Investigating the role of emotions in pre-service teachers' acceptance and use of learning management systems

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Emotions play a significant role in shaping technology adoption decisions, influencing not only perceptions but also behavioural intentions. In this study, we investigated the structural relationships among online learning self-efficacy, positive and negative emotions, perceived ease of use, perceived usefulness and behavioural intention in the context of learning management system (LMS) use and acceptance. Using the technology acceptance model and control-value theory as theoretical frameworks, we tested two research models using data collected from 216 pre-service teachers enrolled in teacher education degree programmes in Turkey. The results revealed that online learning self-efficacy had a positive direct effect on positive emotions, perceived ease of use, perceived usefulness and behavioural intention as well as a negative direct effect on negative emotions. Positive emotions significantly contributed to behavioural intention, whereas negative emotions showed no significant effect, potentially due to the context of mandatory use of the LMS. The findings underscore the importance of fostering positive emotional experiences and enhancing online learning self-efficacy to promote effective LMS adoption. The study makes a novel contribution by integrating class-related achievement emotions into the technology acceptance model framework alongside online learning self-efficacy. Future research should explore the interplay of emotions and cognitive evaluations in diverse contexts, particularly voluntary versus mandatory technology use.

Implications for practice and policy:

- To enhance LMS acceptance and use, we recommend incorporating features in LMS design that foster positive emotions such as pride, enjoyment and hope.
- Teacher education programmes should offer practical training and support to help students build confidence in using LMSs, which can also enhance their emotional engagement.
- Universities and policymakers should provide training for instructors on how to create supportive, confidence-building LMS environments for students.

Keywords: technology acceptance, control-value theory, emotions, online learning self-efficacy, LMS, quantitative, structural equation modelling

Introduction

A learning management system (LMS) is a web-based platform that supports digital content delivery, interaction among learners and instructors, assessment and self-monitoring, while also enabling course registration, grade tracking and updates (Bradley, 2021). Although LMSs have been a part of instructional processes for years, their impact and importance were better understood during the global pandemic, when remote teaching became a necessity (Al-Nuaimi & Al-Emran, 2021; Mohammadi et al., 2021). The beneficial effects of LMSs on learning outcomes have been demonstrated. Etinger (2020) observed that students who showed high achievement in an online course were those who showed high levels of interaction with the course materials in the LMS. Moreover, studies have found that learner behaviours, such as login frequency, duration of access to course materials and number of downloads, are important predictors of academic achievement (Aljaloud et al., 2022; You, 2016). In addition, the use of LMS was found to play an important mediating role in increasing the effectiveness of learner interactions (Costley et al., 2022). Although the positive effects of LMSs on learning outcomes have been noted in research, LMSs, like any technology, must be adopted and used by learners to unlock their potential impact on learning. Studies on the acceptance and use of LMSs have examined variables such as perceived ease of use, perceived usefulness, attitude, performance expectancy, self-efficacy, subjective norms, system design, system accessibility, technical support, information quality and service quality (Al-Nuaimi & Al-Emran, 2021; Bervell & Umar, 2017; Cavus et al., 2022; Hamid et al., 2020; Murillo et al., 2021). However, researchers increasingly emphasise that emotions play a critical role in the acceptance and use of technologies, alongside behavioural and cognitive factors. It has been suggested that technology acceptance is difficult to explain using only cognitive-based approaches, without considering emotion-based models (Beaudry & Pinsonneault, 2010).

Recent studies have revealed the impact of emotions on technology acceptance and use. A study in this field found that positive and negative emotions significantly influenced attitudes towards ChatGPT (S. Lee et al., 2024). Another study, with pre-service teachers, found that enjoyment and frustration significantly affected the behavioural intention to use technology (Şahin & Şahin, 2022). A meta-analysis conducted by Shiau et al. (2021) found that cognitive and affective experiences mutually affect the acceptance and use of information technologies. In this context, examining the impact of emotions on learners' adoption and effective use of LMSs has emerged as an important area of focus in literature. However, investigating the role of emotions in learners' acceptance and use of LMSs within a holistic framework has generally been neglected. In this study, we adopted the technology acceptance model (TAM), developed by Davis (1989) and Davis et al. (1989) to explain individuals' acceptance and use of technology, and achievement emotions, proposed by Pekrun (2006) and based on the control-value theory (CVT; Pekrun et al., 2002) to explain emotions in academic environments, as the theoretical frameworks to examine the factors influencing pre-service teachers' LMS acceptance and use. Through this approach, the study aims to fill an important gap in the field by examining the effect of the emotional aspects on LMS adoption.

Theoretical framework and related literature

TAM

As an information systems theory, TAM was developed to predict technology acceptance by identifying causal relationships between beliefs and attitudes that influence individuals' behavioural intention (Davis et al., 1989). Two important variables of TAM, perceived ease of use – the degree to which an individual believes that using a system will not require effort – and perceived usefulness – the degree to which an individual believes that using a system will improve job performance – explain users' technology acceptance (Davis, 1989). As in many areas of life, TAM has been used to explain the acceptance and use of technology in education as well. Al-Adwan et al. (2023) examined factors affecting university students' use of metaverse-based learning platforms. Perceived usefulness was identified as the strongest effect on behavioural intention, while perceived ease of use showed no significant effect. J.-H. Han and Sa (2022) investigated university students' acceptance of online learning and their level of satisfaction with this learning method. Similar to the findings of Al-Adwan et al., perceived ease of use had no effect on students' acceptance intentions, whereas perceived usefulness had a significant effect. The growing body of research highlights how TAM continues to evolve in educational settings, with researchers introducing new variables to better understand and predict technology acceptance in learning environments.

Acceptance and use of LMSs

Like many educational technologies, the acceptance and use of LMSs have been widely studied. Research shows that perceived ease of use and perceived usefulness also have a significant impact on LMS acceptance and use (Al-Mamary et al., 2024). In addition, Galura et al. (2023) examined the design and user acceptance of a cloud-based LMS, finding strong acceptance among students, instructors and administrators, especially for its collaboration, monitoring and task facilitation features. Al-Shaikhli (2023) examined how LMS monitoring technology influenced students' continuance intention, finding that ease of use and usefulness had indirect effects, while cognitive absorption and self-regulated learning showed direct influence. In a similar study, Elfeky and Elbyaly (2023) examined students' design skills and technology acceptance in an LMS enhanced with data analytics, finding higher perceived ease of use and usefulness and an indirect effect of analytics on technology acceptance. Collectively, these findings emphasise the essential role of perceived ease of use and perceived usefulness in shaping users' acceptance, continued use and overall engagement with LMS platforms.

Online learning self-efficacy

Self-efficacy comprises a generative ability that individuals develop by transforming cognitive, social and behavioural skills into action plans (Bandura, 1982). A study conducted in online learning environments showed that self-efficacy was influenced by attitude towards online learning and digital literacy, which in turn affected peer engagement and interactions with the LMS and instructors (Prior et al., 2016). In another study, self-efficacy was found to predict academic achievement in online and blended learning environments (Broadbent, 2016). Moreover, research revealed that online learning self-efficacy significantly affected learning satisfaction (Lim et al., 2021), fully mediated the relationships between learner engagement and both learner-content and learner-learner interactions (Wang et al., 2022) as well as between perceived support and students' attitudes towards online learning technologies (J. Han & Geng, 2023) and partially mediated the relationship between motivation and learner engagement (Alemayehu & Chen, 2023).

Self-efficacy was first introduced in TAM3 as computer self-efficacy by Venkatesh and Bala (2008) and has since become a key variable in technology acceptance research. Kumar et al. (2020) found that mobile learning self-efficacy significantly influenced students' attitudes and behavioural intentions. Similarly, Liu and Pu (2023) reported a significant effect of self-efficacy on perceived ease of use and perceived usefulness of one-to-one online learning systems. Furthermore, Wang et al. (2024) demonstrated a significant effect of technology self-efficacy on students' technology acceptance among foreign language learners. These studies highlight self-efficacy as a key variable in the acceptance of mobile and online learning platforms and in shaping individuals' attitudes and intentions towards technology use.

Positive and negative emotions in academic settings

CVT examines the antecedents and effects of emotions in academic settings, as well as their impact on learning and performance (Pekrun, 2006). Pekrun et al. (2002) and Pekrun (2006) described emotions in educational settings as achievement emotions and assumed that these emotions are linked to achievement-related activities or outcomes. According to CVT, a learner's achievement emotions depend on their perceived control over the activity or outcome related to the achievement, as well as the value placed on that activity or outcome (Pekrun, 2006; Pekrun et al., 2002). For example, learners who feel competent, in control and value the lesson are more likely to enjoy it, while those lacking interest or motivation may reduce effort and are less likely to reach their full potential (Tze et al., 2022). Achievement emotions is shaped by control-value cognitive appraisals and mediate the dynamic, reciprocal relationships among appraisals, emotions, learning and performance (Pekrun, 2006; Tze et al., 2022).

Emotions have emerged as a variable frequently examined in educational research in recent years (Bakır-Yalçın & Usluel, 2024; Forsblom et al., 2021) due to their impact on learning and performance (Pekrun, 2014; Pekrun & Linnenbrink-Garcia, 2012). Research suggests that positive emotions are positively related to the learning process and outcomes, while negative emotions are negatively related (Wortha et al., 2019); however, some findings contradict this general view (Robinson et al., 2017). Emotions influence beliefs, attitudes, behaviours and decision-making processes, as well as individuals' acceptance and use of technology (Beaudry & Pinsonneault, 2010; Djamasbi et al., 2010; Qu & Chen, 2021). Although anxiety has long been studied in technology acceptance and use (Budhathoki et al., 2024; D. Y. Chen et al., 2024; Huang et al., 2022), research examining the relationship between emotional states and technology use has increased only in recent years. Studies have generally revealed that positive emotions enhance behavioural intention, while negative emotions reduce it (A. S. H. Lee & Tim, 2016). However, different emotions impact individuals' technology use in varying ways (Qu & Chen, 2021). In a pioneering study, Kay (2007) found that emotions such as anxiety, anger, happiness and sadness accompanied pre-service teachers throughout learning new software, and that negative emotions reduced their likelihood of using computers for teaching. Moridis et al. (2017) found that happiness enhanced the positive effects of perceived enjoyment, usefulness, ease of use and content on behavioural intention, while sadness and fear diminished them. In a similar study, S. Park and Yun (2024) found that situational interest influenced perceived ease of use and usefulness, positive emotions affected ease of use and negative emotions had no impact on either construct in augmented reality technology acceptance. In their study on emotional factors in Internet acceptance, Lu et al. (2019) found that continuance intention had a strong positive effect on achievement and challenge emotions and a moderate negative effect on loss and deterrence emotions.

Research shows that emotions significantly influence technology acceptance and use. Emotions such as happiness, anxiety and anger affect perceived ease of use, usefulness and behavioural intention, with positive emotions generally supporting acceptance and negative ones potentially hindering it. These findings highlight that technology adoption is shaped by both cognitive evaluations and emotional experiences. Therefore, as Partala and Saari (2015) argued, understanding users' decision-making processes regarding technology adoption requires considering new variables that examine emotional, social and goal-directed behaviours in research, alongside those already included in TAM.

Purpose and research questions

In addressing the identified research problem, this study aimed to reveal the structural relationships among online learning self-efficacy, positive and negative emotions, perceived ease of use, perceived usefulness and behavioural intention in the context of LMS use. The following research questions guided the study:

(1) What are the structural relationships among online learning self-efficacy, positive emotions, perceived ease of use, perceived usefulness and behavioural intention to use an LMS?
(2) What are the structural relationships among online learning self-efficacy, negative emotions, perceived ease of use, perceived usefulness and behavioural intention to use an LMS?

Development of research hypotheses

In this section, we presented the theoretical and empirical background for the research hypotheses. Sixteen hypotheses were developed to address the research questions, with subscripts a and b denoting models for positive and negative emotions, respectively. Although some hypotheses are identical across models, each was tested and reported here separately. The research models are shown in Figure 1.

Grounded in CVT, emotions in academic settings are shaped by learners' perceptions of control over learning tasks and the value they assign to them (Pekrun, 2006). Online learning self-efficacy, reflecting a learner's perceived competence and control in digital environments, plays a central role in shaping these emotional experiences. Learners with high self-efficacy are more likely to feel confident, engaged and in control, which fosters positive emotions such as enjoyment and satisfaction (Tze et al., 2022). Conversely, low self-efficacy may result in negative emotions, such as anger, anxiety and shame, due to perceived lack of control or competence (Wang et al., 2021). Studies have highlighted that self-efficacy is a key predictor of both learning outcomes and emotional responses in online contexts (Lim et al., 2021; Wang et al., 2022). Accordingly, we proposed the following hypotheses:

- H_{1a} Online learning self-efficacy has a positive direct effect on positive emotions.
- H_{1b} Online learning self-efficacy has a negative direct effect on negative emotions.

Online learning self-efficacy refers to students' belief in their capacity to successfully navigate and use digital learning environments. Empirical evidence consistently shows that individuals with higher self-efficacy perceive educational technologies as more beneficial for academic tasks (Liu & Pu, 2023). Moreover, this enhanced confidence facilitates perceived ease of use (S. Y. Park et al., 2012) and strengthens behavioural intentions to adopt and consistently engage with learning systems (Kumar et al., 2020). Accordingly, we proposed the following hypotheses:

- H_{2ab} Online learning self-efficacy has a positive direct effect on perceived ease of use.
- H_{3ab} Online learning self-efficacy has a positive direct effect on perceived usefulness.
- H_{4ab} Online learning self-efficacy has a positive direct effect on behavioural intention to use an LMS.

CVT argues that learners' achievement emotions, shaped by perceptions of control and task value, play a key role in academic engagement and outcomes (Pekrun, 2006). Emotions not only influence learning and performance but also significantly affect attitudes and behaviours related to technology use (Beaudry & Pinsonneault, 2010; Qu & Chen, 2021). Research indicates that positive emotions, such as happiness, enhance perceived ease of use and usefulness, thereby strengthening behavioural intention (Moridis et al., 2017). Conversely, negative emotions, such as anxiety, anger or boredom, may reduce motivation and hinder technology adoption (Kay, 2007; A. S. H. Lee & Tim, 2016). As technology use increasingly becomes an emotional as well as cognitive experience, examining the effects of positive and negative emotions on behavioural intention is essential. Therefore, we proposed the following hypotheses:

- H_{5a} Positive emotions have a positive direct effect on behavioural intention to use LMS.
- H_{5b} Negative emotions have a negative direct effect on behavioural intention to use LMS.

TAM is a widely used framework in educational research for explaining technology acceptance and use. It proposes that perceived ease of use influences both perceived usefulness and behavioural intention, while perceived usefulness directly affects behavioural intention (Venkatesh & Davis, 2000). Numerous studies, including those involving pre-service teachers, have examined and validated these relationships in educational settings (Almogren et al., 2024; Hsiao & Tang, 2024; Ursavaş et al., 2019). Accordingly, we proposed the following hypotheses:

- H_{6ab} Perceived ease of use has a positive direct effect on perceived usefulness.
- H_{7ab} Perceived ease of use has a positive direct effect on behavioural intention to use an LMS.
- H_{8ab} Perceived usefulness has a positive direct effect on behavioural intention to use an LMS.

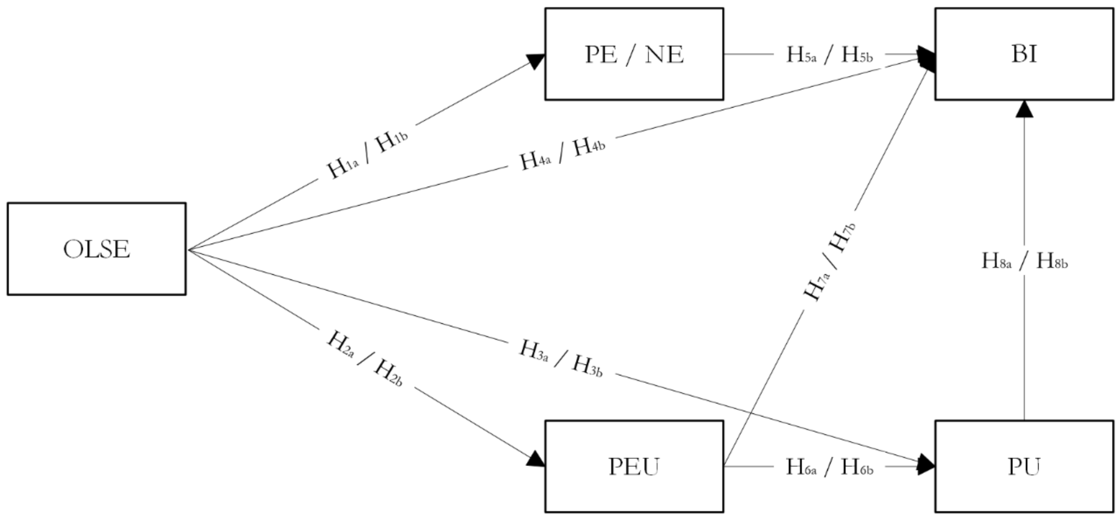


Figure 1. Research model (OLSE: online learning self-efficacy; PEU: perceived ease of use; PE: positive emotions; NE: negative emotions; PU: perceived usefulness; BI: behavioural intention)

Method

Research design

This study employed a cross-sectional survey design. The survey design is a research method in which researchers administer a questionnaire to a sample or the entire population to investigate attitudes, opinions, behaviours or specific characteristics (Creswell & Guetterman, 2019).

Participants

Participants consisted of 216 undergraduate students enrolled in hybrid courses in the Faculty of Education at a state university in Turkey. The sample was obtained through convenience sampling, and the final sample size reflects the number of students who were accessible and voluntarily agreed to participate during the data collection period. The sample group consisted of 61 male (28.2%) and 155 female students (71.8%), with ages ranging from 18 to 50 ($\bar{X}$ = 20.19, *SD* = 2.57). Participants represented five departments at the undergraduate level: Department of Mathematics and Science Education (83; 38.4%), Department of Elementary Education (53; 24.5%), Department of Turkish and Social Sciences Education (41; 19.0%), Department of Educational Sciences (37; 17.1%) and Department of Fine Arts Education (2; 0.9%).

Instruments

This study used data collection instruments with established validity and reliability in the relevant literature. The Online Learning Self-efficacy Scale developed by Sun and Rogers (2021) and adapted into Turkish by Baltacı et al. (2022) was used to measure participants' online learning self-efficacy. The scale consists of four dimensions – technology use self-efficacy (TU), online learning task self-efficacy (OLT), instructor and peer interaction and communication self-efficacy (IPIC) and self-regulation and motivation self-efficacy (SRM) – and a total of 31 items. The development of the scale was grounded in a comprehensive theoretical framework that incorporates four key constructs identified in the literature as essential to online learning success: technology self-efficacy, social presence, self-regulation and self-motivation. The scale has been consistently used in higher education settings and has demonstrated good internal consistency (M. Chen, 2024; Yessenova et al., 2023). The scale items are scored between 1 (*strongly disagree*) and 6 (*strongly agree*). In this study, the overall scale and its dimensions separately demonstrated very good internal consistency reliability (overall scale α_{OLSE} = .957 and dimensions separately α_{TU} = .892, α_{OLT} = .865, α_{IPIC} = .930, α_{SRM} = .930).

The emotions included in the study were positive (i.e., PE) and negative (i.e., NE) class-related achievement emotions as identified by Pekrun et al. (2005). Positive emotions included pride, enjoyment and hope, while negative emotions included anger, hopelessness, anxiety, shame and boredom. Participants were asked which emotions they experienced when using LMSs and to what extent, with responses measured on a scale ranging from 1 (*never*) to 5 (*always*). The internal consistency coefficients were α_{PE} = .850 for positive emotions and α_{NE} = .822 for negative emotions.

Finally, to measure the TAM variables – perceived ease of use, perceived usefulness and behavioural intention – the relevant items from the Mobile Learning Acceptance Scale for Pre-service Teachers, developed by İslamoğlu et al. (2021), were adapted and used in the current study. This scale was selected because it had previously demonstrated good internal consistency with Turkish higher education students. Although originally developed for a mobile learning context, the items were conceptually consistent with the core TAM constructs and were adapted to fit the LMS context. The resulting scale consisted of a total of 10 items, three items for perceived ease of use, four items for perceived usefulness and three items for behavioural intention, and these items were scored on a scale ranging between 1 (*strongly disagree*) and 5 (*strongly agree*). In this study, the internal consistency coefficient of each scale was obtained as follows: α_{PEU} = .819, α_{PU} = .884, and α_{BI} = .872.

Data collection

Data were collected via Qualtrics during the fall semester of 2023–2024, following ethics committee approval. The survey link and study information were shared with students through email and virtual classrooms, and data collection concluded in December 2023.

Data analysis

Path analysis, a multivariate technique for modelling direct and indirect effects and testing causal relationships among variables, was used to address the research questions and test the hypotheses. Model fit was assessed using the chi-square goodness-of-fit test and the root-mean-square error of approximation (RMSEA), comparative fit index (CFI) and Tucker-Lewis index (TLI). The following cut-off values were adopted for the fit indices used (Hu & Bentler, 1999):

- RMSEA: less than 0.05 (good fit), between 0.05 and 0.08 (reasonable fit), greater than 0.08 (poor fit)
- CFI/TLI: greater than 0.95 (good fit), between 0.95 and 0.90 (reasonable fit), less than 0.90 (poor fit).

IBM SPSS version 29 was used for descriptive statistics and Mplus version 8.3 for path analysis. Maximum likelihood was chosen as the estimation method.

Results

Descriptive statistics

Given the sample size and the good internal consistency of the scales, variables were arranged in the composite form by taking the arithmetic means of the scale items. This approach reduced the number of parameters and minimised the model complexity. Descriptive statistics for the composite variables are presented in Table 1.

Table 1
Descriptive statistics

Variable	$\overline{X}$	SD	Skewness	Kurtosis
TU	4.52	.904	-.704	1.242
OLT	4.27	1.019	-.513	.506
IPIC	4.18	1.038	-.636	.510
SRM	4.20	.873	-.595	.670
PE	2.91	.929	-.168	-.292
NE	2.77	.849	.119	-.526
PEU	3.59	.765	-.534	.881
PU	3.71	.783	-.818	1.603
BI	3.72	.751	-.968	2.220

$\overline{X}$: Mean

The arithmetic means of the variables ranged from 2.77 to 4.52, with standard deviations ranging from 0.751 to 1.038. Skewness and kurtosis values varied between -.968 and .119 and between -.526 and 2.220, respectively, and are within the limits of univariate normality (Hair et al., 2019). Because the maximum likelihood estimation method was used in data analysis, the assumption of multivariate normality was also examined. For this purpose, Mardia's multivariate kurtosis values were calculated for the positive and negative emotions models as 19.101 and 19.362, respectively. These values were compared with the value of 80, obtained using the formula $p \times (p + 2)$ from Raykov and Marcoulides (2008) where p represents the number of observed variables in the model. The Mardia multivariate kurtosis values were considerably smaller than the value obtained from this formula, indicating that the data met the assumption of multivariate normality.

Model fit

To test the research hypotheses, two models – positive emotions and negative emotions – were created, and model fit was examined using the Chi-square goodness-of-fit test and the RMSEA, CFI and TLI values. Although the initial models produced fit indices within acceptable limits, a correlated error was added for the TU and OLT dimensions of online learning self-efficacy in both models to improve model fit, based on the modification indices and the variable structure. Table 2 presents the Chi-square goodness-of-fit test results and fit indices for the revised models.

Table 2
Chi-square goodness-of-fit test and fit indices values for research models

Model	χ^2	*df*	RMSEA (90% CI)	CFI	TLI
Positive emotions model	29.819 (p < . 05)	15	.068 (.030–.103)	.984	.970
Negative emotions model	24.273 (p = .061)	15	.053 (.000–.091)	.990	.981

According to these values, although the chi-square test was significant in the positive emotions model, the RMSEA, CFI and TLI values fell within acceptable limits. In the negative emotions model, a statistically insignificant chi-square goodness-of-fit test was accompanied by the RMSEA, CFI and TLI values within the limits of good fit. Based on these results, model fit was confirmed, and the hypothesis testing phase was initiated.

Hypothesis testing

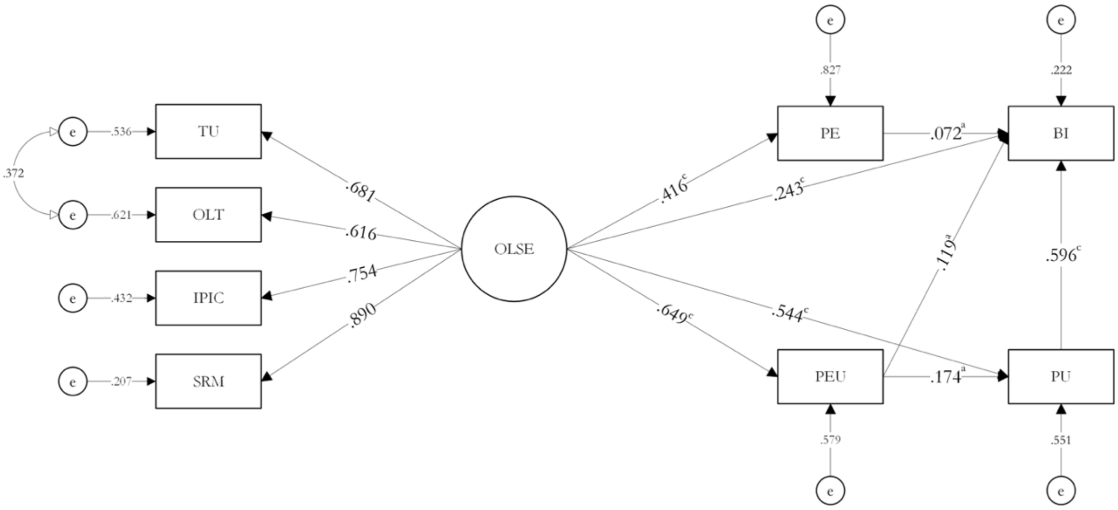
After confirming the model fit, the relationships between study variables were examined, and hypotheses were tested. The results of the hypothesis tests are presented in Table 3.

Table 3
Hypothesis testing results

Parameter	Coefficient (Std)	SD	Status
H_{1a}: OLSE→PE	.416***	.061	Supported
H_{1b}: OLSE→NE	-.474***	.057	Supported
H_{2a}: OLSE→PEU	.649***	.045	Supported
H_{2b}: OLSE→PEU	.643***	.046	Supported
H_{3a}: OLSE→PU	.544***	.072	Supported
H_{3b}: OLSE→PU	.548***	.071	Supported
H_{4a}: OLSE→BI	.243***	.061	Supported
H_{4b}: OLSE→BI	.284***	.063	Supported
H_{5a}: PE→BI	.072*	.037	Supported
H_{5b}: NE→BI	.037	.039	Not supported
H_{6a}: PEU→PU	.174*	.073	Supported
H_{6b}: PEU→PU	.175*	.072	Supported
H_{7a}: PEU→BI	.119*	.046	Supported
H_{7b}: PEU→BI	.127**	.047	Supported
H_{8a}: PU→BI	.596***	.044	Supported
H_{8b}: PU→BI	.595***	.044	Supported

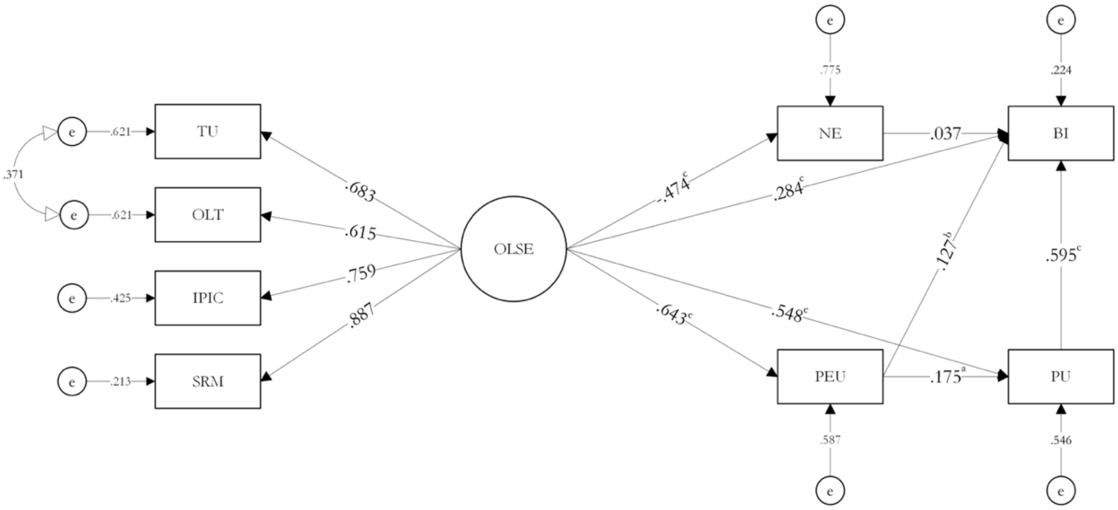
* p < .05; ** p < . 01; *** p < .001. Std: standardised

According to these results, in the positive emotions model, OLSE had a positive, significant effect on PE (β = .416, p < .001), PEU (β = .649, p < .001), PU (β = .544, p < .001), and BI (β = .243, p < .001). In addition, the effect of PE on BI was also positive and significant (β = .072, p < .05). Furthermore, PEU had positive, significant effects on PU (β = .174, p < .05) and BI (β = .119, p < .05). Finally, PU had a positive, significant effect on BI (β = .596, p < .001). These findings support all the hypotheses proposed for the positive emotions model. The total explained variance of BI in this model was 77.8%. In the negative emotions model, OLSE had a negative, significant effect on NE (β = -.474, p < .001). In addition, OLSE had positive, significant effects on PEU (β = .643, p < .001), PU (β = .548, p < .001), and BI (β = .284, p < .001). Furthermore, PEU had positive, significant effects on PU (β = .175, p < .05) and BI (β = .127, p < .01). Finally, PU had a positive, significant effect on BI (β = .595, p < .001). In the negative emotions model, NE did not have a significant effect on BI (β = .037, p = .333). These findings support all the hypotheses, except H_{5b}, proposed for the negative emotions model. The total explained variance of BI in this model was 77.6%. The structural relationships among the variables are shown in Figures 2 and 3.



a p < .05; b p < .01; c p < .001

Figure 2. Standardised coefficients of the positive emotions model



a p < .05; b p < .01; c p < .001

Figure 3. Standardised coefficients of the negative emotions model

Discussion

This study explored how positive and negative emotions, behavioural intention and self-efficacy influence learners' acceptance of LMSs for academic tasks. Separate structural models for each emotion type were tested with pre-service teachers, explaining 77.8% and 77.6% of the variance, respectively. Findings are discussed in relation to prior research and the theoretical framework.

Self-efficacy and emotions

Self-efficacy is usually shaped by the individual's experiences within a given context and evolves as the experience grows. Emotions, in a sense, have a similar connection with experience, where supportive and favourable experiences lead to positive emotions and unfavourable experiences or inexperience lead to negative emotions (Pekrun, 2006). Our path models verified that online learning self-efficacy is a direct determinant of positive and negative emotions. More specifically, our models showed that higher self-efficacy is linked to experiencing positive emotions, while lower self-efficacy is associated with negative emotions. Recent research established a similar relationship between self-efficacy and emotions (Chao, 2019; J. Han & Geng, 2023; Wang et al., 2024). Moreover, Wang et al. (2022) found that higher online learning self-efficacy predicted greater enjoyment and less frustration and boredom among college students. At the middle school level, An et al. (2022) found positive emotions influenced learners' technology self-efficacy. These findings suggest a reciprocal relationship between emotions and self-efficacy wherein each can affect the other in a bidirectional manner.

Self-efficacy, user perceptions and behavioural intention

Consistent with TAM research, our models showed that higher online learning self-efficacy directly enhances perceived ease of use, perceived usefulness and behavioural intention, with confident learners viewing the LMS as more usable and beneficial for academic tasks. These findings align with research showing a consistent positive relationship between self-efficacy and TAM constructs. Arpaci et al. (2019) reported the direct effect of self-efficacy on perceived ease of use when using a block-based programming platform among computer engineering students, whereas Musyaffi (2022) observed the influence of accounting students' self-efficacy on their behavioural intention to use LMS. Moreover, computer self-efficacy has been found to predict perceived ease of use and perceived usefulness in technology-mediated learning environments (Thongsri et al., 2020). Additionally, academic self-efficacy was found to be influenced by students' perceptions of ease of use and usefulness, which indicates the reciprocal interaction between self-efficacy and TAM constructs (Alamri, 2022; Hanham et al., 2021).

Emotions and behavioural intention

Research shows that emotions play a critical role in shaping technology acceptance through their effect on perceived ease of use and perceived usefulness (e.g., Humida et al., 2022). We hypothesised that both positive and negative emotions directly influence behavioural intention; however, we observed a marginally significant relationship in the case of positive emotions, while negative emotions failed to reach significance. In technology acceptance research, positive emotions – often represented by perceived enjoyment – typically influence behavioural intention through perceived ease of use and perceived usefulness in higher education settings (Humida et al., 2022). Similarly, negative emotions are often represented by anxiety, where perceived ease of use mediates its relationship with behavioural intention (İslamoğlu et al., 2021). Meanwhile, technology acceptance studies encompassing wider ranges of positive or negative emotions such as achievement emotions are scarce (e.g., Wang et al., 2024). S. Park and Yun (2024) found that positive emotions influenced perceived ease of use but had no significant effect on perceived usefulness in augmented reality acceptance among education students. In addition, negative emotions did not influence either variable. S. Lee et al. (2024) found that both positive and negative emotions influenced attitudes towards ChatGPT among adults, though the effects were minimal. Although emotions play a complex, context-dependent role in technology acceptance, our findings indicate that cognitive evaluations more strongly shape pre-service teachers' behavioural intentions towards LMS use, with several potential explanations. First, although emotions are important, their effects may be secondary to cognitive factors such as perceived ease of use and usefulness, which directly relate to practical and functional aspects of LMS use. Second, the context in which pre-service teachers used an LMS as a required part of their studies could have potentially reduced the role of emotions relative to cognitive evaluations. As students felt they were obligated to use the LMS, they focused on more instrumental factors compared to emotional responses. Third, our findings revealed the major impact of online learning self-efficacy on other variables in the model. Given the strong relationships between self-efficacy, emotions and behavioural intention, the influential role of self-efficacy may have diminished the effect of emotions in predicting LMS acceptance.

Implications

The study has theoretical and practical implications. Theoretically, the study expands TAM with constructs from CVT. It demonstrates that online learning self-efficacy and achievement emotions jointly influence behavioural intention, highlighting the importance of integrating emotional variables into technology acceptance research. The findings suggest a reciprocal relationship between self-efficacy and emotions, highlighting that technology adoption is shaped not only by cognitive evaluations but also by emotional experiences. Practically, the findings suggest that, in addition to perceived ease of use and perceived usefulness, positive emotions and online learning self-efficacy significantly influence behavioural intention to use LMSs. These findings underscore the importance of considering factors that induce positive class-related achievement emotions, such as pride, enjoyment and hope, in the design and implementation of LMSs to enhance the adoption of this technology. To foster such emotions, universities and LMS developers could integrate elements like personalised feedback, milestone recognition, user-friendly interfaces and social features that support collaboration and engagement. Our findings also underscore the dual role of online learning self-efficacy, which not only influences cognitive evaluations of technology but also shapes emotional experiences. Teacher education programmes should therefore implement evidence-based interventions (e.g., scaffolded LMS training, peer-supported tasks and reflective practices) that build students' confidence in accomplishing tasks within LMS environments. Enhancing self-efficacy in this way may lead to broader gains in both emotional engagement and technology adoption.

Limitations

There are several limitations to the study. First, the study's cross-sectional design limits its ability to establish causal relationships between variables. Although path analysis provides insights into relationships, it cannot determine long-term effects. Second, the use of convenience sampling and a single-faculty sample from one Turkish university limits the generalisability of the findings to other populations, settings or cultures. Third, using self-reported data may introduce response bias, as participants might not accurately assess their own experiences. Finally, the emotional impact may be underestimated due to limitations in measurement instruments or sample composition.

Recommendations for future research

We believe this study is a rational attempt to understand the roles emotions and online learning self-efficacy play in LMS adoption. To contribute to this understanding, future researchers should consider conducting longitudinal studies to track changes in emotions, self-efficacy and technology adoption. Furthermore, expanding the sample to include more diverse groups of participants, such as graduate students or learners from different cultural contexts, would provide a better understanding of how various demographics affect LMS acceptance and use. Finally, emotional experiences can be influenced by whether the technology use is voluntary or mandatory. Therefore, future researchers should explore the effect of emotions on LMS adoption in both conditions to reveal the impact of the nature of the use.

Conclusion

This study expanded TAM by integrating class-related positive and negative achievement emotions and online learning self-efficacy to understand pre-services teachers' acceptance and use of LMS. The findings highlight that while cognitive evaluations remain central to LMS adoption, positive emotions and self-efficacy also significantly contribute to shaping behavioural intentions. However, the limited impact of negative emotions suggests that mandatory contexts may reduce their influence. These results underscore the need to foster positive emotional experiences and enhance online learning self-efficacy to promote effective LMS adoption. By combining TAM with emotion-based constructs and self-efficacy, this study offers a novel lens for understanding LMS acceptance in higher education. Future research should explore these relationships across diverse learner groups and investigate how the nature of LMS use regulates the role emotions play in technology acceptance and use.

Author contributions

Author 1: Data curation, Formal analysis, Project administration, Software, Supervision, Visualisation, Writing – original draft, Writing – review and editing; **Author 2**: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – review and editing; **Author 3**: Visualisation, Writing – review and editing; **Author 4**: Writing – review and editing.

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Please cite as: Yalçın, Y., Bakır-Yalçın, E., İslamoğlu, H., & Ursavaş, Ö. F. (2025). Investigating the role of emotions in pre-service teachers' acceptance and use of learning management systems. *Australasian Journal of Educational Technology*, *41*(4), 32–47. https://doi.org/10.14742/ajet.10201