E-learning engagement and effectiveness during the COVID-19 pandemic: The interaction model

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ABSTRACT

COVID-19 has disrupted the education environment. But, little is known on how e-learning engagement impacts learning effectiveness and satisfaction with the interaction of computer self-efficacy in the study from home context. We examine how students' expectations to adopt e-learning contribute to e-engagement that influences e-learning effectiveness and satisfaction and explore the moderating role of computer self-efficacy between e-learning engagement and effectiveness using structural equation modelling. Results from the 212 usable data reveal that e-learning expectations to adopt e-learning contribute positively to e-learning engagement, which is fundamental for effective learning that leads to learning satisfaction. Computer self-efficacy appears to have a significant positive effect on e-learning effectiveness, but no evidence on e-learning engagement. Computer self-efficacy moderates the relationship between e-learning engagement and perceived e-learning effectiveness in the study from home context during the pandemic. The findings have important managerial implications for administrators in the universities. Students are adjusting and facing a steep learning curve as they work through the mechanics of e-learning in the new normal COVID-19 environment. They learn to interact with peers and lecturers via electronic means, digest and absorb complicated content and concepts through unfamiliar e-learning platforms in home spaces. Limitations and future research are discussed.

Keywords: COVID-19 environment, e-learning, engagement, computer self-efficacy, effectiveness, satisfaction

1. Introduction

The COVID-19 pandemic outbreak has resulted in universities going digital, hastening the acceptance and proliferation of e-learning worldwide (Bao, 2020). Consequently, universities incorporate e-learning or web-based learning into their vision aiming to transform the ways students learn and engage (Aldholay et al., 2018; Poon et al., 2004). The drastic shifts from traditional face-to-face (F2F) engagement to e-learning results in the emergence of new educational challenges. The past two decades witnessed a surge in the adoption and application of digital media which greatly enhanced e-learning experience (Dumford & Miller, 2018). Nevertheless, the occurrence of COVID-19 introduced a host of new education challenges in online teaching and learning (Amir et al., 2020). The abrupt need for and shift to "emergency online course delivery" has impacted both educators and students. The educators are challenged in planning and delivering lessons due to additional workload, time, and resource constraints (Gares et al., 2020), while students face a steep learning curve in their attempt to learn online from home via an unfamiliar and remote e-learning platform (Baber, 2021; Walker & Koralesky, 2021). Subsequent to the lockdown students who engage in remote learning are forced to identify new learning routines and ways to engage in virtual learning. Amidst the occurrence of the pandemic, studying from home has become the sole option for learners to acquire tertiary education (Zheng et al., 2020). Consequently, higher institutions are challenged to develop and deliver e-learning programs that are centred on students' dynamic participation, enriching their personal experiences for impactful learning (Muthuprasad et al., 2021). Improving student learning outcomes requires implementing innovative remote learning approaches and encompasses active engagement with the learner using appropriate techniques that fit virtual instructions (Sarwar et al., 2020). While the support systems have improved since virtual learning was first rolled out in response to the university closure, this is still a striking indictment, particularly on students' dynamic participation, enriching their personal experiences for impactful learning.

Technology has a progressive impact on learning experiences and outcomes. The differential outcomes in technology-mediated learning result from students' learning engagement that impinge on learning effectiveness and satisfaction (Tseng et al., 2020; Piccoli et al., 2001). Past studies on students' learning experiences explored specific aspects of e-learning courses, including interaction with the instructor (Adarkwah, 2021; Bollinger & Martin, 2018), learning management system (Alexander & Golja, 2007), course or program characteristics (Engelbrecht, 2005), learning achievements and course satisfaction (Paechter et al., 2010). Further, learner engagement in a distance education environment is influenced by the perception of self-efficacy for technology (Tseng et al., 2020) and student characteristics (Zheng et al., 2020). Highly motivated, self-disciplined students with time management skills found online education delivery to be effective (Jacob & Radhai, 2016). Other scholars show the influence of emotional responses, such as frustrations and anxiety hinder students with a low level of self-efficacy and computer skills from engaging in a proactive approach to e-learning (Mac Callum et al., 2014). In summary, the existing literature shows that engagement has an impact on learning effectiveness and learning satisfaction among students. Nevertheless, the research framework investigating engagement in e-learning is yet to explicitly identify issues related to engagement in the context of study from home (Walker & Koralesky, 2021). By synthesizing previous research, we develop a structural model premise on learning engagement, while examining the impact of computer technology self-efficacy on learning effectiveness and satisfaction.

Traditional learning pedagogies are increasingly being criticized for failing to gain students' engagement and contribute to learning satisfaction (O'Flaherty & Phillips, 2015). Engagement is a consequence of students' interaction with their immediate environment (Sun & Rueda, 2012). Most studies involving learners' engagement are limited to the context of a traditional or hybrid classroom environment that combines F2F with e-learning (Burke & Fedorek, 2017). The existing knowledge on e-learning engagement within the environment of merely studying from home is limited. Learning engagement within the context of study from home results in different sets of issues and challenges, positively or negatively influencing students' engagement and subsequent learning effectiveness. The current pandemic outbreak resulted in the restructuring of education and delivery methods globally further emphasizing the importance of effective online delivery of education (Favale et al., 2020). Consequently, studying from home has become the sole option for many learners to acquire tertiary education. However, little is known whether students' expectation to adopt e-learning is associated with e-learning engagement and computer self-efficacy. Thus, the effect of e-learning engagement on learning effectiveness and satisfaction in coping with the environmental reality of the COVID-19 era is of interest**.**

This study aims to address the following research question: *Within the context of studying from home as a consequence of the Covid-19 pandemic, how students' expectations to adopt online learning contribute to e-learning engagement, thereby influencing learning effectiveness and satisfaction?*

This study makes three contributions to the literature. Firstly, this is the first study that examines how students' expectations to adopt virtual learning contribute to e-learning engagement in a new context of study from home during the COVID-19 pandemic. Secondly, we seek to empirically explore whether an increased engagement reflects better learning outcomes concerning effectiveness and satisfaction in the virtual learning context. Thirdly, this study also examines the interaction (moderation) of computer self-efficacy between e-learning engagement and effectiveness during the pandemic. This research contributes behavioural and psychological insights to educational institutions on ways to improve students' online engagement to positively influence the quality of learning outcomes.

2. Literature review

2.1. Theoretical framework

This study applies engagement theory and the social identity theory in the context of study from home. The engagement theory framework emphasizes meaningful engagement among students through interaction and active learning. While engagement may occur without the aid of technology, Hu and Hui (2012) argue that the use of technology facilitates and enhances students' engagement. Engagement theory presents a learning model that incorporates various learning theories in a technology-based teaching and learning environment by emphasizing relate, create and donate principles (Kearsley & Shneiderman, 1998). The "relate" principle accentuates collaboration and teamwork, highlights communication skills, planning and management, and social skills. The "create" component includes students' efforts and creativity in completing tasks (cognitive and emotional). The "donate" principle emphasizes the outcome or contribution of the completed task, including learning effectiveness. A further dimension of engagement theory incorporates four common approaches to engagement: behavioural, emotional, cognitive, and social (Lu & Churchill, 2014). These four dimensions are dynamically interrelated. Hence, the theoretical framework involving engagement incorporates a multidimensional construct that explains how students think, feel, and behave, which obliges different skill sets and learning styles (Zheng et al., 2020). As students access education from home, the lecturer is not physically present; the quality of e-learning hinges on the learner's competence in using the technology (Orlov et al., 2021; Al-Ansi et al., 2021; Al-Ansi & Al-Ansi, 2020).

Students' engagement is relatively low in the virtual setting can be explained by the Social Identity Theory (Tajfel, 1979), stating that a sense of belonging to the social group is an essential source of social identity. Social identity theory is based on intergroup relations, that is viewing self as part of the in-group or the out-group (Stets & Burke, 2000). Belonging is the mechanism by which one helps community members develop a sense of social presence in a community where they feel a bond. A stronger sense of belonging with the group is an outcome of full peer participation virtually (Venn et al., 2020). In comparison, introverted students may isolate themselves as they may lack social skills. Computing technology can convey social presence and influence users to engage with the content.

2.2. Learning engagement

Learning engagement accentuates the importance of behavioural engagement in learning, and often has a positive association with emotional engagement, signified by learning interest or satisfaction (Fredricks et al., 2004). The importance of student engagement is growing due to emerging issues in university education quality and impact (Baporikar, 2020). The higher the students' involvement by investing time and effort to study, interact with others and participate in the academic task, the better the learning outcome. To encourage student engagement, it is reinforced by the resources and opportunities supported by institutional learning communities (National Survey of Student Engagement, 2003).

There are four approaches to engagement: behavioural, emotional, cognitive (Walker & Koralesky, 2021), and social aspects (Lu & Churchill, 2014). Behavioural engagement refers to students' participation and involvement, such as asking questions, participation in activities and discussions, attendance, and complying with rules (Sun & Rueda, 2012; Li & Lerner, 2011). Behaviourally disengaged students involved in the act of defiance, refusal to follow the instructions, and school avoidance (Tseng et al., 2020; Buhs et al., 2006). Behavioural engagement can be measured based on students' active participation in completing the given tasks, such as quizzes, posts to the forum, and views of recorded lectures (Jung & Lee, 2018). Emotional engagement refers to students' reactions towards the institution, academics, and peers (Fredricks et al., 2004). These two dimensions of engagement are positively related. Cognitive engagement "incorporates thoughtfulness and willingness to exert the effort necessary to comprehend complex ideas and master difficult skills'' (Fredricks et al., 2004, p. 60). It may range from simple memorization to self-initiated learning and preference for challenges. Social engagement dimensions involve social interactions and socio-emotional factors concerning a learning community (Lu & Churchill, 2014).

2.3. The expectation of adopting e-learning and e-learning engagement

According to Paechter et al. (2010), there are five dimensions in explaining students' expectations to adopt e-learning, including course design, individual learning process, interaction with the instructor, interaction with peers, and learning achievement. Careful course design is crucial because low retention rates in online offerings are often associated with a deficiency of student accountability, engagement, and sense of belonging within the e-classroom (Zhu et al., 2020; Cooper & Scriven, 2017). E-learning provides better access to learning resources online; however, the quality of the content and delivery impose significant barriers preventing the effectiveness of e-learning instruction. When remote instruction was commanded in March 2020 due to COVID-19, lecturers may not have sufficient training or scaled-up efforts to redesign the existing unit into a thoughtful online instruction course to account for an unexpected fix (Hodges et al., 2020).

The individual learning process involves active learning activities (Paechter et al., 2010; Al-Ansi et al., 2019). There are many learning activities to reinforce pre-lecture learning material to increase accountability by engaging students in the learning process. As a result, the student's learning process shifts from lecture-focused to self-directed learning. Students appreciate real-time feedback that helps identify gaps in knowledge and areas of strength. Lecturers who fail to provide instant feedback to resolve students' questions may cause adverse learning outcomes (Kim et al., 2005).

Interaction with peers and interaction with instructors are another two dimensions (Bolliger & Martin, 2018). Successful transition to virtual teaching and learning depends on the rising use of formative assessments and peer review sessions. To maintain a glimmer of normalcy, the course sessions are taught synchronously. Teaching sessions, including didactics, formative assessments, pre-exam and post-exam review sessions, are held through live platforms (e.g., Zoom, Google Meets, Microsoft Teams, and Webex). Lecturing faculty logs into these platforms as a host and presents didactic material via shared screen. Students maintain engagement by asking questions through the utilization of the chat features for Q&A. Small group formative assessments may also facilitate engagement and clarify difficult concepts (Lepe et al., 2020). All assessments in the unit learning outcomes must be specific and mapped to the course learning outcomes to ensure continuous curriculum improvement. Many pedagogical tools promote student e-engagement and active learning, including self-testing, group discussion in the forum, pre- or post-class activities associated with better student engagement in the e-learning experience (Hernández et al., 2021). These interactions help bridge the gap between theory and practice and provide exposure to role models that emulate future rotations.

H1a: The expectation of adopting e-learning has a significant positive influence on e-learning engagement

2.4. The quadratic effect of expectation to adopt e-learning on e-engagement

We argue that there may be a quadratic spillover effect in the educational context. High e-learning engagement students may influence less engaged peers, stimulating the less engaged group to join the crowd and expecting them to adopt e-learning. Over time, however, the more engaged students in e-learning activities may feel that their learning is less efficient as they compensate for the lower engagement group. Hence the more e-learning engagement group may end up less enthusiastic on the expectation to adopt e-learning. Therefore, understanding how e-learning engagement interacts to shape the expectation to adopt e-learning should be further investigated. We use a non-linear model by adding a quadratic term into the equation between e-learning engagement and expectation to adopt e-learning. Note that when a non-linear relationship is found, the shape of this relationship is not directly proportionate to the outcomes.

This spillover effect represents the inclusion of a non-linear quadratic term. If the quadratic term significantly improves the fit of the model, then there is the quadratic effect for the expectation to adopt e-learning. An inverted U-shaped relationship is a quadratic relationship when there is a positive (negative) slope for the lower (higher) e-learning engagement level. The inverted U-shaped relationship is commonly used in economics. For inverted U-shaped relationships identification, it must meet three significant requirements: 1) The slope of the squared independent variable is negative; 2) The slope at the lowest (highest) variable value is positive (negative); 3) The turning point (i.e., the first derivative of the equation) and its calculated 95% confidence interval are within the data range (Hirschberg & Lye 2005). Therefore, we posit the first hypothesis as follows:

H1b: There is an inverted U-shaped relationship between the expectation to adopt e-learning and e-learning engagement.

2.5. Computer self-efficacy and e-learning engagement and effectiveness

The changing education landscape towards e-learning increasingly highlights the importance of a robust sense of computer self-efficacy among students to succeed (Chen, 2017). Computer self-efficacy is defined as "a judgment of one's capability to use a computer" (Compeau & Higgins, 1995, p.192). Self-efficacy relates to the students' perception of their ability to apply computer skills to complete tasks (Bandura, 1989). The higher the computer self-efficacy, the stronger the commitment to learning engagement (Tseng et al., 2020). Self-efficacy beliefs motivate students to be more perseverant to heighten students' learning engagement (Komarraju & Nadler, 2013). Furthermore, it facilitates deep learning if learners know how to acquire knowledge from the technology-enabled learning platform (Martens et al., 2007).

The application of e-learning is complementary to the advancement of the learning management system, such as Canvas, Moodle, Blackboard, and WebCT. E-learning depends on the computer as the online education delivery tool. Students' access to materials from computers and technology assists in facilitating interaction and communication between learners and instructors (Orlov et al., 2021). Hence, maintaining learning effectiveness requires a positive attitude towards technology use. Prior studies identify confidence in the use of online technology and self-efficacy for technology skills significantly influence learning effectiveness, that is the extent to which a student acquires important knowledge or skills (Hu & Hui, 2012; Garad et al., 2021).

Despite its many advantages, technology-driven education faces a fundamental challenge of student retention (Martinez, 2003). Technology-mediated learning, such as pre-programmed videos, negatively affects learning engagement, perceived learning effectiveness and satisfaction (Hu & Hui, 2012; LapitanJr et al., 2021). Moreover, students' engagement and learning satisfaction heavily rest on their intrinsic motivation to learn, including self-discipline, a sound pedagogical design, and guideline to enable deep learning (Muthuprasad et al., 2021). Therefore, we posit the following hypotheses:

H2: Perceived computer self-efficacy has a significant positive influence on e-learning engagement.

H3: Perceived computer self-efficacy has a significant positive influence on learning effectiveness.

H4: E-learning engagement has a significant influence on perceived learning effectiveness.

H5: Perceived computer self-efficacy moderates the relationship between e-learning engagement and perceived learning effectiveness, such that the relationship is weaker when perceived computer self-efficacy is high.

2.6. Perceived learning effectiveness and learning satisfaction

Ke and Kwak (2013, p. 44) define learning satisfaction as "the student's perception of the course experience and the perceived value of the education received while attending the educational institution". Learning satisfaction represents a student's evaluation of his learning experience (Wang, 2003). Prior studies emphasize the importance of learner satisfaction on the perceived outcome of online studies (Eom et al., 2006). Sun et al. (2008) identify 6-dimensional e-learning satisfaction, and find that learner computer anxiety, instructor attitude toward e-learning, e-learning course flexibility and quality, perceived usefulness, perceived ease of use, and diversity in assessments influence learners' perceived satisfaction. Overall, past studies demonstrate that e-learning approaches positively affect learning effectiveness and satisfaction (Adler et al., 2021; Zhang et al., 2006). Therefore, we posit a hypothesis as follows:

H6: Perceived learning effectiveness has a significant positive influence on learning satisfaction.

Figure 1 depicts the research conceptual model for this study.

3. Methodology

3.1. Sample frame and procedure

This study employed correlational design using a survey method to examine students' expectations to adopt virtual learning contribute to e-learning engagement, learning effectiveness and satisfaction in the study from home context during the pandemic. A survey instrument was designed to collect empirical evidence to verify the proposed hypotheses. The sample involved university students above 18 years old, specifically those engaged in virtual learning from home during the pandemic lockdown period. This research adheres to the ethical principle outlined by the Monash University Human Research Committee in conducting research. Students' participation was voluntary and anonymous. The data was collected online for a period of three months (August to October 2020). The online survey link was distributed to students in a private university in Malaysia who were engaged in virtual learning from home.

A total of 212 usable data were collected. Table 1 shows the demographic information of the respondents. Among 212 respondents who returned valid samples, 126 (59.4%) were females and 86 (40.6%) were males. Ethnicity statistics show that 9 (4.2%) were Malays, 161 (75.9%) were Chinese, 9 (4.2%) were Indians, 33 (15.6%) were others. A total of 78.8% of the respondents were Malaysians.

3.2. Measurement development

Expectation to adopt e-learning was a 5-dimension reflective-formative construct, consisting of course design, interaction with the instructor, interaction with peer students, individual learning process, and learning achievement. We used the scale consisting of 22 items from Paechter et al. (2010). Students were asked to answer a list of questions regarding their expectations to adopt e-learning in a response format of a 7-point Likert scale. A sample item to measure course design is "a clear and organized structure of the course and learning material". A sample item to measure interaction with the instructor is "fast feedback from the instructor". A sample item to measure interaction with peer students is "easy and fast exchange of information and knowledge with peer students". A sample item to measure individual learning processes is "flexibility of learning with regard to time and place". A sample item to measure learning achievement is "acquiring skills in communication and cooperation".

E-learning engagement was measured using the scale by Wang et al. (2016). It was conceptualized as a 4-dimensional reflective-formative construct, consisting of cognitive engagement (8-item), behavioural engagement (8-item), emotional engagement (10-item), and social engagement (7-item). The answer format was on a 7-point Likert scale. An example item to measure cognitive engagement includes "I go through the work for online class and make sure that it's right". An example item to measure behavioural engagement includes "I put effort into learning my units". An example item to measure emotional engagement includes "I look forward to online classes". An example item to measure social engagement includes "I try to understand other people's ideas in online class".

Computer self-efficacy was assessed with a scale of 8 items by Hu and Hui (2012). An example item includes "In general, I can use computer technology to complete a task if I would call someone for help if I got stuck". Respondents were asked to report their agreement toward the questions related to this construct in a response format of a 7-point Likert scale ranging from 1 – strongly disagree to 7 – strongly agree.

Perceived learning effectiveness was measured using a 5-item scale by Hu and Hui (2012). Respondents were requested to indicate the degree to which they agreed with each of the items on a 7-point Likert scale (1 – strongly disagree to 7 – strongly agree). A sample item is "this online class (e.g., tutorial) gives me chances to practice what I learn".

Learning satisfaction was assessed using a 7-item scale by Hu and Hui (2012). Items were scored on a 7-point Likert scale, ranging from 1 – strongly disagree to 7 – strongly agree. An item to represent the construct includes "my learning in online class (e.g., tutorial) is pleasant".

Expectation to adopt e-learning and e-learning engagement were conceptualized as reflective-formative constructs for three reasons (Jarvis et al., 2003; Koay et al., 2020). First, for the lower-order constructs, the direction of causality is from the constructs to the indicators, whereas for the higher-order constructs, the direction of causality is from the indicators to the constructs. Second, the nomological net of the construct indicators is not the same for the higher-order constructs. Third, the indicators of lower-order constructs are highly correlated because they measure a similar theme. On the other hand, the indicators of the higher-order constructs represent different conceptual domains of their respective constructs. Hence, the formative indicators are not highly correlated, and removing a formative indicator from a construct can potentially alter the essence of the construct.

4. Data analysis

As highlighted by Hair et al. (2019), it is essential to justify our choice of structural equation modelling. This study opted for partial least squares structural equation modelling (PLS-SEM) instead of covariance-based structural equation modelling (CB-SEM) for several important reasons. First, PLS-SEM is more suitable for exploratory research but not for theory confirmation research (Hair et al., 2019). This study is exploratory in nature aiming to explore the underlying mechanism through which learning satisfaction is derived in the context of study from home. Second, PLS-SEM should be used when a research model has higher-order constructs, especially formative-reflective constructs

(Benitez et al., 2020). The complexity of the research model involving two higher-order constructs was a justifiable reason for PLS-SEM use. Third, PLS-SEM has the advantage of handling small data sizes and non-normal data (Hair et al., 2019).

4.1. Common method variance

It is necessary to check for common method variance (CMV), defined as "variance that is attributable to the measurement method rather than to the constructs the measures are assumed to represent'' (Podsakoff et al., 2003, p. 879), as our data were collected using the survey method for both the independent and dependent variables. Two statistical remedies were performed to examine whether CMV was a problematic issue in this research. First, an exploratory factor analysis by having all the measurement items in it, a method known as Harman's single factor test, was conducted to unravel any factor that can explain a significant amount of the variance (Podsakoff & Organ, 1986). The results showed that the first extracted factor accounted for 31.247% of the variance, which was less than 50% (Fuller et al., 2016). Second, a full-collinearity test was performed to identify whether the data were contaminated with CMV. Following Kock's (2015) guidance, we generated a dummy variable with random numbers as the dependent variable, which was then regressed on all the variables in this study. The variance inflation factor (VIF) values were less than the cut-off value of 3.3 (Table 2). Based on the evidence of two statistical results, we can confidently declare that CMV was not a major concern, posing minimal threats to the validity of our results.

4.2. Measurement model

We applied the disjoint two-stage approach to model the higher-order constructs (Sarstedt et al., 2019). The assessment of the measurement model was separated into two stages. In the initial stage, we first assessed all the first-order reflective constructs and other reflective constructs for internal consistency reliability, convergent validity, and discriminant validity, following Hair et al. (2019). As shown in Table 3 on the full measurement model results, the internal consistency reliability was not a major concern because all the values for Cronbach's alpha, rho_A, and composite reliability were greater than the recommended value of 0.7. Next, we evaluated the convergent validity by ensuring all the factor loadings were above 0.7 and average variance extracted (AVE) values were greater than 0.5. Items with poor factor loadings were deleted to achieve the desired threshold values for the loadings and AVEs. Table 3 shows that the standard evaluation criteria to achieve convergent validity was met, hence we can safely conclude that convergent validity was ascertained. Next, discriminant validity was assessed based on the heterotrait-monotrait ratio of correlations (HTMT) (Henseler et al., 2015). Given that both cross-loadings and Fornell and Larker criterion methods were criticized for their insensitivity to detect discriminant validity, we decided not to report the results (Benitez et al., 2020). For the HTMT criterion, the HTMT value should not be greater than 0.9 for a pair of two reflectively measured constructs (Henseler et al., 2016). Our result showed that we did not violate the rule as none of the HTMT values were greater than 0.9 (Table 4).

In the second stage of evaluating the measurement model, we assessed the higher-order formative constructs (Expectation to adopt e-learning and E-learning engagement). We extracted the latent variable scores of the reflective constructs to serve as the indicators of their respective higher-order formative constructs. The assessment of formative constructs involves examining indicators' multicollinearity and the size and significance of indicators' weight (Hair et al., 2017). As shown in Table 5, all the VIF values were less than 5, suggesting each indicator was not highly correlated and showed no sign of multicollinearity issue. Although not all of the indicators' outer weights were significant, their outer loadings were greater than 0.5. Their relative contribution to their respective constructs might not be strong, but their absolute contribution was still substantial (Hair et al., 2019). As a result, all indicators were retained.

4.3. Structural model

The full structural model results were presented in Table 6. Path coefficients and t-statistics were assessed using a bootstrapping procedure with 5000 resamples recommended by Hair et al. (2017). To test the significance of the quadratic effect of expectation to adopt e-learning on e-learning engagement, we created a quadratic term using the two-stage approach by interacting with the construct of expectation to adopt e-learning itself. The results showed that H1 was supported as expectation to adopt e-learning was found to have a significant positive quadratic influence on e-learning engagement ($\beta = 0.087$, $t = 2.435$, $p < 0.01$). Next, it was found that computer self-efficacy has no significant influence on e-learning engagement ($\beta = 0.011$, $t = 0.146$, $p > 0.05$) but it has a significant positive influence on perceived learning effectiveness ($\beta = 0.191$, $t = 3.021$, $p < 0.01$). Hence, H2 was not supported, but H3 was supported. Support for H4 was found as e-learning engagement has a significant positive influence on perceived learning effectiveness ($\beta = 0.667$, $t = 16.849$, $p < 0.001$). Lastly, the influence of perceived learning effectiveness on learning satisfaction was found to be positively significant ($\beta = 0.711$, $t = 17.937$, $p < 0.001$), thus supporting H6. We also reported the effect size (f^2) to examine the strength of the hypothesized relationships. According to Cohen (1998), 0.02, 0.15, and 0.35 suggested small, medium, and large f^2 effect sizes, respectively.

The moderating effect of computer self-efficacy on the relationship between e-learning engagement and perceived learning effectiveness was significant ($\beta = -0.081$, $t = 1.662$, $p < 0.05$), supporting H5. The simple slope plot graph was presented in Fig. 2. The interaction term was created using the two-stage approach. Therefore, the results will be the same regardless of how the product term is generated (unstandardized, mean-centred, or standardized).

According to Hair et al. (2019), a research model should be evaluated for its in-sample predictive power and out-of-sample predictive power. The coefficient of determination (R^2) for each dependent variable was reported in Table 6, ranging from 0.421 to 0.516, considered to have considerably moderate in-sample predictive power (Hair et al., 2011). Apart from that, a hybrid measure (cross-validated redundancy measure Q^2) of validating a research model's in-sample predictive power and out-of-sample predictive power was also generated by performing a blindfolding procedure (Stone, 1974). The Q^2 values for perceived learning effectiveness and learning satisfaction were 0.404 and 0.424, respectively, greater than 0, indicating that the PLS-path model has predictive relevance. To assess the out-of-sample prediction of the research model, we conducted PLSpredict that executes k-fold cross-validation using the recommended setting of k = 10. The Q^2 values for perceived learning effectiveness and learning satisfaction were 0.432 and 0.285, respectively. Given that the values were greater than 0, we can conclude the model has a reasonable out-of-sample predictive power (Shmueli et al., 2019).

5. Discussion

The results of this study identify the important characteristics of e-learning expectation influencing learning engagement, effectiveness, and satisfaction. The prevailing COVID-19 pandemic crisis is creating a new norm of teaching and learning requiring students to attend purely virtual classes. Virtual classes remain a challenge for students with learning difficulties, working in isolation and lacking infrastructure and supporting resources (Muthuprasad et al., 2021). Consequently, disengagement and learning loss occurs, negatively impacting the quality of the learning outcomes. The occurrence of the pandemic demands a conversion from a traditional method of teaching to incorporate a blended and inclusive approach. Hence there is a need to revise the existing teaching and learning approach, syllabus and delivery modes (Pham & Ho, 2020), aiming to offer quality education for a diverse set of learners towards IR4.0 and 5G.

The results support H1 that the expectation of adopting e-learning has a significant positive influence on e-learning engagement. Student’s engagement is often unobservable in a virtual environment. The virtual learning environment influences the pedagogic, learning material, and course design (LapitanJr et al., 2021). Moreover, a cohesive e-environment is required to support student-lecturer interaction for knowledge construction (Bolliger & Martin 2018; Paechter et al., 2010) and to minimize student distancing effects by being attentive. Therefore, re-designing the e-learning platform for similar learning experiences regardless of their location is crucial to e-learning engagement. The individual learning process is highly dependent on utilizing self-regulated learning opportunities to apply what they learn (Narciss et al., 2007), and self-tests to measure learning progress.

The result suggests an insignificant association between computer self-efficacy and e-learning engagement (H2), but computer self-efficacy positively impacts students' perceived e-learning effectiveness (Support H3). Our finding is consistent with Hu and Hui (2012) argument. Self-efficacy significantly affects students' engagement in technology-mediated learning, but not as significant in F2F learning (Spence & Usher, 2007). Students with high computer self-efficacy learn new applications more effectively than those with low computer efficacy. The results support Shu et al.'s (2011) argument on the importance of minimizing technostress among employees (negative impact on thoughts, emotions and behaviour) to encourage perceived efforts. Feeling of stress and anxiety arising from a lower perceived self-efficacy (Poon & Lee, 2012), impacts thoughts and emotions and hinders learning of new skills (Bandura, 1989). Techno-invasion (inability to adopt evolving technological changes), techno-overload (the need to work faster and longer) and techno-exhaustion (exhaustion from extensive use of computer) results in avoidance, anxiety and learning fatigue (Lee et al., 2022). For example, the expectation on students to learn and practice multiple computer applications within a short period of time such as TEAMs, ZOOM, Google slides and Blackboard, challenges students' judgement of their capability to cope and perform. In addition to individual factor, Rieder et al. (2021) found that task-related and situational factors influence self-efficacy to use technology in managing health. Likewise, in addition to the judgement of personal capacity, student's perception of their ability to rapidly learn and adapt to new technology while in isolation influence their motivation to engage in e-learning effectively. Consequently, preparing students to adjust to these changes is fundamental at the early stage of higher education exposure. Thus, with the growing number of online courses, universities should invest to develop staff and students' digital literacy skills via digital literacy programs. Essentially, developing and providing easy access to a wide range of online e-learning skills training via university websites or in collaboration with the library or external providers is crucial to encourage staff and students to upskill digitally at their individual pace.

Technology integration in learning pedagogy is needed in the teaching and learning activities (Salam et al., 2019). The use of mobile technology as an additional avenue to aid student-lecturer interaction may minimize social isolation (Gan & Balakrishnan, 2018; Poon & Koo, 2010). A study by Chen and Gao (2022) found that higher social media self-efficacy resulted in lower level of loneliness and higher self-esteem among older adults. Easy access to library information and user-friendly websites contribute to e-learning effectiveness (Johnston, 2020). The government's effort to eradicate poverty among the marginalized populations through the Shared Prosperity Vision 2030 emphasizes education among the poorest households in the country. There is also a need to prepare the graduates for the Fourth Industrial Revolution (IR 4.0), equipping them with the required digital skills to address the rapidly evolving employment landscape. Public-private sector collaboration is essential to eradicate technological barriers and to invest in digital infrastructure to lessen connectivity costs for marginalized groups, including poorer students.

The result shows that e-learning engagement significantly and positively influences perceived learning effectiveness (Support H4). Our findings contradict Hu and Hui's (2012) evidence that indicates an insignificant moderating effect between computer self-efficacy and learning medium on learning effectiveness of Adobe Photoshop software. Learning engagement is fundamental for effective learning, which supports learning effectively. Nonetheless, pre-informed class activities may not reflect the true value of class participation. For example, students may be less attentive during the class if they are aware that a quiz is only scheduled after a learning session (Raes et al. 2020). The use of flipped classroom model may be ineffective as learning style differs among students (Chen et al., 2019). Moreover, students commonly engage in cyberslacking behaviour in the e-learning environment (Koay & Poon, 2022a), such as playing online games during online classes, potentially affecting their class engagement (Koay & Poon, 2022b). Thus, pre-informed class activities may not be sufficiently effective for desired e-learning outcomes. An emphasis on active learning class design with high level of interactivity during the session to gain students' interest and engagement is crucial. The influence of perceived learning effectiveness is found to be positively associated with learning satisfaction (Support H6). Effective learning leads to learning satisfaction (Keller, 1983), and both learning effectiveness and satisfaction represent imperative measures of learning outcomes (Piccoli et al., 2001).

Our result supports the moderating effect of computer self-efficacy on the relationship between e-learning engagement and perceived learning effectiveness (support H5). Therefore engagement, learning effectiveness, and satisfaction associated with technology-mediated learning vary among students with different computer self-efficacy levels. While self-disciplined students may cope with technology related stress better to demonstrate higher self-efficacy and satisfaction, the dependent learners with lower readiness to adopt compulsory e-education may face difficulties (Lee et al., 2022). Thus, screening students with lower computer related skills and providing support is necessary. Consistent with previous studies, technology intensifies expectations of learning outcomes (Francescato et al., 2006). Past research suggests the importance of computer self-efficacy in determining learning effectiveness (Gist et al., 1989). Our result contradicts Hu and Hui (2012), who suggest technology-mediated learning does not significantly change the nature of the relationships between learning satisfaction and engagement. Compared to high self-efficacy peers, students with low computer-self efficacy engage lesser in virtual learning activities thus, are disadvantaged in terms of learning effectiveness and satisfaction. Student engagement is of interest to educators. It functions as motivation to get students to be enthusiastic, energized, stay emotionally attached and present in the classroom, and positively interact with the academic task. Engagement involves active learning. Hence, precautionary measures should endeavour to enable students to use technology-mediated learning and evade disadvantaged positions (Angelino et al., 2007).

5.1. Theoretical implications

These results resonate with engagement theory and confirm that a shift from traditional to online learning increases students' responsibility to stay engaged while impacting peer-to-peer and student-lecturer engagement. Digital literacy and inclusion are essential for students to maximize their learning outcomes. However, rapid technological advancements minimize engagement and lower interaction. Time requirement, resistance to change, and technological skills are significant barriers to effective learning (Annansingh & Bright, 2010). Hence, in the study from home context, an institutional challenge is to motivate students to self-engage in learning as students' engagement measures the institutional quality of education. For example, the use of interactive video via e-learning resulted in higher learner satisfaction and better learning performance (LapitanJr et al., 2021; Zhang et al., 2006).

Institutions are challenged in developing courses and learning to design, executing pedagogical strategies and technological systems to support the e-learning experiences (Raes et al., 2020). Education delivery via online platforms is problematic as students may develop exhaustion, and losing attentiveness or motivation to participate, consequently curtailing involvement. As a strategy to increase students' involvement and interaction, the content of online platforms needs to include engagement-inducing functions such as chatbox or forums. Moreover, technical impediments may hinder students' engagement in virtual classes. Thus, the technology moderators need to identify issues related to the functionality of technology.

Social identity theory states the need for a sense of belonging to encourage engagement. Our results conform to the theory and indicate that higher students' relatedness stimulates virtual participation of more students resulting in increased perception of in-group and a sense of belonging. A sense of in-group may motivate students to interact and contribute to group online learning, accomplishing the learning goals. By profoundly engaging in learning, students absorb and internalize what they learn and engage further in learning activities. Students undertake more effort to meet the learning requirements and accomplish the learning goal by acquiring focal knowledge or skills (Robinson and Hullinger 2008).

5.2. Managerial implications

It is challenging for instructors to manage a non-physical classroom. While teaching online, it is crucial for instructors to monitor and assess students' involvement for better learning outcomes. Instructors may use interactive platforms with functions such as chatbox, forums, and blogs as communication tools to encourage student involvement. For example, instructors could post a question and ask the students to post chat responses. To encourage students' participation, lecturers may skim students' answers and respond with comments and follow-up questions. This creates and facilitates conversation between student-instructor and is particularly helpful in instances when students are apprehensive. Online chatting offers the opportunity to keep the student engaged and follow the material. Alternatively, instructors could use polling feature sites (e.g., Poll Everywhere) to check students' level of understanding. Polls are suitable even when students' cameras are turned off.

6. Conclusion

The coronavirus pandemic is reshaping education and has created an enormous disruption of education systems in history (Muthuprasad et al., 2021). The ongoing pandemic crisis has created a new norm of teaching and learning conditions in virtual classes. Brief shutdowns of the institution may have hindered learning. While the negative impact of the switch to virtual learning has been felt, the shift to e-learning, ushered in by the COVID-19 pandemic has delayed students' learning. The existing literature is mostly exploratory in the non-100% virtual learning environment; mostly focus on learning environment influences on pedagogic, learning material, and course design and how technology impacts learning effectiveness. But, how engagement impacts e-learning effectiveness and satisfaction with the moderator role of computer self-efficacy in the study from home context with 100% virtual learning environment is unknown. This study fills this research gap by setting up an empirical, theory-driven study to investigate engagement theory and social identity theory.

We addressed the research question on how students' expectations to adopt online learning contribute to e-learning engagement, thereby influencing learning effectiveness and satisfaction in the context of studying from home during the COVID-19 environment.

The results explain how expectations of virtual learning affect e-learning engagement, effectiveness, and satisfaction. SEM-PLS modelling approach is applied in the context of virtual learning space within the study from home context. Our key results reveal that e-learning expectations to adopt e-learning contribute positively to e-learning engagement, which is fundamental for effective learning that leads to learning satisfaction. The impact on e-learning effectiveness is moderated by computer self-efficacy on e-learning engagement and perceived learning effectiveness nexus in the study from home context during the pandemic.

We contribute to extant computer self-efficacy e-learning literature by empirically testing the nature of its influences on e-learning effectiveness and satisfaction. Student's engagement is often unobservable in a virtual environment, therefore, re-designing the e-learning platform to offer students comparable learning experiences regardless of their location is crucial to e-learning engagement. With the continuously prolonged online classes, universities should invest in developing digital literacy skills among teaching staff and learners. Our results contradict prior literature by indicating that computer self-efficacy insignificantly impacts e-learning engagement, suggesting that learning engagement is a crucial element of learning outcomes that deserve future research attention. The findings advance our understanding of the strength and constraints of technology-self efficacy. The appropriate design of the technology learning management system encourages various teaching strategies to facilitate and reward active engagement.

Engagement theory suggests integrating learning theories in a technology-based teaching and learning environment. With the paradigm shift of the virtual learning environment, the current surge in virtual learning due to the COVID-19 pandemic requires students to be independent, self-motivated, and self-disciplined. With computer self-efficacy, virtual learning could promote continuity of instruction and uphold student engagement given that students meet their expectations to adopt e-learning and hence engage continuously in the virtual classroom. According to the Social Identity Theory, when students are engaged in a social group, they have a sense of social presence in the peer group, hence a stronger sense of belonging when they engage in virtual classroom activities.

6.1. Limitations and future recommendations

Given the ongoing shutdowns, the full impact of this unprecedented shift to virtual learning plays out for years to come. It is too early to assess completely the pandemic impact on student learning. While some universities suspended their usual year-end assessments and examinations at the end of the semester, others re-formatted the assessment tasks to 100% within the semester. Due to the cumulative impact of learning loss, students are expected to be behind the academic milestones for certain subjects following this disadvantaged experience. Specifically, a lack of face-to-face interactions minimizes the development of soft skills. Hence, future research could investigate the pandemic toll on learning. We would also suggest future research to investigate how to engage students in the e-learning environment using instructional interventions using virtual breakout room within the study from home context. Furthermore, as universities start to open up again, filling students' learning gaps will become a priority. It is also interesting to study the lecturers' skills in the implementation of e-learning in influencing students' engagement level, e-learning effectiveness, and satisfaction level. Another limitation of this study is the use of cross-sectional data to verify the proposed hypotheses. Data were collected only from university students studying in Malaysia. Hence, the findings might not be generalizable to other countries. Hence, future research could use a longitudinal study in assessing causation compared to a cross-sectional research design.

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Tables and Figures

Table 1. Demographic profile of the respondents.

Variable	Frequency	Percentage
Gender		
Female	126	59.4
Male	86	40.6
Ethnicity		
Malay	9	4.2
Chinese	161	75.9
Indian	9	4.2
Others	33	15.6
Nationality		
Malaysian	167	78.8
Non-Malaysian	45	21.2

Table 2. A full-collinearity test.

Variables	VIF values
Computer self-efficacy	1.027
E-learning engagement	1.262
Expectation to adopt e-learning	1.159
Learning satisfaction	1.837
Perceived learning effectiveness	1.717

Table 3. Measurement model.

Constructs	Items	Loadings	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Cognitive Engagement	COG2	0.820	0.804	0.816	0.866	0.569
	COG3	0.802				
	COG4	0.809				
	COG7	0.543				
	COG1	0.762				
Behavioural Engagement	BEH1	0.772	0.817	0.827	0.868	0.525
	BEH2	0.805				
	BEH3	0.781				
	BEH6	0.596				
	BEH7	0.682				
	BEH8	0.689				
Emotional Engagement	EMO1	0.772	0.891	0.894	0.913	0.516
	EMO10	0.708				
	EMO2	0.529				
	EMO3	0.577				
	EMO4	0.791				
	EMO5	0.742				
	EMO6	0.775				
	EMO7	0.857				
	EMO8	0.578				
	EMO9	0.780				
Social engagement	SOC2	0.712	0.822	0.830	0.871	0.530
	SOC3	0.692				
	SOC4	0.781				
	SOC5	0.741				
	SOC6	0.781				
Course design	CD1	0.909	0.850	0.854	0.909	0.770
	CD2	0.892				
	CD3	0.830				
Interaction with the instructor	II1	0.865	0.926	0.927	0.944	0.773
	II2	0.888				
	II3	0.844				
	II4	0.920				
	II5	0.876				
Interaction with peer students	IP1	0.886	0.898	0.900	0.929	0.766
	IP2	0.860				
	IP3	0.880				
	IP4	0.875				
Individual learning process	LP1	0.891	0.924	0.925	0.943	0.769
	LP2	0.915				
	LP3	0.912				
	LP4	0.888				

	LP5	0.771				
Learning achievement	ACH1	0.932	0.927	0.929	0.945	0.776
	ACH2	0.891				
	ACH3	0.896				
	ACH4	0.852				
	ACH5	0.830				
Computer self-efficacy	CSE2	0.701	0.878	0.899	0.907	0.619
	CSE3	0.810				
	CSE4	0.812				
	CSE5	0.818				
	CSE6	0.789				
	CSE7	0.783				
Learning satisfaction	LS1	0.868	0.970	0.973	0.975	0.849
	LS2	0.908				
	LS3	0.936				
	LS4	0.955				
	LS5	0.918				
	LS6	0.932				
	LS7	0.931				
Perceived learning effectiveness	PLE1	0.803	0.936	0.944	0.951	0.797
	PLE2	0.879				
	PLE3	0.937				
	PLE4	0.921				
	PLE5	0.917				

Table 4. Discriminant validity (HTMT criterion – 0.90).

	BEH	COG	CSE	CD	EMO	LP	IP	II	ACH	LS	PLE	SOC
BEH												
COG	0.831											
CSE	0.089	0.126										
CD	0.365	0.376	0.228									
EMO	0.568	0.490	0.205	0.589								
LP	0.345	0.351	0.193	0.631	0.601							
IP	0.297	0.324	0.212	0.690	0.493	0.616						
II	0.252	0.347	0.317	0.688	0.416	0.509	0.631					
ACH	0.458	0.467	0.290	0.804	0.662	0.787	0.727	0.625				
LS	0.393	0.302	0.267	0.570	0.873	0.580	0.448	0.393	0.579			
PLE	0.459	0.371	0.303	0.663	0.746	0.653	0.583	0.519	0.721	0.741		
SOC	0.695	0.658	0.210	0.314	0.434	0.349	0.315	0.196	0.393	0.282	0.383	

BEH: Behavioural engagement; COG: Cognitive engagement; CSE: Computer self-efficacy; CD: Course design; EMO: Emotional engagement; LP: Individual learning process; IP: Interaction with peer students; II: Interaction with the instructor; ACH: Learning achievement; LS: Learning satisfaction; PLE: Perceived learning effectiveness; SOC: Social engagement

Table 5. Results of the formative higher-order constructs.

Higher-order constructs	Formative items (indicators)	Outer weights	Outer loadings	*t*-value	*p*-value	95% CI	VIF
E-learning engagement	Behavioural engagement	0.055	0.602	0.437	0.662	[-0.198, 0.294]	2.198
	Cognitive engagement	0.072	0.538	0.600	0.548	[-0.156, 0.302]	1.975
	Emotional engagement	0.881	0.983	10.647	0.000	[0.709, 1.019]	1.353
	Social engagement	0.121	0.521	1.207	0.227	[-0.083, 0.310]	1.596
Expectation to adopt e-learning	Course design	0.223	0.806	1.797	0.072	[-0.030, 0.453]	2.394
	Individual learning process	0.314	0.857	2.640	0.008	[0.091, 0.558]	2.190
	Interaction with peer students	0.032	0.705	0.309	0.757	[-0.175, 0.233]	2.078
	Interaction with the instructor	-0.038	0.598	0.306	0.760	[-0.294, 0.191]	1.829
	Learning achievement	0.573	0.961	4.107	0.000	[0.289, 0.840]	3.357

Table 6. Structural model results.

Hypothesis	Relationships	β	SE	*t*-value	*p*-value	5.0%	Remarks	R^2	f^2	Q^2	Q^2predict
H1	Expectation to adopt e-learning -> E-learning engagement	0.704	0.053	13.228	0.000	[0.609, 0.784]	Significant		0.702		
	Expectation to adopt e-learning² -> E-learning engagement	0.087	0.036	2.435	0.007	[0.036, 0.145]			0.032		
H2	Computer self-efficacy -> E-learning engagement	0.011	0.073	0.146	0.442	[-0.113, 0.125]	Not significant	0.439	0.000	0.213	0.369
H3	Computer self-efficacy -> Perceived learning effectiveness	0.191	0.063	3.021	0.001	[0.090, 0.295]	Significant		0.071		
H4	E-learning engagement -> Perceived learning effectiveness	0.667	0.040	16.849	0.000	[0.591, 0.722]	Significant	0.516	0.885	0.404	0.432
H6	Perceived learning effectiveness -> Learning satisfaction	0.711	0.040	17.937	0.000	[0.637, 0.769]	Significant	0.506	1.023	0.424	0.285
Moderating effect											
H5	E-learning*computer -> Perceived learning effectiveness	-0.081	0.049	1.662	0.048	[-0.153, 0.006]	Significant		0.016		

Note(s): Results were based on bootstrapping with 5,000 subsamples (one-tailed); $p < 0.05$ (1.645); $p < 0.01$ (2.327); $p < 0.001$ (3.092).

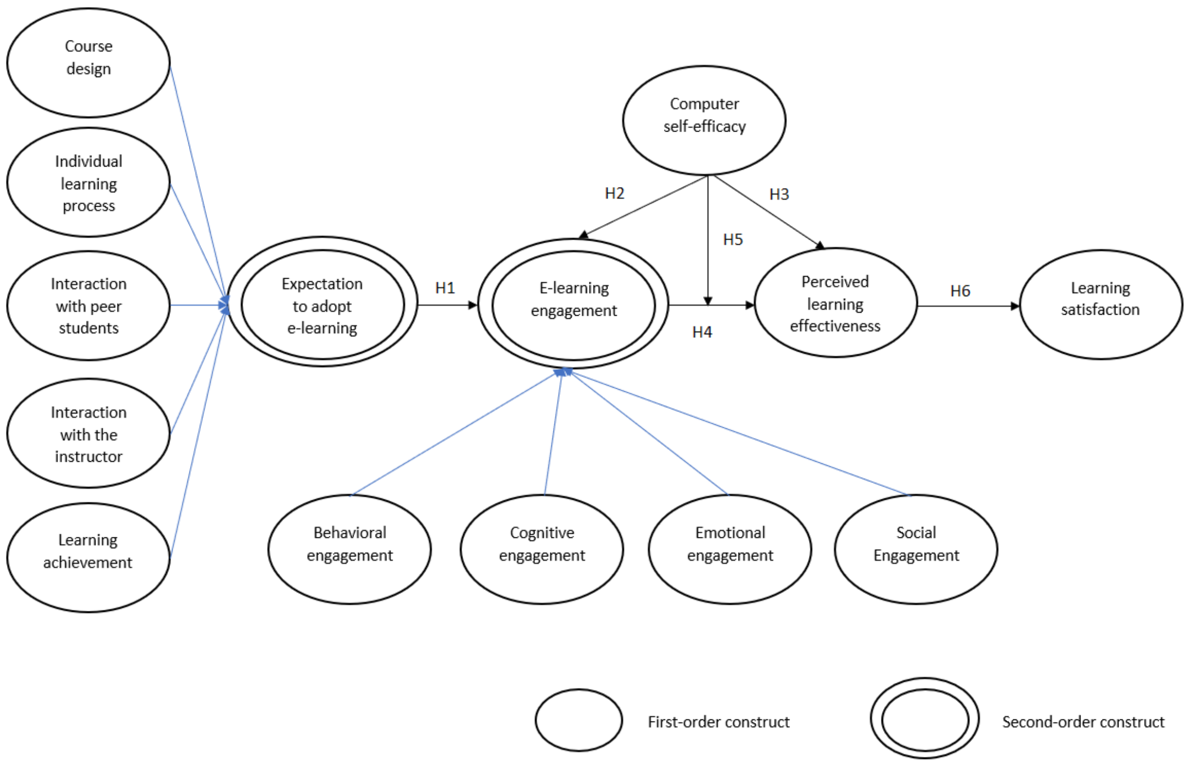

Figure 1. Research model.

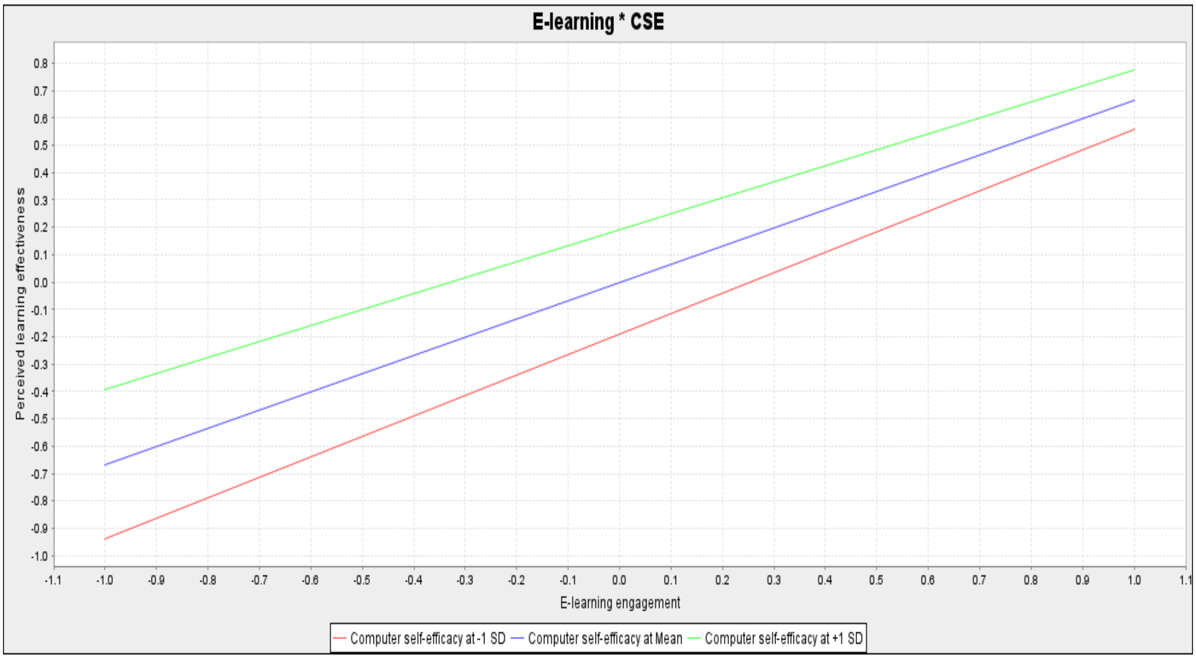

Figure 2. The moderating effect of computer self-efficacy on the relationship between e-learning engagement and perceived learning effectiveness.

Appendix 1

Questionnaire constructs and items

Construct		Statements	Sources
Course design	CD1	A clear and organised structure of the course and learning material	Paechter et al. (2010)
	CD2	Usability of the platform	
	CD3	Favourite cost-benefit ratio of effort and learning outcomes	
Interaction with the instructor	II1	Fast feedback from the instructor	Paechter et al. (2010)
	II2	Counselling and support of learning by the instructor	
	II3	Possibility to establish personal contact with the instructor	
	II4	Easy and fast accessibility of the instructor	
	II5	Expertise of the instructor in the implementation of e-learning courses	
Interaction with peer students	IP1	Easy and fast exchange of information and knowledge with peer students	Paechter et al. (2010)
	IP2	Variety of communication tools for exchanging information with peer students (e.g., email, chat, newsgroups)	
	IP3	Support of cooperative learning and group work with other course participants	
	IP4	Personal contact with peer students	
Individual learning process	LP1	Flexibility of learning with regard to time and place	Paechter et al. (2010)
	LP2	Flexibility of choice of learning strategies and pace of learning	
	LP3	Opportunities for self-paced chapter exercises and application of one's knowledge	
	LP4	Opportunities for controlling one's learning outcomes (e.g., by self-tests)	
	LP5	Support for maintaining learning motivation	
Learning achievement	ACH1	Acquiring knowledge and skills in the subject matter	Paechter et al. (2010)
	ACH2	Acquiring skills on how to apply the knowledge	
	ACH3	Acquiring skills in communication and cooperation	
	ACH4	Acquiring skills in self-regulated learning (personal competence)	
	ACH5	Acquiring skills in using the internet for scientific practice (internet skills)	
Cognitive Engagement	COG1	I go through the work for online class and make sure that it's right.	Wang et al. (2016)
	COG2	I think about different ways to solve a problem.	
	COG3	I try to connect what I am learning to things I have learned before.	
	COG4	I try to understand my mistakes when get something wrong.	
	COG5	I would rather be told the answer than have to do the work.	
	COG6	I don't think that hard when I am doing work for class.	
	COG7	When work is hard I only study the easy parts.	
	COG8	I do just enough to get by in class.	
Behavioural Engagement	BEH1	I stay focused.	Wang et al. (2016)
	BEH2	I put effort into learning my units.	
	BEH3	I keep trying even if something is hard.	
	BEH4	I complete my assignment on time.	
	BEH5	I talk about units outside of class.	
	BEH6	I don't participate in class.	
	BEH7	I do other things when I am supposed to be paying attention.	
	BEH8	If I don't understand, I give up right away.	
Emotional Engagement	EMO1	I look forward to online classes.	Wang et al. (2016)
	EMO2	I enjoy learning new things about units.	
	EMO3	I want to understand what is learned in online class.	
	EMO4	I feel good when I am in online class.	
	EMO5	I often feel frustrated in online class.	
	EMO6	I think that online class is boring.	
	EMO7	I don't want to be in online class.	
	EMO8	I don't care about learning any units in online class.	
	EMO9	I often feel down when I am in online class.	
	EMO10	I get worried when I learn new things in whatever units in online class.	
Social Engagement	SOC1	I build on others' ideas.	Wang et al. (2016; 2019)
	SOC2	I try to understand other people's ideas in online class.	

	SOC3	I try to work with others who can help me in online class.	
	SOC4	I try to help others who are struggling in online class.	
	SOC5	I don't care about other people's ideas.	
	SOC6	When working with others, I don't share ideas.	
	SOC7	I don't like working with classmates.	
		During the lockdown period,	
Learning satisfaction	LS1	I like the idea of learning online in class (e.g., tutorial) like this	Hu and Hui (2012)
	LS2	Learning in an online class (e.g., tutorial) like this is a good idea	
	LS3	My learning experience in online class (e.g., tutorial) is positive	
	LS4	Overall, I am satisfied with online class (e.g., tutorial)	
	LS5	My learning in online class (e.g., tutorial) is pleasant	
	LS6	Learning in an online class (e.g., tutorial) like this is enjoyable	
	LS7	As a whole, the online class (e.g., tutorial) is effective for my learning.	
Perceived learning effectiveness	PLE1	The online class provides adequate resources and tools to learn a unit/subject.	Hu and Hui (2012)
	PLE2	This online class (e.g., tutorial) gives me chances to practice what I learn.	
	PLE3	This online class (e.g., tutorial) allows me to improve my understanding of the basic elements of a unit/subject.	
	PLE4	This online class (e.g., tutorial) allows me to appreciate the important issues about a unit/subject.	
	PLE5	This online class (e.g., tutorial) allows me to learn the fundamental aspects of a unit/subject.	
Computer self-efficacy		In general, I can use computer technology to complete a task:	Hu and Hui (2012)
	CSE1	Even if there was no one around to tell me what to do as I go.	
	CSE2	If I had only the user manuals for the reference.	
	CSE3	If I had seen someone else using it before trying it myself.	
	CSE4	If I could call someone for help if I got stuck	
	CSE5	If someone else had helped me get started.	
	CSE6	If I had a lot of time to complete the job/assignment for which the software/search engine was provided.	
	CSE7	If I had just the built-in help facility for assistance.	
	CSE8	If someone showed me how to do it first.	