Glynn, Brickman, Armstrong, & Taasoobshirazi, 2011; Tseng & Tsai, 2010). Lin, Liu, and Yuan (2001) found that when carrying out online activities, students learn effectively only when they are highly motivated. Early research looking at TEL usage suggests that those that are intrinsically motivated may also be more driven to seek out opportunities to explore their interests, possibly in the form of TEL (Sharples et al., 2009; Oudeyer et al., 2016) and that students who use more technology tend to have higher motivation levels (Trimmel & Bachman, 2004). Tseng and Tsai (2010) showed that intrinsic motivation and self-efficacy to be highly related when engaging with online tasks, in that students who tended to engage were intrinsically motivated to do so and demonstrated high levels of self efficacy. They argue that that self-efficacy is central for enhancing intrinsic motivations to engage in an online learning environment. In line with this, there is an emerging literature which aims to explore ways in which TEL can be designed to appeal to users’ intrinsic motivations, in order to further *engage* students with TEL itself (Nacke & Deterding, 2017; Hamid, 2002). Given these previous studies’ designs, it has been difficult to disentangle the individual effects of motivation and TEL on academic attainment. One of few studies that has addressed this is Huang, Su, Yang and Liou (2017), who showed that when implementing a specific TEL-based learning technique, learning achievement improved but not learning motivation. One mediating factor between learning achievement and learning motivation may have been engagement. Thus, it is important to investigate the interrelation between learning motivations, TEL engagement and learning achievement.

1.3. The Heterogeneity of TEL

Another area in need of attention is the manner with which TEL itself is defined and measured in educational research. A closer inspection of the literature reveals that much of the apparent ambiguity of findings is explained by the heterogeneity of TEL. For instance, whilst Fonesca and colleagues (2014) focused on the application of augmented reality in architecture projects, Jacobsen and Forste (2011) looked at electronic messaging and found this to be a distraction to learning. Whereas Huang, Su, Yang and Liou (2017) found the use of digital pen learning systems (DPLS) to improve learning achievement. Other studies have conflated various forms of TEL, thus making it difficult to know which of the very different technologies may be driving any effects (e.g., Chowdhry, Sieler, & Alwis, 2014). Consequently, the specialised forms of TEL that have typically been studied (e.g., AR, DPLS etc.), arguably do not reflect the common means with which TEL is currently utilised in higher education institutions. A recent review suggests that UK institutions overwhelmingly tend to deliver TEL via the medium of VLEs (Virtual Learning Environments; UCISA, 2016). Thus, the majority of UK institutions rely on forms of TEL such as lecture slides provided online, lecture recordings provided online, additional content posted online (e.g., research articles, links to other sources), course blogs, course-specific discussion forums, and student-created social media groups (SMG). The core issue with extrapolating findings into practice is that when actually delivered, TEL comprises a wide range of separate technologies, ranging from repositories of lecture slides/recordings, to more recent advancements such as gamification and augmented reality (Becker et al., 2017). The most commonly employed VLE-style of TEL make up a range of individual technologies and the current study focused on the most frequently delivered forms. In contrast, uptake of augmented reality and gamification approaches seem to be measured. Consequently, there is a clear need to assess (a) individual contributions of specific components of TEL most commonly employed and (b) engagement with TEL as a whole.

1.3. Purpose of this study

The purpose of the current study was to compare the relative predictive power of usage of, and engagement with, TEL on academic achievement, in the context of students' motivation levels. Research focused on academic attainment/ success have operationalised this in a number of ways, such as completion rates, but most commonly, student grades (e.g., Boticki et al., 2015). Consistent with the wider literature, the current study used self-report grades, an approach which has been validated in previous studies (e.g., Rashid & Asghar, 2016). As previously mentioned, there is currently no specific measure of engagement with TEL. However, Havens (2014) provided a series of questions for researchers to use to investigate the topic. From these items, we selected the questions relevant to cognitive, emotional and behavioural engagement for use in the current study. Furthermore, we aim to investigate what motivational factors predict engagement with TEL and what specific forms of commonly available TEL were associated with academic achievement. Hence, our initial aim was to validate our engagement with TEL scale, which drew upon items provided by Havens (2014), via assessing its internal consistency and model fit, using Exploratory and Confirmatory Factor Analysis, in line with established guidelines (e.g., Cabrera-Nguyen, 2010).

Following this, we aimed to address our core hypothesis, which was:

> Does engagement, based on three components of general learning engagement (Emotional, Cognitive, Behavioural) predict student grades, over and above usage?

We also had the following research questions:

1. What types of learning motivation lead to *engagement* with TEL?
2. What types of learning motivation lead to *usage* of TEL?
3. What specific types of commonly used TEL predict academic performance?

2. Method

2.1. Participants

Data were collected during the 2016 academic year from a large U.K. Higher Education institution with an undergraduate cohort of 16,150. The study was advertised via an internal intranet to psychology students received course credits for their participation. Consequently, all respondents were undertaking psychology or psychology-related courses at undergraduate level. The resulting self-selected sample of students comprised a total of 524 participants. The mean age of respondents was 19.83 years old (SD = 2.63) with a gender distribution of 85% female and 15% male. Of the sample, 30% were completing their first year of study, 44% their second year, and 26% their third year. The majority of students stated their domicile as ‘National’ (91%).

2.2. Measures

The survey comprised three distinct sections aimed at measuring demographic information (including academic achievement), students’ motivation to learning, and TEL usage (see Appendix A). Academic achievement was assessed by asking students to estimate as accurately as possible their average grade obtained so far during their studies (as a percentage).

Learning motivations were measured using the Science Motivation Questionnaire II (SMQII) (Glynn, et al., 2011). The scale comprises twenty-five items measuring five types of learning motivation (intrinsic, career, self-determination, self-efficacy, & grade motivation). Intrinsic motivation can be described as an inherent reward gained from the learning process itself; self-determination refers to the degree to which a student feels they have control over their learning; self-efficacy relates to a student’s belief in their ability to achieve a learning outcome; career and grade motivation are goal-orient motivations that tap a more general form of extrinsic motivation, which involves learning for the purpose of gaining external rewards (Glynn et al., 2011; Koballa & Glynn, 2013). Response requires participants to rate their level of agree to each scale item using a five-point Likert scale ranging from ‘never’ to ‘always’. With the maximum score per item being 5, the maximum score per subscale (each containing five items) was 25. The SMQII has been shown to demonstrate reliable and valid psychometric properties across a range of science and non-science subjects (Glynn et al., 2011).

However, due to the lack of reliability analysis both in the UK and on psychology-specific cohorts, Exploratory (EFA) and Confirmatory Factor Analysis (CFA) were performed to establish reliability and dimensionality in the current study. Factor analysis with varimax rotation indicated a five-factor structure, as determined by employing parallel analysis (Zwick & Velicer, 1982, 1986). Using a number of well-established metrics (see section 2.4 for cut-offs), CFA of a five latent-factor model was shown to be a good fit of the data (x^2[corrected for sample size] (807.65/265) = 3.05, CFI = 0.91, RMSEA = 0.06, SRMSR = 0.05). Owing to recognised limitations of Cronbach's alpha as a measure of internal consistency (Dunn, Baguley & Brunsden, 2013), McDonald's omega, along with 95% confidence intervals, was calculated for each subscale as a metric of internal consistency. Omegas for each subscale were as follows: intrinsic = 0.78 [0.74-0.81]; self-determinism = 0.90 [0.88-0.92]; career = 0.82 [0.79-0.84]; self-efficacy = 0.85 [0.82-0.87]; grade = 0.82 [0.79-0.85]. This suggests the SMQII to be a reliable measure, in terms of internal consistency of each subscale and overall factor structure, when applied in a UK psychology-specific cohort.

TEL usage was assessed by asking subjects to estimate their frequency of TEL usage per day across a range of TEL applications. TEL applications included, lecture slides provided online, lecture recordings provided online, additional content posted online (e.g., research articles, links to other sources), course blogs, course-specific discussion forums, and student-created social media groups (SMG). Response was captured using a five-point Likert scale ranging from '0 times' to '7+ times' per week, during term-time.

2.3. Procedure

Participants were recruited via an online recruitment process and were awarded research credits for their time. The survey link was placed on an internal participation recruitment website where students were informed about the research aims. Ethical approval was provided prior to data collection by the host institution. All participants were provided with informed consent prior to taking part and were reminded of their right to withdraw at any point, without consequence. Anonymity was ensured via the use of unique identifiers and all participants were informed that their data would be dealt with confidentially and that it was only to be used to research purposes.

2.4. Data analysis

Analysis was conducted in line with standard guidelines (Chin, 1998; Hair et al., 2010; Zwick & Velicer, 1982, 1986). Specifically, exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were used to test the reliability and dimensions of multiple item scales (i.e., SMQII and TES). Regarding the Structural Equation Models (SEM), we followed Hair and colleagues' (2010) guidelines. Having outlined our theoretical model, we constructed relevant path diagrams (see Figure 1) and then specified a series of latent and observed factors comprising the relevant variables for each model (see Figure 1 and Table 4). Unstandardized parameters estimates were calculated using maximum likelihood estimation.

Indices measuring model fit for both CFA and SEM models included the Chi-square goodness of fit value (p>0.05), Comparison of Fit Index (CFI>0.95), Root Mean Square Error of Approximation (RMSEA<0.05), Standardized Root Mean Square Residual (SRMR<0.08), and Akaike Information Criterion (a lower AIC is better). A model with a good level of fit should meet the criteria set out above in parentheses (Kline, 2011; Hu & Bentler, 1999). Linear modelling was used when only observed, not latent, variables comprised the model (e.g., Model 4 – Academic achievement predicted by frequency of TEL use). Internal consistency (reliability) for each scale/subscale was calculated using McDonalds Omega (see Dunn et al., 2013).

3. Results

3.1. A measurement of TEL engagement (TES)

To address the first objective of this research, a scale for measuring TEL engagement was constructed and assessed for its psychometric properties. After selecting relevant items from Haven's conceptualisation of TEL engagement and the consensus of what comprises learning engagement more generally, a seven-item scale was developed (see Table 1 for the scale items).

Table 1. All items comprising the TEL Engagement Scale (TES)

Component of TEL engagement	*Item*
Emotional	How meaningful do you find the topics you study using TEL
	I am personally interested in the topics I learn about in TEL
	I have meaningful interactions with other students while using TEL
Cognitive	I feel like I can improve my learning by working on TEL
	The content and questions in TEL challenge me
	Using TEL helps me understand the content
Behavioural	How often do you go back and review material from earlier sessions using TEL

Three items were included to represent emotional engagement, three items cognitive engagement, and one item behavioural engagement. A factor analysis using varimax rotation indicated a one-factor solution, as determined by way of parallel analysis (Zwick & Velicer, 1982, 1986). Inspection of the factor loadings showed all items, with the exception of Item 3 ("I have meaningful interactions…"), met the minimum requirement as set out by Hair, Anderson, Tatham and Black (1998) (i.e., loading>0.30). The six remaining items explained close to 50% of the variance in the latent factor and were retained for the TES. In order to confirm dimensionality of the scale, one-factor and three-factor solutions were compared. Results showed the one-factor solution to be a significantly better fit of the data (see Table 2), suggesting all items are measuring a single underlying construct (i.e., TEL engagement). Absolute fit indices showed the one-factor solution to be a good fit of the data (see Table 3). Internal consistency of the scale was assessed using McDonald's Omega (see Dunn et al., 2013). Results showed internal consistency of the measure to be good with an Omega value of

0.74 (95% CI = 0.69-0.79), suggesting items are consistently measuring the same underlying construct of TEL engagement.

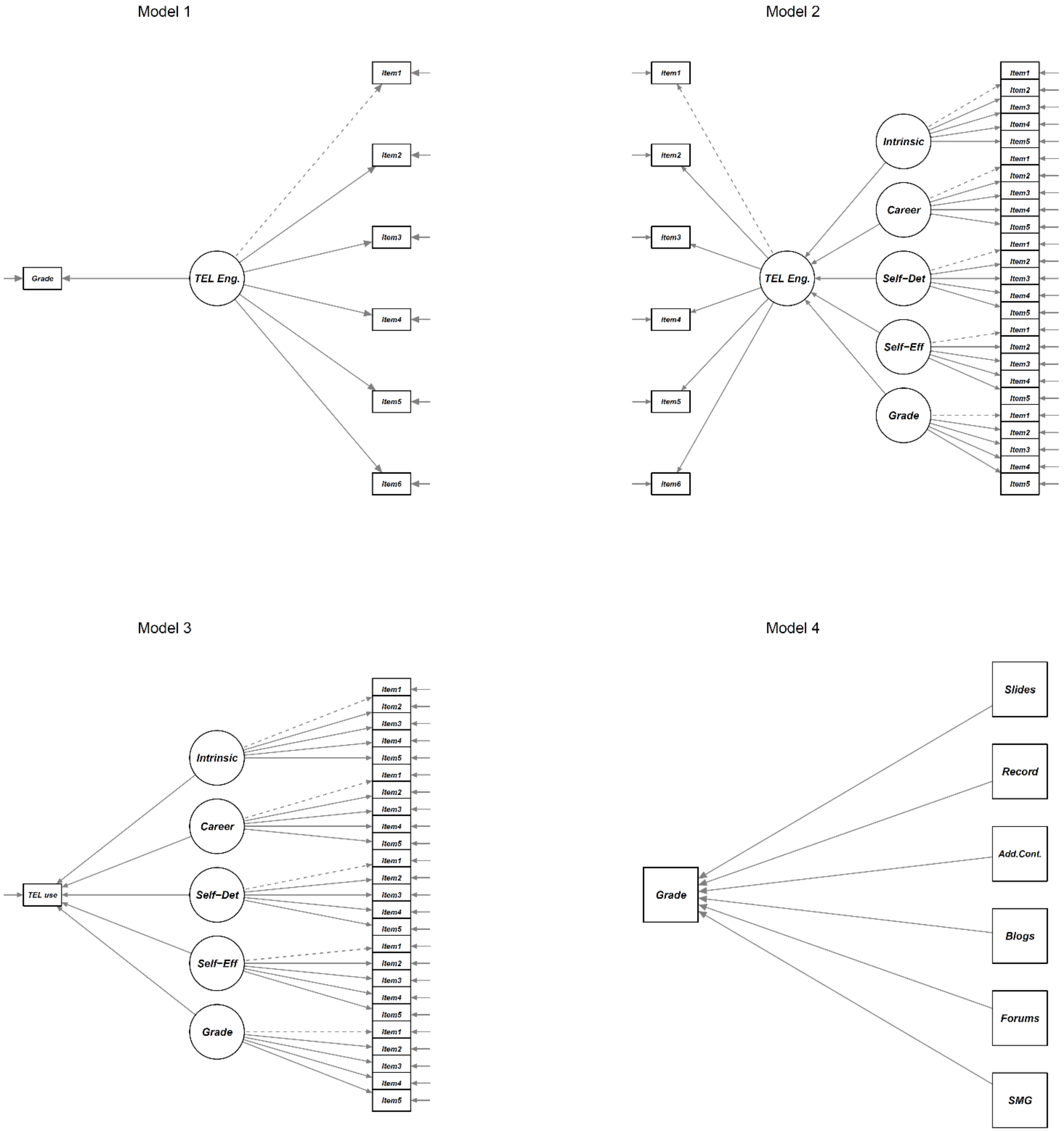
Table 2. Model comparisons for a one- and two-factor model of TEL engagement

	Df	*AIC*	*BIC*	x^2	*p*-value
Three-factor model	12	7659	7725	61.39	
One-factor model	14	7663	7722	70.16	0.01

3.2. TEL Engagement predicting academic achievement

SEM was used to examine the power of TEL engagement (as measured using the TES) as a predictor of academic performance. Results showed that the overall model was a good fit of the data (see Figure 1 and Table 3 – Model 1) and that TEL engagement significantly predicts academic achievement (see Table 4 – Model 1). This suggests that as TEL engagement increases, so too does grade.

Figure 1. Path diagrams for all structural and linear models



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3.3. Students' learning motivations as predictors of TEL engagement and TEL usage

In order to explore which general learning motivations might predict TEL engagement, an SEM was specified (see Figure 1 and Table 3 – Model 2). Results showed intrinsic learning motivations and grade motivations to significantly predict TEL engagement (see Table 4 – Model 2), suggesting individuals who are predominantly motivated by the intrinsic nature of learning or enhancing their grades tend to engage with TEL. As previously highlighted, the distinction between TEL usage and TEL engagement is an important one. In line with this, further analysis was conducted to established whether the same or different learning motivations where related to TEL usage as opposed to engagement. Results showed different learning motivations were related to TEL usage as opposed to engagement. Specifically, results show that self-determined learning motive predicts TEL usage (see Figure 1 and Table 4 – Model 3).

Table 3. Absolute fit indices for all CFA and SEM models

Model type	Model	x^2	*df*	*SRMR*	*RMSEA*	*CFI*	*AIC*
CFA							
	TEL engagement scale	15.58	9	0.03	0.04	0.99	8167.92
SEM							
	Model 1: Academic achievement ~ TEL engagement	28.99	379	0.03	0.05	0.97	8717.34
	Model 2: TEL engagement ~ Learning Motivations	1075.38	419	0.06	0.05	0.90	30450.80
	Model 3: TEL usage ~ Learning Motivations	846.94	285	0.05	0.06	0.91	26603.75

Table 4. Parameter estimates for all specified models

Model		*Estimate*	*SE*	*Z*-value	p-value
1	**Academic achievement ~**				
	TEL engagement	2.28	0.91	2.49	0.01*
2	**TEL engagement ~**				
	Intrinsic	0.39	0.14	2.79	0.01**
	Career	-0.04	0.09	-0.46	0.64
	Self-determined	0.06	0.06	0.97	0.33
	Self-efficacy	0.03	0.05	0.64	0.52
	Grades	0.30	0.11	2.84	0.01**
3	**TEL usage ~**				
	Intrinsic	0.69	0.89	0.79	0.43
	Career	0.82	0.58	1.42	0.16
	Self-determined	0.98	0.40	2.48	0.01**
	Self-efficacy	-0.26	0.340	-0.78	0.44
	Grades	-0.93	0.67	-1.39	0.16
4	**Academic achievement ~**				
	Intercept	67.83	1.92		
	Lecture slides	-0.65	0.42	-1.52	0.13
	Recordings (lectures)	-0.21	0.45	-0.59	0.55
	Additional content	-0.06	0.39	-0.15	0.87
	Blogs	-0.60	0.57	-1.04	0.29
	Discussion forums	-0.14	0.60	-0.23	0.81
	Social media groups	0.58	0.30	1.09	0.05*

Note: ‘*’= $p<0.05$; ‘**’= $p<0.01$; ‘~’ = predicted by

3.4. Frequency of TEL usage predicting academic achievement

Results of linear modelling show that TEL usage, as measured by way of summing frequency of use across all TEL formats, is not sufficient to predict academic achievement ($\beta = -0.09$, $t\,(393) = -0.95$, $p = 0.34$). However, when broken down into constituent forms of TEL, it does show that frequency of social media groups usage does significantly predict academic achievement (see Figure 1 and Table 4 – Model 4). With more frequent use of social media groups, academic achievement increases.

4. Discussion

The current study makes three important contributions to the literature. Most centrally, with regards to how we conceptualise engagement with TEL. Specifically, our findings suggest that engagement with TEL when defined as comprising emotional, cognitive and behavioural components confers a direct benefit to educational attainment. Critically, in contrast there was no association between TEL behavioural engagement alone (i.e., usage) and academic achievement. This finding is line with the education literature more generally (e.g., Fredericks, Blumenfeld, & Paris, 2004) which show that engagement is better understood as a broader concept than how it is typically operationalised in TEL research (e.g., Fikes et al., 2018).

Our results raise concerns about the common reliance upon usage as an indicator of engagement with, and consequently the pedagogical value of, TEL. Specifically, the frequency of which students used TEL as a whole was a poor indicator of academic attainment, relative to levels of emotional, cognitive and behavioural engagement. Furthermore, if the aim is, as it is often argued to be, to increase levels of intrinsic motivations and consequently ‘deeper’ learning, reliance on usage alone is misleading, as usage was found to be predicted by extrinsic motivation, whereas engagement was found to be predicted by intrinsic motivations. Also, our results show that students who rated themselves as high in self-determination also used TEL more frequently. In this scale, self-determination refers to the “control students believe they have over their learning” (Glynn et al., 2011). Various authors have argued that TEL has the capacity to allow students to take greater responsibility for their own learning (e.g., Kirkwood & Price, 2014). The current study partly supports this argument in that self-determined students used TEL more frequently, but did not engage to a greater extent. One possible explanation for this is that self-determined students tend to devise strategies for their learning (Glynn et al., 2011) and that accessing TEL appears from the current results to form part of these strategies, albeit in a relatively superficial manner.

This research also contributes to the field by way of a psychometrically valid measure of TEL engagement. Taken from Haven’s (2014) conceptualisation of what engagement in education should comprise, this study has constructed, empirically tested and applied three components of educational engagement to the specific domain of TEL. The findings being in line with previous theory as to how outcomes (i.e., academic achievement) relate to usage compared to engagement, illustrate the measure as being one of value for future research.

In terms of motivations, our results suggest that students who are intrinsically motivated and those who are motivated by attaining high grades tend to engage more with TEL. This is perhaps not surprising, given the wealth of literature on looking at educational attainment more generally, where intrinsic motivations and grade motivations are consistently associated with academic attainment (Whitehead, 1984). However, the current research expands upon this by being the first to look at this specifically in relation to TEL in a sample of UK-based higher education students. It could be argued that such motivations mediate the association between TEL engagement and academic attainment. In other words, TEL engagement is itself a consequence of student motivation and it is motivation, rather than TEL usage which predicts grades. However, the association between TEL engagement and academic attainment held when motivations were entered into the model, suggesting that this is not the case and that TEL engagement makes a unique contribution towards student grades.

A further contribution of the current study was the ecologically valid approach of looking at various TEL alongside one another, rather than focus on a single technology in isolation. In doing so, we were able to investigate the associations between each technology and academic achievement, whilst controlling for the effects of others. Our findings raise concern about the pedagogical value of institution-lead communicative technologies, e.g., course blogs and discussion boards, which were found to not be independent predictors of grades. In contrast, student created social media groups were a significant predictor of academic attainment. It is beyond the scope of the current study to answer exactly why this was the case, but previous work (e.g., Kennedy & Dunn, 2018) suggests that relative ease of access, mobile phone compatibility and general usability may go some way to explaining this finding. Additionally, research shows benefits of peer assessment (PA), which arguably could be considered an active component of SMG participation and lead to higher grade attainment. Topping (2009) highlights that peer feedback tends to be available more quickly and in larger quantities than teacher feedback. It also provides learners with an understanding of other students' approaches and ideas during the learning process (Butler & Hodge, 2001; Falchikov, 1995).

4.1. Limitations and future research

The current study is not without limitations. First, we employed a cross-sectional, correlation design. Consequently, it could be argued that causality is difficult to determine. An alternative explanation could include better grades increasing student self-efficacy, rather than the other way around. In order to address this issue, future research should aim to employ repeated-measures designs. Second, the current sample contained a high proportion of females. Whilst quite typical of the social sciences and many other subjects, this does mean that it may be difficult to generalise the findings to other students with a greater proportion of male students. Third, academic achievement was captured via self-report. This may have led to some bias and students may have over-estimated their grades. In order to address this, the current study used a model which allowed for some error in student grades.

Importantly, there is an ever-increasing range of TEL available, such as learning analytics and gamification (Gañán et al., 2016). It may well be the case that for some pedagogical reason, such technologies may well contribute directly to student grades. The inclusion of such technologies was beyond the scope of the current study, which aimed to address the contribution of technology currently used, rather than new and novel approaches.

A further limitation of the study was arguably our measurement of engagement with TEL. Specifically, we relied on pre-existing items identified in the literature, as there is currently no published scale. Our results suggest that the items chosen represented a good model fit, had high internal consistency and clearly demonstrated predictive validity, which are core components of scale validation (Bostic, Rubio & Hood, 2000). However, we would argue that there is a clear need for a broader measure which has been validated in more ways. Until such a scale is created, we argue that the smaller scale used here (TES) is appropriate for use.

Future research should aim to utilise experimental designs, which will help overcome some of the issues associated with cross-sectional work, such as the current study. For instance, it is likely that the media with which students receive information will have an impact on memory recall (e.g., live lecture recordings vs online lecture recordings). Accordingly, manipulating such variables would go some way to inform TEL's impact on the processes that underlie learning (although the current study does highlight the importance of intrinsic motivations to learn). Furthermore, given the negative associations and the suggestions from the wider literature that students may engage with TEL at the detriment of engaging with learning more generally, future work should include variables such as attendance as covariates. Given the link between self-determination and accessing, but not engaging with TEL, an important direction for future research could be to look at why students do not go on to engage with TEL.

5. Conclusions

Consistent with educational literature on academic engagement more generally, behavioural engagement with TEL should be considered alongside emotional and cognitive engagement, rather than in isolation. Consequently, whilst data on frequency of use and duration of time spent logged into a VLE or accessing certain materials may be readily generated by software, such data is likely to be a poor predictor of academic attainment. Whilst TEL is highly valued by students and institutions are eager to implement it, it is clear that simply providing resources is insufficient. Furthermore, whilst institution lead discussion boards and user generated social media groups might on the face of it play similar roles, the former were not found to predict grades, the latter was.

Highlights

- Engagement with, rather than usage of, TEL predicted academic achievement.
- Intrinsically motivated students were more likely to engage with TEL.
- In terms of specific technologies, student-created social media activity was most predictive of grades.

References

Australian Council for Educational Research. (2010). Doing more for learning: Enhancing engagement and outcomes. Australasian Student Engagement Report. Camberwell: ACER.

Becker, S. A., Cummins, M., Davis, A., Freeman, A., Hall, C. G., & Ananthanarayanan, V. (2017). *NMC horizon report: 2017 higher education edition* (pp. 1-60). The New Media Consortium.

Beetham, H., & Sharpe, R. (Eds.). (2013). *Rethinking pedagogy for a digital age: Designing for 21st century learning*. Routledge.

Bostic, T. J., Rubio, D. M., & Hood, M. (2000). A validation of the subjective vitality scale using structural equation modeling. *Social Indicators Research*, *52*(3), 313-324.

Boticki, I., Baksa, J., Seow, P., & Looi, C. K. (2015). Usage of a mobile social learning platform with virtual badges in a primary school. *Computers & Education*, *86*, 120-136.

Butler, S. A., & Hodge, S. R. (2001). Enhancing student trust through peer assessment in physical education. *Physical Educator*, 58, 30−41.

Cabrera-Nguyen, P. (2010). Author guidelines for reporting scale development and validation results in the Journal of the Society for Social Work and Research. Journal of the Society for Social Work and Research, 1(2), 99-103.

Capie, W., & Tobin, K. (1981). Pupil engagement in learning tasks: A fertile area for research in science teaching. Journal of Research in Science Teaching, 18(5), 409 – 417.

Chin, W. W. (1998). Issues and Opinion on Structural Equation Modeling. *Management Information Systems Quarterly*, 22(1).

Chowdhry, S., Sieler, K., & Alwis, L. (2014). A study of the impact of technology-enhanced learning on student academic performance. *Journal of Perspectives in Applied Academic Practice*, *2*(3).

De Jong, T., & Van Joolingen, W. R. (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of educational research*, *68*(2), 179-201.

Dunn, T. J., Baguley, T., & Brunsden, V. (2013). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British Journal of Psychology*, *105*(3), 399-412.

Falchikov, N. (1995). Peer feedback marking: Developing peer assessment. *Innovations in Education and Training International*, 32(2), 175−187.

Fikes, T., Arcuria, P., Morgan, W., & Pugliese, L. (2018). ASU Online Performance Gap Analysis. Retrieved September 23, 2018, from Arizona State University website: https://doingwhatmatters.cccco.edu/portals/6/docs/OCC/CACC_Performance_Gap_Analysis_Working_Paper_Summary_02082018.pdf

Flowerday, T., & Schraw, G. (2003). Effect of choice on cognitive and affective engagement. *Journal of Educational Research*, *96*(4), 207 – 215.

Fredericks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, 74, 59 – 109.

Fonseca, D., Martí, N., Redondo, E., Navarro, I., & Sánchez, A. (2014). Relationship between student profile, tool use, participation, and academic performance with the use of Augmented Reality technology for visualized architecture models. *Computers in Human Behavior*, *31*, 434-445.

Gañán, D., Caballé, S., Clarisó, R., & Conesa, J. (2016, November). Evaluation of an eLearning platform featuring learning analytics and gamification. In *International*

Conference on P2P, Parallel, Grid, Cloud and Internet Computing (pp. 947-959). Springer, Cham.

Glynn, S. M., Brickman, P., Armstrong, N., & Taasoobshirazi, G. (2011). Science motivation questionnaire II: Validation with science majors and nonscience majors. *Journal of research in science teaching*, *48*(10), 1159-1176.

Hamid, A. A. (2002). e-Learning: Is it the "e" or the learning that matters? The Internet and Higher Education, 4, 311−316.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2010). SEM: An introduction. *Multivariate data analysis: A global perspective*, 629-686.

Havens, D. (2014). Measuring student engagement with learning technology. Available at: https://cdn.nearpod.com/1447960561378/w3/pdf/Measuring-Student-Engagement-with-Learning-Technology.pdf

HEA (2019). *Technology enhanced learning*. Retrieved from: https://www.heacademy.ac.uk/individuals/strategic-priorities/technology-enhanced-learning#section-2

Heflin, H., Shewmaker, J., & Nguyen, J. (2017). Impact of mobile technology on student attitudes, engagement, and learning. *Computers & Education*, *107*, 91-99.

Henderson, M., Selwyn, N., Finger, G., & Aston, R. (2015). Students' everyday engagement with digital technology in university: exploring patterns of use and 'usefulness'. *Journal of Higher Education Policy and Management*, *37*(3), 308-319.

Huang C.S.J., Su A.Y.S., Yang S.J.H. & Liou H.-H. (2017). A collaborative digital pen learning approach to improving students' learning achievement and motivation in mathematics courses, *Computers & Education*, doi: 10.1016/j.compedu.2016.12.014.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*, 1–55.

Jacobsen, W. C., & Forste, R. (2011). The wired generation: Academic and social outcomes of electronic media use among university students. *Cyberpsychology, Behavior, and Social Networking*, *14*(5), 275-280.

Kahu, K. (2013) Framing student engagement in higher education, *Studies in Higher Education, 38*(5), 758-773.

Kennedy, M. & Dunn, T. (2018). Improving the use of VLEs in Higher Education in the UK: A Qualitative Visualisation of Students' Views. *Contemporary Educational Technology*.

Kirkwood, A., & Price, L. (2014). Technology-enhanced learning and teaching in higher education: what is 'enhanced' and how do we know? A critical literature review. *Learning, media and technology*, *39*(1), 6-36.

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. New York: Guilford Press.

Koballa, T. R., & Glynn, S. M. (2013). Attitudinal and motivational constructs in science learning. In *Handbook of research on science education* (pp. 89-116). Routledge.

Margaryan, A., Littlejohn, A., & Vojt, G. (2011). Are digital natives a myth or reality? University students' use of digital technologies. *Computers & education*, *56*(2), 429-440.

Nacke, L. E., & Deterding, S. (2017). The maturing of gamification research. *Computers in Human Behavior*, *71*, 450-454.

Oudeyer, P. Y., Gottlieb, J., & Lopes, M. (2016). Intrinsic motivation, curiosity, and learning: Theory and applications in educational technologies. In *Progress in brain research* (Vol. 229, pp. 257-284). Elsevier.

Pechenkina, E., & Aeschliman, C. (2017). What Do Students Want? Making Sense of Student Preferences in Technology-Enhanced Learning. *Contemporary Educational Technology, 8*(1), 26-39.

Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior, 63*, 604-612.

Saye, J. W., & Brush, T. (2007). Using technology-enhanced learning environments to support problem-based historical inquiry in secondary school classrooms. *Theory & Research in Social Education, 35*(2), 196-230.

Sharples, M., Arnedillo-Sánchez, I., Milrad, M., & Vavoula, G. (2009). Mobile learning. *Technology-enhanced learning* (pp. 233-249). Springer, Dordrecht.

Topping, K. (2009). Peer assessment. *Theory into Practice*, 48, 20−27.

Trimmel, M., & Bachmann, J. (2004). Cognitive, social, motivational and health aspects of students in laptop classrooms. *Journal of Computer Assisted Learning, 20*, 151-158.

Tseng, S. C. and Tsai, C. C. (2010). Taiwan college students' self-efficacy and motivation of learning in online peer assessment environments, *The Internet and Higher Education*, 13(3), 164-169.

Universities and Colleges Information Systems Association. (2016). *2016 Survey of technology-enhanced learning for higher education in the UK*, University of Oxford, Oxford.

Wang, M. T., & Eccles, J. S. (2012). Adolescent behavioral, emotional, and cognitive engagement trajectories in school and their differential relations to educational success. *Journal of Research on Adolescence, 22*(1), 31-39.

Whitehead, J. (1984). Motives for higher education: A study of intrinsic and extrinsic motivation in relation to academic attainment. *Cambridge Journal of Education*, *14*(2), 26-34.

Wu, H. K., & Huang, Y. L. (2007). Ninth- grade student engagement in teacher- centered and student- centered technology- enhanced learning environments. *Science Education*, *91*(5), 727-749.

Zwick, W. R., & Velicer, W. F. (1982). Factors influencing four rules for determining the number of components to retain. *Multivariate Behavioral Research, 17*, 253-269.

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin, 99*, 432-442.

Appendix A; Questionnaires used in the current study

Table A1; Motivation scale – adapted Science Motivation Questionnaire II (SMQII) (Glynn et al., 2011).

Item	*Response format*				
	Never				*Always*
01. The course content I learn is relevant to my life.	0	1	2	3	4
02. I like to do better than other students on tests.	0	1	2	3	4
03. Learning my course content is interesting.	0	1	2	3	4
04. Getting a good grade is important to me.	0	1	2	3	4
05. I put enough effort into learning my course content.	0	1	2	3	4
06. I use strategies to learn my course content well.	0	1	2	3	4
07. Learning my course content will help me get a good job.	0	1	2	3	4
08. It is important that I get high grades in my course.	0	1	2	3	4
09. I am confident I will do well on tests/assessments.	0	1	2	3	4
10. Knowing my course content will give me a career advantage.	0	1	2	3	4
11. I spend a lot of time learning my course content.	0	1	2	3	4
12. Learning my course content makes my life more meaningful.	0	1	2	3	4
13. Understanding my course content will benefit me in my career.	0	1	2	3	4
14. I am confident I will do well on my course projects/ assignments.	0	1	2	3	4
15. I believe I can master my course’s knowledge and skills.	0	1	2	3	4
16. I prepare well for course tests and assignments.	0	1	2	3	4
17. I am curious about discoveries/ innovations in my chosen area.	0	1	2	3	4
18. I believe I can earn a high grade.	0	1	2	3	4
19. I enjoy learning my course content.	0	1	2	3	4
20. I think about the grade I will get.	0	1	2	3	4
21. I am sure I can understand my course content.	0	1	2	3	4
22. I study hard to learn my course content.	0	1	2	3	4
23. My career will involve my course content.	0	1	2	3	4
24. Scoring high on tests and assignments matters to me.	0	1	2	3	4
25. I will use skills taught on my course in my career.	0	1	2	3	4

Note; The SMQII is copyrighted and registered and is reproduced here under fair use for research. For more information about the scale and access to the scoring manual please see https://coe.uga.edu/assets/downloads/mse/smqii-components.pdf

Table A2; TEL Engagement

Component of TEL engagement	*Item*	*Response format*				
		Strongly disagree				*Strongly agree*
Emotional	How meaningful do you find the topics you study using TEL	1	2	3	4	5
	I am personally interested in the topics I learn about in TEL	1	2	3	4	5
	I have meaningful interactions with other students while using TEL	1	2	3	4	5
Cognitive	I feel like I can improve my learning by working on TEL	1	2	3	4	5
	The content and questions in TEL challenge me	1	2	3	4	5
	Using TEL helps me understand the content	1	2	3	4	5
Behavioural	How often do you go back and review material from earlier sessions using TEL	1	2	3	4	5

Table A3; TEL Usage

Item	*Response format*				
	Number of times per week				
On average during term time, how often per week do you use:					
Online lecture slides	0	1-2	3-4	5-6	7 or more
Online lecture recordings	0	1-2	3-4	5-6	7 or more
Online additional content (e.g., research articles, links to other sources)	0	1-2	3-4	5-6	7 or more
Blogs provided by the University	0	1-2	3-4	5-6	7 or more
Student created social media	0	1-2	3-4	5-6	7 or more