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Effectiveness of e-learning: the mediating role of student engagement on perceived learning effectiveness

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Abstract

Purpose – This study extends the literature on the effectiveness of e-learning by investigating the role of student engagement on perceived learning effectiveness (PLE) in the context of Indian higher education. Further, the impact of personal factors (Internet self-efficacy (ISE)) and environmental factors (information, system and service quality parameters) on various dimensions of student engagement (behavioral, emotional and cognitive) is studied through the lens of social cognitive theory (SCT).

Design/methodology/approach – An online management information systems (MIS) course is delivered to a batch of 412 postgraduate students. An online survey was conducted to measure the factors affecting their PLE. In addition to the survey, a summative assessment is conducted to evaluate the students in terms of their marks to assess their achievements (actual learning). Covariance-based structural equation modeling (CB-SEM) is used to validate the developed research model.

Findings – It is discovered that the IS (information system) quality parameters (environmental factors) positively impact PLE. The ISE affects the PLE through the mediating effect of all the dimensions of student engagement. Furthermore, there exists a positive relationship between PLE and student marks.

Originality/value – This study develops a research model using personal and environmental factors to understand PLE through the lens of SCT and then empirically validates it. The psychological process from the students' ISE to the PLE is explained through the mediating effects of various dimensions of engagement. Further, it is found that the PLE is positively related to student marks.

Keywords E-learning, Learning effectiveness, Student engagement, Social cognitive theory

Paper type Research paper

Introduction

E-learning is the asynchronous or synchronous mode of communication for knowledge construction or confirmation via an electronic medium (Garrison, 2011). E-learning is widely adopted by organizations because of its consistent worldwide training, reduced delivery cycle time, increased learner convenience, reduced information overload, improved tracking and lower expenses (Welsh *et al.*, 2003). For learners, the issue of different time zones and distance is resolved by providing them with asynchronous learning where they can learn anytime and anywhere (Ally, 2004). E-learning has been successfully applied in academia and industry with a reported increase in the quality of teaching and learning and increased revenue, learning outcomes and satisfaction (Chang, 2016). The increasing popularity of e-learning can also be attributed to the flexibility it offers at reduced costs. The global e-learning market is estimated to reach US $65.41 bn by 2023, with a growth rate of 7.07% (Research and market report, 2018). In addition to this, the fourth goal of United Nations Sustainable Development Goals [1] emphasizes on affordable and quality technical,

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vocational and tertiary education by 2030, and e-learning can emerge as an option to resolve the primary problems in higher education such as access, quality and affordability (Yeld, 2016). With the advancements in Internet technology, more and more organizations are investing in e-learning with an aim to improve their learning outcomes, one of which is learning effectiveness. Learning effectiveness can be defined as the degree to which the learning outcomes are achieved. Studies, for example, Kankanhalli *et al.* (2011), have found that there is a positive correlation between the learning effectiveness and actual marks. Once the factors that impact learning effectiveness are identified, we can model and validate their relationships.

The underlying difference between traditional classroom education (face-to-face) and e-learning is the environment in which students learn. While in a traditional classroom, learning activities are more or less restricted in the physical classroom, in e-learning platforms, students enjoy the benefit of learning asynchronously anytime and from anywhere. E-learning can be classified based on the purpose of education or professional training. The former is used by educational institutions such as schools, colleges and universities, and the participants obtain degrees or diplomas. The latter is generally used by individuals for building or upgradation of skill set(s) or by business organizations/corporate as a part of their professional training programs initiatives. Although there are some similarities in terms of increasing the cost-effectiveness of learning, accessibility, affordability and the delivery method (use of platforms such as mobiles, cloud, etc.), there exist some differences with regard to the purpose (knowledge creation vs sharing) or context of learning (target groups, pedagogy, assessment, etc.).

The ever-increasing popularity of e-learning has captured the attention of several researchers to study its effectiveness. Most research on the subject measures effectiveness in terms of pre- and posttests (Broadbent, 2017; Reychav and McHaney, 2017). However, research on developing and validating a model to understand the factors affecting perceived learning effectiveness (PLE) is limited. Facilitating e-learning alone does not guarantee the required learning outcomes. The participation of learners is essential to achieve the required level of outcomes. Student engagement is one of the predominant antecedents of learning outcomes (Hu and Hui, 2012; Rashid and Asghar, 2016). Moreover, the literature suggests that the engagement construct is multifaceted, encompassing behavioral, emotional and cognitive dimensions (Fredricks *et al.*, 2004). Although studies, for example, Hu and Hui (2012), have investigated the effect of engagement on PLE, there is limited research on the effect of different dimensions of engagement on PLE in the e-learning environment.

According to the social cognitive theory (SCT), personal and environmental factors contribute to an individual's behavior (Bandura, 1986). In an e-learning environment, the students learn over the Internet. Thus, Internet self-efficacy (ISE) plays a significant role in student learning. Although ISE positively affects Internet use (Eastin and LaRose, 2000), which further affects student engagement (Rashid and Asghar, 2016), the relationship from ISE to student engagement is scantly researched. Furthermore, it is essential to understand the psychological process from ISE to PLE through mediation, which can provide insights into how ISE impacts PLE. The delivery of course content occurs on the e-learning platform where the information system acts as the students' immediate learning environment. Since the system plays an interface between the learning materials and the end learners, the system's quality parameters are critical in achieving satisfaction and use intentions (Delone and McLean, 2003). Although several researchers have studied the IS (information system) quality parameters to understand the use intentions (Almarashdeh, 2016; Mohammadi, 2015), the role of IS quality parameters to understand the student engagement is underresearched even though a relationship exists between engagement and use intentions (Hussein and Hassan, 2017).

Therefore, the objective of our study is to understand the role of various dimensions of engagement on PLE and the relationship between PLE and student marks in an e-learning environment. Further, we also aim to investigate the role of personal and environmental factors on the behavior of an individual (in our case, student engagement). By using the SCT, we develop a conceptual model for learning effectiveness. The conceptual model is validated using structural equation modeling (SEM) on the collected data.

The organization of the paper is as follows: Section 2 presents the theoretical foundation. Section 3 develops the conceptual model and formulates the hypotheses. Section 4 presents the research methodology followed by data analysis and results in section 5. Further, the results are discussed in section 6, followed by theoretical and practical implications and limitations in sections 7 and 8, respectively.

Theoretical foundation

The drivers for the extensive use of e-learning are accessibility, affordability and quality content (Barteit *et al.*, 2020). The growth and popularity of e-learning depend on its use by educators and learners across the globe. The demand of e-learning is because of the learning innovations in various educational fields such as health and engineering (Rodrigues *et al.*, 2019), analytics dashboard applications for feedback to support learning regulation (Sedrakyan *et al.*, 2020), artificial intelligence–based assessment (Cruz-Benito *et al.*, 2019) and so on. The supply of e-learning is carried out by various content developers, open education resources (OER), open courseware (OCW) and so on. Apart from meeting the demand and supply of e-learning, a conducive environment or ecosystem or the environmental enablers such as industry acceptance of e-learning, government policies, cloud platforms, m-learning, virtual environments (simulation, games, etc.), social media are vital for the success in e-learning. The availability of mobile technology and OER resolves the problems related to accessibility and affordability for anyone who wants to learn and enhances the interactions in online collaborations (Ally and Prieto-Blázquez, 2014). The proper integration of gamification with e-learning in higher education has a positive impact on motivation, engagement, satisfaction and better academic achievement for practical assignments (De-Marcos *et al.*, 2014).

Learning effectiveness

The ever-evolving e-learning landscape has necessitated the need to assess the quality of the accreditation as traditional quality measurement practices cannot do justice to the new web-based climate (Blicker, 2005). The quality of an online course can be assessed by measuring the effectiveness of e-learning. Learning effectiveness is defined as the degree to which the learning outcomes are achieved (Blicker, 2005). "Learning outcomes are statements of what a learner is expected to know, understand and/or be able to demonstrate after completion of a process of learning" (ECTS Users' Guide, 2005, p. 47). The focus on the learning outcomes to understand student achievements is primarily due to the paradigm shift from teacher-centered to learner-centered learning methods (Žiliukas and Katiliūtė, 2015). According to Kennedy (2006), learning outcomes focus on the learner's achievements and what they can demonstrate at the end of a course or activity rather than the expectations of the instructor. The literature suggests that behavioral intentions lead to actual behaviors (Agudo-Peregrina *et al.*, 2014; Renaud and Van Biljon, 2008). Further, there is a positive correlation between the learning effectiveness and actual grades (Kankanhalli *et al.*, 2011). Therefore, measuring the learning outcomes is beneficial for various stakeholders, such as students, instructors, academic advisors, accreditation agencies and so on, to achieve defined learning outcomes (Mahajan and Singh, 2017).

Several researchers have measured learning effectiveness in terms of comparing whether e-learning performs better than traditional face-to-face learning (Cavanaugh and Jacquemin, 2015; Walczak and Taylor, 2018). However, there are limited studies on the factors affecting the learning effectiveness from a theoretical perspective (Gámiz-Sánchez *et al.*, 2016; Pradana and Amir, 2016; Shin and Kang, 2015). Understanding the factors affecting learning effectiveness benefits not only the e-learning providing organizations but also the students because both stakeholders can use them to optimize learning outcomes.

Social cognitive theory

The SCT draws a triadic relationship between personal, environmental and behavioral aspects of human beings (Bandura, 1986). The roots of SCT lie in the social learning theory (Bandura, 1978), where individuals learn from observing and imitating others. The SCT explores human behavior in the learning context (Wagner *et al.*, 2010). SCT presents a central role to cognitive, vicarious, self-regulatory and self-reflective processes (Bandura, 2009). Human beings have an exceptional capacity for symbolization, which acts as a powerful tool for understanding the environment and creating and regulating environmental events that touch all aspects of their lives. The external influences or experiences affect human behavior through cognitive processes that guide for judgment and action of individuals. The self-regulation of motivation, affect and action functions through the set internal standards and evaluative reaction to an individual's own behavior (Bandura, 2009). Individuals are not just agents of action but self-examiners of their functioning. The ability of self-reflection and adequacy of one's thoughts and actions is one of the distinct attributes in SCT. People cannot live in individual autonomy; rather, they work together or learn from others to obtain what they cannot achieve on their own. Both cognitive factors and environmental factors affect human behavior (Wood and Bandura, 1989). The environment people select and create can have some influence on their lives. People undertake activities or environments they believe themselves capable of managing, whereas people tend to avoid activities or environments they consider that will exceed their capabilities (Wood and Bandura, 1989).

Conventionally, a learning environment consisted of physical and social environments in a classroom setting. Cognitive factors and environmental factors affect the learner's behavior and performance (Wu *et al.*, 2010). Piccoli *et al.* (2001) have expanded the conventional definition of the learning environment by providing five dimensions of environmental factors – technology, content, interaction, learner control and learning model in the virtual learning environment context. SCT is also widely applied with established validity by several researchers in the e-learning context (Chen, 2014; Jin *et al.*, 2015; Wang and Lin, 2007; Zhang *et al.*, 2012). According to SCT, individuals learn from the consequences of their own actions and also those of others' actions. Consequently, they develop understandings or capabilities by observing others and through their own actions. The interaction between the personal and the environmental factors contributes to the behavior (in our case, engagement) of an individual. In an e-learning system, the IS used to deliver course content acts as the immediate environment of the users that influences their ability to complete the required behavior. Although the SCT is used to predict continuation intention, knowledge contribution behavior and so on, its use to understand PLE is underresearched. Thus, in this study, we aim to understand the phenomena of PLE using the theoretical lens of SCT.

Conceptual model and hypothesis development

Effect of engagement in e-learning

Several studies state that students' educationally purposeful activities or practices are the single best predictors of their academic development (Kuh, 2009; Pascarella and

Terenzini, 2005). These practices or activities encourage student engagement and promote learning (Hu and Kuh, 2002). Engagement is found to be a crucial antecedent for learning outcomes (Hu and Hui, 2012). Academic engagement refers to the quality of the effort, which students make to perform well and achieve desired outcomes (Hu and Kuh, 2002). It is found that active users and high levels of interaction (forums, video lectures/course) predict grades (Sinha and Cassell, 2015; Pérez-Sanagustín *et al.*, 2016). Further, research also suggests that the nature of engagement is multifaceted and includes three dimensions of engagement – behavioral, emotional and cognitive (Fredricks *et al.*, 2004). The behavioral engagement (BEng) focuses on participation, which includes following rules, classroom norms, positive conduct, active attendance, homework completion, involvement in cocurricular activities and so on. (Fredricks *et al.*, 2004). Emotional engagement (EEng) focuses on affective reactions in the classroom. This includes interest, enjoyment, sense of belongingness, students' willingness to participate and so on. Cognitive engagement (CEng) draws on the concept of psychological investment in learning. It involves students' willingness to go beyond minimum course requirements and prefer challenges (Kuh, 2009). Here, students are self-regulated and strategic toward achieving desired learning outcomes (Fredricks *et al.*, 2004).

The multidimensional engagement construct is found to positively impact academic outcomes (Hu and Hui, 2012; Kuh, 2009). The behavioral norms of the BEng dimension, such as active attendance, following classroom norms, completing homework and so on, are critical for achieving positive academic outcomes (Kuh, 2008). Regularity is related to performance. First, regular students follow the course structure and hence, achieve higher attainment. Second, having high regularity in class positively impacts certain factors internal to the students, that is, motivation, commitment and learning strategies (Boroujeni *et al.*, 2016). There is evidence that when students are not emotionally engaged in their academic life, they tend to be at risk for poor academic outcomes (Hirschfield and Gasper, 2011). The CEng that draws on the psychological investment of the students toward achieving desired learning outcomes is crucial as students go beyond the minimum course requirements, set the learning goals and seek the challenge to increase competence (Kuh, 2009). Therefore, the effort and strategy used by the students to achieve the desired outcome positively impact the academic outcomes. Furthermore, in technology-mediated learning, student engagement positively impacts academic performance through self-directed learning (Rashid and Asghar, 2016). A study by Hu and Hui (2012) finds that learning engagement has a positive effect on PLE. From the literature, it is observed that the multidimensional engagement construct is studied in education (Fredricks *et al.*, 2004). However, the effect of each dimension, individually, on PLE has received little research attention. Hence, we hypothesize that engagements are positively related to PLE. The conceptual model is presented in Figure 1.

H1a, b, c. Behavioral, emotional and cognitive engagements are positively related to PLE in an e-learning environment.

Effects of personal factors in e-learning

The personal factor, which is the internal belief of an individual toward performing the task, influences the behavior. Self-efficacy is widely used as a personal factor in the SCT framework. It is defined as "People's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura, 1986, p. 94). It does not in itself represent the actual skills and capabilities, rather a belief of individuals to perform or execute a skill. Although self-efficacy is commonly confused with motivational constructs, such as outcome expectations, self-control and perceived control, it is distinct in terms of specificity and close association to performance tasks and is a better predictor of academic performance (Zimmerman, 2000). Numerous studies have identified self-efficacy as one of the predominant indicators of student motivation, learning and performance (Robbins

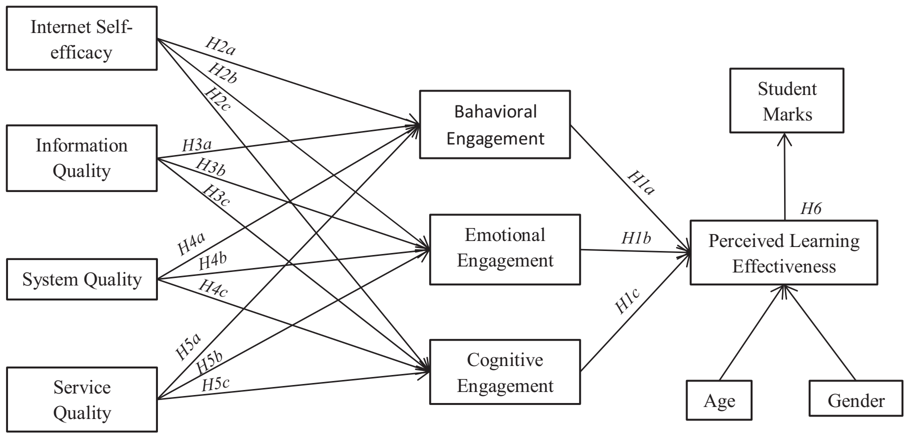


Figure 1.
Conceptual model

et al., 2004; Zimmerman, 2000). Besides, self-efficacy is derived from four principal sources of information – performance accomplishments, vicarious experience, verbal persuasion and physiological states (Bandura, 1977). The predictors of self-efficacy consist of various dimensions of social learning, that is, individuals learn from others in a social environment by imitating others (vicarious learning).

Many researchers have applied the SCT framework to understand the behavior of individuals in e-learning environments. The user's self-presentation has a positive impact on online knowledge contribution behavior (Jin *et al.*, 2015). Additionally, studies have used self-efficacy as a personal factor to understand the intention to continue participation in e-learning systems (Zhang *et al.*, 2012). With a self-regulated learning view of SCT, Wang and Lin (2007) suggest that students with higher levels of motivation apply effective strategies and respond appropriately to the environment demands in a web-based learning environment. Self-efficacy is also found to be one of the critical factors impacting students' stickiness in a web-based learning environment (Chen, 2014) and also determines the learning outcome expectations. Pellas (2014) identifies the predictors such as self-efficacy, metacognitive self-regulation and self-esteem for engagement construct (behavioral, emotional and cognitive) in virtual world scenarios. Furthermore, perceived self-efficacy affects the intention to use blogs (Ifinedo, 2017). Computer self-efficacy is defined as "a judgement of one's capability to use a computer" (Compeau and Higgins, 1995, p. 192) and has a significant effect on perceived ease of use and behavioral intention to use (Hsia *et al.*, 2014), and it also determines the learning engagement (Chen, 2017). On the contrary, Sun and Rueda (2012) opine that computer self-efficacy is not related to any of the engagement variables in the distance learning context. However, studies, for example, Chaudhary *et al.* (2012a) and Chaudhary *et al.* (2012b), find that self-efficacy positively affects work engagement in the Indian context.

E-learning consists of an additional component of learning, that is, the Internet, unlike traditional classroom learning. ISE is defined as "the belief in one's capability to organize and execute Internet actions required to produce given attainments" (Eastin and LaRose, 2000, p. 1), and it is crucial for the students using e-learning platforms because they primarily learn over the Internet. Therefore, the comfortableness with the Internet plays a major role in student learning. ISE determines Internet use (Eastin and LaRose, 2000), and Internet use is found to be positively related to student engagement (Rashid and Asghar, 2016). Thus, the following hypotheses are proposed.

H2a, b, c. ISE is positively related to behavioral, emotional and cognitive engagement in an e-learning environment.

Effects of environmental factors in e-learning

Environmental factors constitute the external environment of the individual, which influences their ability to complete a task. In an e-learning system, the information system used to deliver course content acts as the immediate environment of the users. The design or environmental dimensions of a virtual learning environment are technology, content, learning model, learner control and interaction (Piccoli *et al.*, 2001). The IS success model developed by Delone and McLean (2003) identifies the role of information quality (InfQ), system quality (SysQ) and service quality (SerQ) on user satisfaction and usage intentions/use. Building on the work of Shanon and Weaver (1949) on communications, and the work of Mason (1978) on measuring information output, DeLone and McLean (1992) define the factors of IS success. Each level of information processing has a measure associated with it, for example, the technical level or production of the information is associated with SysQ, and the semantic level or the product itself is associated with the InfQ. The emergence of end-user computing resulted in the addition of the service provider's role to the existing role of information provider in IS organizations. This resulted in the addition of SerQ in addition to the information and system quality in the DeLone and McLean's IS success model to measure the success of information systems (Delone and McLean, 2003).

The IS success model is used by several researchers in the context of e-learning for identifying the relationship of IS quality parameters with satisfaction and continuous use of information systems. For example, the perceived InfQ, SerQ and knowledge quality has a positive impact on user satisfaction, knowledge adoption and continuation intention to consume and provide information in virtual communities (Zheng *et al.*, 2013; Chou *et al.*, 2015). Dong *et al.* (2016) use an integrated model with SCT and IS success to explain the knowledge-sharing behavior in knowledge management systems (KMS). The content quality affects KMS self-efficacy, which, in turn, determines the knowledge-sharing intention. The perceived SysQ, InfQ, SerQ and computer self-efficacy affect the students' behavioral intentions to use e-learning websites and instructor satisfaction in e-learning and distance learning context (Chang and Tung, 2008; Mohammadi, 2015; Almarashdeh, 2016; Pituch and Lee, 2006). System characteristics and digital material features are identified as critical success factors impacting students' stickiness in a web-based learning environment (Chen, 2014). The InfQ and SysQ have a significant effect on satisfaction in both self-paced tools and instructor–student interactive e-learning tools (Hsieh and Cho, 2011). The InfQ, SysQ, support SerQ and instructor quality have a positive relationship with user beliefs such as perceived usefulness, confirmation and flow. These beliefs lead to satisfaction and continuance intention (Cheng, 2014). Technology, educational content, motivation and attitude significantly influence an employee's e-learning satisfaction (Navimipour and Zareie, 2015).

Several studies have identified that IS quality parameters are important for predicting continuation intention (Mohammadi, 2015) and that a relationship exists between continuation intention and engagement (Hussein and Hassan, 2017); however, the role of IS quality parameters on engagement is understudied. Therefore, a positive relationship is established between IS quality factors and engagement.

H3, b, c. InfQ is positively related to behavioral, emotional and cognitive engagement in an e-learning environment.

H4a, b, c. SysQ is positively related to behavioral, emotional and cognitive engagement in an e-learning environment.

H5a, b, c. SerQ is positively related to behavioral, emotional and cognitive engagement in an e-learning environment.

Numerous studies have found that intention for a behavior leads to the actual behavior (Agudo-Peregrina *et al.*, 2014; Renaud and Van Biljon, 2008). The self-efficacy, which is the belief of an individual to organize and execute certain courses of action to achieve desired outcomes, leads to the actual competence and academic performance (Baartman and Ruijs, 2011; Hong *et al.*, 2015; Robbins *et al.*, 2004; Zimmerman, 2000). Moreover, there is a positive correlation between the learning effectiveness and actual grades (Kankanhalli *et al.*, 2011). Thus, we propose the following hypothesis.

H6. PLE is positively related to student marks in an e-learning environment.

Literature suggests that the role of gender and age are significant in the effectiveness of e-learning (Islam *et al.*, 2011). Females perceive that they learn more than male students in an e-learning context (Rovai and Baker, 2005). While investigating a particular relationship, it is important to control for other extraneous variables that might affect the relationship of our interest. Identification and control of such variables are essential to ensure the generalizability of the empirical results. Therefore, this paper develops and validates a model for PLE while controlling for age and gender.

Literature suggests that students' self-efficacy significantly affects achievement and is a better predictor of academic performance (Hong *et al.*, 2015; Robbins *et al.*, 2004; Zimmerman, 2000). The self-efficacy in using technology is positively related to the academic grade of students in an e-learning context (Wang *et al.*, 2013). However, ISE, which is an individual's psychological state, might not directly impact the PLE because the psychological state does not in itself represent a behavior, rather a determining factor of the behavior (Bandura, 1986). Wan *et al.* (2012) use SCT in organizational settings and posit that virtual competence affects cognitive outcomes and skill developments via self-regulated learning. Further, studies have posited that self-efficacy positively affects academic performance through student engagement (Chen, 2017). The study also finds that work engagement fully mediates the relationship between computer self-efficacy and learning performance in a job for students. There is also evidence of the mediating effect of student engagement on the positive relationship between technology use and academic performance (Rashid and Asghar, 2016).

It is apparent from the literature that the research on the mediating effect of various dimensions of engagement on the positive relationship between ISE and PLE is limited. Since the engagement construct is multifaceted, including behavioral, emotional and cognitive dimensions, it is of great significance to understand the psychological process that occurs from students' ISE to PLE through the mediation of the engagement construct. Therefore, the following hypotheses are proposed.

H7a, b, c. Behavioral, cognitive emotional engagement mediates the positive effect of ISE on PLE in an e-learning environment.

Research method

Participants and procedure

An online management information systems (MIS) course is delivered for a batch of 412 postgraduate students. The course was provided in a fully online learning mode through multimedia formats such as text files, pdfs and video lectures. A section of frequently asked questions was provided with answers for clarification regarding the e-learning course. The SerQ constituted resources, faculty and admin staff, technical support, the accessibility of resources and the responsiveness from admin and technical support for the e-learning course to help the students in case they face any problems. The institution help desk provided toll-free technical support for issues related to connectivity, hardware and software. The responsiveness included the quick turnaround time on questions and the effort and readiness to help students to solve their problems. The emails regarding any support were responded in a reasonable amount of time.

After the course completion, an online survey was conducted to measure the factors affecting PLE. In addition to the survey, a summative assessment is conducted to grade the students to demonstrate their achievements (actual learning). For the assessment, quiz, term exam and assignment are used. Revised Bloom's Taxonomy is used for designing the questions for the quiz (20% weightage), term exam (60% weightage) and assignment (20% weightage) (Krathwohl and Anderson, 2009). For the quiz, multiple-choice questions and fill in the blanks are used; for term exam, matching, short answers, concept maps and open questions are used; for the assignment, practice exercises and problem-solving questions are used. It is made sure that the questions designed follow Bloom's six different levels of learning, which are knowledge, understanding, application, analysis, synthesis and evaluation.

The participants were assured that their responses would be treated as confidential. The sample size followed the recommended size between 30 and 460 (Wolf *et al.*, 2013) and contained 49.76% males and 50.24% females. The majority of participants (50.73%) were in the age group of 20–25 years, 43.69% were in the age group of 26–30 years and the remaining 5.58% were in the age group of 31–35 years. The demographic characteristics of the sample are presented in Table 1.

Measurement development

To measure the latent constructs in our model, we borrow the instruments from the literature. Since the questionnaire was developed in different contexts – both culturally and environmentally, a pretest was conducted to ensure that there were no unanticipated difficulties (Alreck and Settle, 1995). We conducted pretesting with 30 students who had experience in e-learning. After a discussion with the participants, we modified the questionnaire in the e-learning context to simplify some terms and remove ambiguities. The measurement sources are presented in Table 2 with the study, item, description and item codes. All the items are measured using a five-point Likert scale (where 1 = strongly disagree and 5 = strongly agree). The ISE scale is borrowed from Easting and LaRose (2000), which has eight items. The IS quality parameters (information, system and service quality) scale is borrowed from Cheng (2014) with four, four and three items, respectively. In order to measure various types of engagement, the engagement scale is borrowed from Fredricks *et al.* (2004). The behavioral, emotional and cognitive engagement subscales consist of five, six and eight items, respectively. The PLE scale is borrowed from Wan *et al.* (2008) with five items. Additionally, we also check for the reliability of the instruments with Cronbach's alpha values of 0.92 (ISE), 0.896 (InfQ), 0.829 (SysQ), 0.879 (SerQ), 0.939 (BEng), 0.925 (EEng), 0.911 (CEng) and 0.875 (PLE).

		Number of participants	Percentage of participants %
Gender	Male	205	49.76
	Female	207	50.24
Age	20–25	209	50.73
	26–30	180	43.69
	31–35	23	5.58

Table 1. Demographic characteristics

Study	Item	Description	Item code
Eastin and LaRose (2000)	Internet self-efficacy	It focuses on whether the individuals are confident in understanding the hardware and software, troubleshooting, gathering the data on the Internet, carrying out online discussions, etc.	ISE
Cheng (2014)	Information quality	It is the quality of the information or content provided in an e-learning platform, which is expected to be new, updated, flexible and sufficient for the learners with appropriate difficulty level	InfQ
	System quality	It is defined as the quality of the information system, which is used to deliver the content in multimedia and readable format to e-learners and is expected to be consistent, fast and with interactive communication features	SysQ
	Service quality	It is defined as the perceived support and administrative services provided by the help desk and support service administrators to help in learning	SerQ
Sun and Rueda (2012)	Behavioral engagement	It is student engagement in terms of participation and behavioral norms such as paying attention, completing homework, following rules, etc.	BEng
	Emotional engagement	It is defined as the student engagement in terms of affective reactions such as whether the student likes the online class, feel interested, happy, etc.	EEng
	Cognitive engagement	It is the student engagement at a cognitive level to achieve the desired outcome. This comprises of revising the course, studying extra materials, engaging in discussion with people about the course, etc.	CEng
Wan *et al.* (2008)	Perceived learning effectiveness	It is the perception of students about learning the factual material, identifying the central issue of the course, ability to communicate about the subject, etc.	PLE

Table 2.
Measurement sources

Data analysis and results

The participants were asked to fill out the online survey questionnaire to measure the factors affecting PLE. Additionally, a summative assessment is conducted to grade the students to demonstrate their achievements (actual learning). The responses and the marks are used to perform confirmatory factor analysis (CFA) and structural model in AMOS.

Structural equation modeling

The conceptual model presented in Figure 1 is tested through SEM using IBM SPSS AMOS version 24. Our proposed model is a theory testing exercise that confirms the relationship between a set of variables. SEM is a popular method to analyze similar relationships in business studies (Babin *et al.*, 2008). The primary reason behind the widespread applicability of SEM is its capability to test multiple relationships simultaneously into a single model (Sarstedt *et al.*, 2014). In SEM, the most popular approach to establish the cause–effect relationship is covariance-based SEM (CB-SEM). Statistically, CB-SEM is used for theory testing and confirmation (Hair *et al.*, 2011; Sarstedt *et al.*, 2014). AMOS is a software used for CB-SEM to test or confirm the theory. The objective of our research is to fit data to the model (confirming an established model with minor changes). The normality of data is one of the assumptions of CB-SEM. As we are using AMOS (CB-SEM), we have to determine the distribution of data. We have examined the values of skewness and kurtosis for determining normality. We obtained the skewness value between −1 and +1 (lowest value: −0.974, highest value: 0.744) and kurtosis values between −2 and +2 (lowest value: −1.010, highest value: 1.916). For satisfying the normality condition, the value of skewness and kurtosis should lie between ±1 and ± 2, respectively (Kline, 2011; Hair *et al.*, 2010). Thus, our data is normally distributed. Additionally, the number of items per construct is more than 3. The sample size satisfies the advisable sample size, $N > 50 + 8m$, where N is the sample size, and m is the predictor variable (Tabachnick and Fidell, 2007, p. 123). SEM comprises the measurement and structural models.

Measurement model. The CFA is carried out in AMOS 24 software. We obtain a good model fit (χ^2 = 1566.96, df = 829, χ^2/df = 1.89, RMR = 0.027, TLI = 0.935, CFI = 0.94, RMSEA = 0.047) [2] after adjusting the modification indices (MIs). Based on high values of MIs, three pairs of error items from the same constructs were allowed to covariate (Byrne, 2016).

The validity and reliability measures achieved for the model are shown in Table 3. The factor loadings should be greater than 0.5 and preferably more than 0.7 (Hair *et al.*, 1998), which is satisfied in our measurement model. The convergent validity can be determined by composite reliability (CR) and average variance extracted (AVE) (Fornell and Larcker, 1981). The CRs for all the constructs should be greater than 0.7, and AVEs should be greater than 0.5 (Hair *et al.*, 1998). The CRs for all the constructs are greater than 0.7 in the measurement model. The CR for CEng is 0.908, ISE is 0.916, InfQ is 0.895, SysQ is 0.837, SerQ is 0.873, BEng is 0.937, EEng is 0.925 and PLE is 0.878. The maximum reliability (MaxR(H) in the table) values are also greater than 0.7, indicating the reliability is satisfied. The AVEs for all the constructs are greater than 0.5, as shown in Table 3. The square root of AVEs (in the diagonal fields of Table 3) is greater than the correlations between the constructs indicating that the discriminant validity is satisfied (Fornell and Larcker, 1981). Additionally, the maximum shared variance (MSV) is also less than the AVE values implying that the discriminant validity is satisfied.

Common method variance. Common method bias (CMB) is caused because of the instrument of data collection rather than the appropriate representation of the construct items. Since the data is collected through the online survey methodology from the respondents, it has the potential to introduce CMB (Batista-Foguet *et al.*, 2014). The presence of CMB in the data can inflate or deflate the correlations among variables. Therefore, it is essential to take procedural measures prior to data collection to minimize the probable CMB in actual data collection (Podsakoff *et al.*, 2003). We create psychological separation by asking to fill the response variable immediately and giving time to the respondents to answer the rest of the variables at a different time. Moreover, we improve the scale items by defining unfamiliar or ambiguous terms and keeping the items simple and concise.

We conduct a statistical test for common method variance in the data to check whether the majority of variance is explained by a single factor. Harman's single-factor test is conducted in SPSS to detect the presence of common method variance as it is accepted as good statistical criteria for CMB (Harman, 1976). The result shows that no single factor accounts for more than 50% of the variance. Therefore, no general factor is identified that explains the majority of the variance. This implies that common method variance is not likely to influence our results. Additionally, we conduct a statistical test for common method variance using the "single common method factor" in the data suggested by Podsakoff *et al.* (2003). Here, a common latent factor is used to represent a "method" effect (Schwarz *et al.*, 2017). The process of testing common method variance through the common method factor involves conducting a Chi-square difference test on an unconstrained model to a fully constrained model. The results indicate that the models (unconstrained and fully constrained) are not different ($\Delta\chi^2$ = 166.2) with a p-value of more than 0.05, which implies that common method variance is not likely to influence our results.

Structural model. Before proceeding with the structural model, we test for the multivariate assumptions such as influencers and multicollinearity. The influencer analysis is performed

	CR	AVE	MSV	MaxR(H)	CEng	ISE	InfQ	SysQ	SerQ	BEng	EEng	PLE
CEng	0.908	0.554	0.477	0.915	*0.745*							
ISE	0.916	0.578	0.312	0.92	0.445	*0.76*						
InfQ	0.895	0.682	0.274	0.897	0.404	0.421	*0.826*					
SysQ	0.837	0.564	0.19	0.85	0.322	0.296	0.238	*0.751*				
SerQ	0.873	0.697	0.476	0.875	0.453	0.389	0.406	0.394	*0.835*			
BEng	0.937	0.749	0.476	0.943	0.592	0.475	0.438	0.436	0.69	*0.865*		
EEng	0.925	0.674	0.356	0.933	0.451	0.559	0.523	0.386	0.597	0.498	*0.821*	
PLE	0.878	0.59	0.477	0.879	0.691	0.405	0.362	0.268	0.473	0.546	0.497	*0.768*

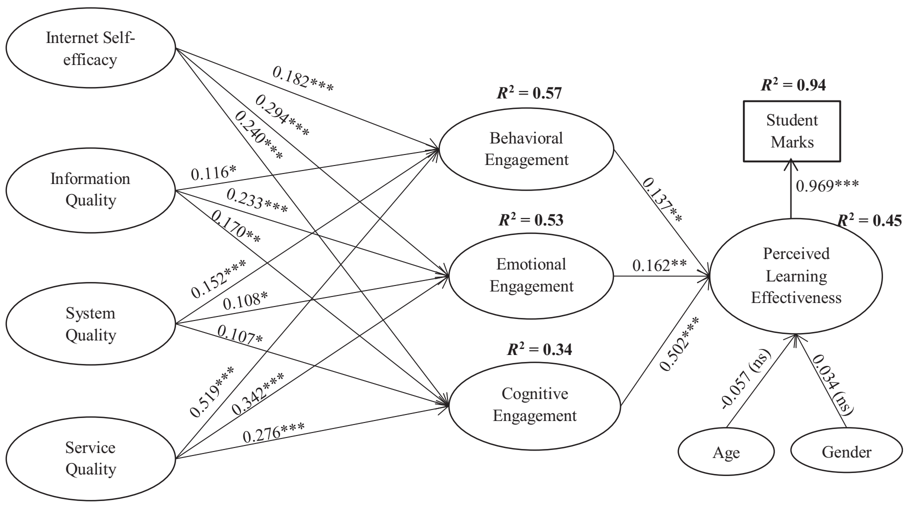
Table 3.
Test for validity and reliability

in SPSS with Cook's distance (Cook, 1977). We obtain Cook's distance less than 0.06 for all observations, which are below the threshold value of 1. The presence of multicollinearity in the data set is checked in SPSS for identifying the presence of collinearity among predictor variables. The multicollinearity is checked with the variance inflation factor (VIF) and tolerance values. We obtain VIF values of less than 3.5 and tolerance values of more than 0.29 for the constructs (with a required threshold of less than 10 for VIFs and greater than 0.1 for tolerance) (Hair *et al.*, 1998).

The structural path testing for the hypotheses is performed in AMOS post CFA. All the proposed hypotheses are supported by the data. The hypothesis test results are presented in Table 4 and Figure 2. The behavioral, emotional and cognitive engagements positively impact the PLE with path coefficients 0.137 ($p < 0.001$), 0.162 ($p < 0.01$) and 0.502 ($p < 0.01$), respectively. This supports hypotheses H1a, H1b and H1c. The result shows that ISE

	Path coefficient	Standard error	Critical ratio	p value	Hypothesis
H1a: BEng → PLE	0.137	0.044	2.700	0.007	Supported
H1b: EEng → PLE	0.162	0.035	3.144	0.002	Supported
H1c: CEng → PLE	0.502	0.053	8.895	0.000	Supported
H2a: ISE → BEng	0.182	0.038	3.975	0.000	Supported
H2b: ISE → EEng	0.294	0.052	5.996	0.000	Supported
H2c: ISE → CEng	0.240	0.042	4.336	0.000	Supported
H3a: InfQ → BEng	0.116	0.038	2.545	0.011	Supported
H3b: InfQ → EEng	0.233	0.051	4.814	0.000	Supported
H3c: InfQ → CEng	0.170	0.042	3.092	0.002	Supported
H4a: SysQ → BEng	0.152	0.035	3.368	0.000	Supported
H4b: SysQ → EEng	0.108	0.045	2.319	0.020	Supported
H4c: SysQ → CEng	0.107	0.038	2.001	0.045	Supported
H5a: SerQ → BEng	0.519	0.054	9.552	0.000	Supported
H5b: SerQ → EEng	0.342	0.066	6.512	0.000	Supported
H5c: SerQ → CEng	0.276	0.054	4.685	0.000	Supported

Table 4. Hypothesis testing



Note(s): ***$p < 0.001$, **$p < 0.01$, and *$p < 0.05$

Figure 2. Path analysis with standardized estimates

positively impacts behavioral, emotional and cognitive engagement with path coefficients 0.182 (p < 0.001), 0.294 (p < 0.001) and 0.240 (p < 0.001), respectively. This supports hypotheses H2a, H2b and H2c. The InfQ has a positive impact on behavioral, emotional and cognitive engagements with path coefficients 0.116 (p < 0.05), 0.233 (p < 0.001) and 0.170 (p < 0.01), respectively. This supports hypotheses H3a, H3b and H3c. The SysQ positively impacts behavioral, emotional and cognitive engagement with path coefficients 0.152 (p < 0.001), 0.108 (p < 0.05) and 0.107 (p < 0.05), respectively. This supports hypotheses H4a, H4b and H4c. The SerQ has a positive effect on behavioral, emotional and cognitive engagement with path coefficients 0.519 (p < 0.001), 0.342 (p < 0.001) and 0.276 (p < 0.001), respectively. Therefore, hypotheses H5a, H5b and H5c are supported. The effect of control variables – age and gender on the PLE is found to be nonsignificant with path coefficients −0.057 and 0.034, respectively. The variance explained by BEng is 57%, EEng is 53%, CEng is 34% and that of PLE is 45%. The PLE positively determines student marks with a path coefficient of 0.969 supporting hypothesis H6.

Figure 2 represents the research model with ISE, InfQ, SysQ, SerQ, BEng, EEng, CEng and PLE. The standardized estimates or the regression weights are mentioned with significance levels. *** represents a significance level of 0.001, ** represents a significance level of 0.01 and * represents the significance level of 0.05. Here, ns represent nonsignificant paths.

Mediation. For hypotheses, H7a, H7b and H7c, the mediation effect of behavioral, emotional and cognitive engagements is tested on the positive effect of ISE on PLE shown in Table 5. We test the hypotheses using the Baron and Kenny approach (Baron and Kenny, 1986). The direct effects are measured without the mediators by removing the mediator variables from the model in AMOS. The standardized regression weights for the direct effect of ISE on PLE are significant and found to be 0.371 with a p-value of less than 0.001. Then the direct effect with the mediator is performed. The mediating effect of behavioral engagement on the relationship between ISE and PLE is tested. The relationship is not found to be significant, with a regression weight of −0.003. This indicates that BEng fully mediates the positive effect of ISE to PLE. Similarly, the direct effect of ISE to PLE with the mediators EEng and CEng is not significant with beta values of −0.006 and −0.014, respectively. This indicates that EEng and CEng fully mediate the positive effect of ISE on PLE.

The Baron and Kenny (1986) method of mediation deals with testing whether the direct path from the independent and dependent variable is statistically significant after the introduction of the mediator variable. However, several researchers have noted numerous shortcomings of the Baron and Kenny (1986) method of mediation. For instance, Holmbeck (2002) notes that it is possible to observe a change from significant to nonsignificant path because of the addition of a mediator variable with a very small change in the absolute size of the coefficient and vice versa. Therefore, testing the indirect effects involving the mediator variable paths addresses the mediation more directly (Preacher and Hayes, 2004). Additionally, the indirect effects can be measured by the bootstrapping approach, which is implemented in AMOS (Arbuckle, 2016). Hence, the indirect effect is checked for its significance by using the bootstrapping method in AMOS (Hayes, 2009).

Table 5.
Mediation results: Baron and Kenny approach

Relationship	Direct without mediator (ISE → PLE)	Direct with mediator (ISE → PLE)	Comments
ISE → BEng → PLE	0.371 (0.001)	−0.003(ns)	Full Mediation
ISE → EEng → PLE	0.371 (0.001)	−0.006(ns)	Full Mediation
ISE → CEng → PLE	0.371 (0.001)	−0.014(ns)	Full Mediation

We perform bootstrapping with 2000 bootstrap samples and a 95% bias-corrected confidence interval. As shown in Table 6, all the mediations or indirect effects are found to be significant for the mediators, BEng (95% CI = 0.004 [lower], 0.050 [upper]; p = 0.0010), EEng (95% CI = 0.016 [lower], 0.091 [upper]; p = 0.004), and CEng (95% CI = 0.053 [lower], 0.177 [upper]; p = 0.001) using the Preacher and Hayes (2004) (bootstrapping) method. We also check for the standardized direct effects with the bootstrap two-tailed significance and find that the direct effects are not significant with estimates of −0.003 (BEng), −0.006 (EEng) and −0.014 (CEng).

Hence, from the Baron and Kenny (1986) approach and Preacher and Hayes (2004) (bootstrapping) method, we infer that there is full mediation of BEng, EEng and CEng on the positive effect of ISE to PLE. Therefore, the hypotheses H7a, H7b and H7c are supported.

Discussion and conclusion

In this study, we validate the theoretical model for PLE through the lens of the SCT. This theory is an effective framework used to explain the multidimensional engagement construct from personal and environmental factors. The empirical results validate the importance and significance of the framework to understand the engagement constructs.

The findings suggest that the behavioral, emotional and cognitive engagement dimensions positively impact PLE. This confirms and is aligned with the findings of Hu and Hui (2012) and Rashid and Asghar (2016). Our research extends both the studies by investigating the role of different dimensions of engagement (behavioral, emotional and cognitive) on PLE in e-learning environments. In our study, the total variance (R^2) explained by the PLE is 0.45, whereas the study by Hu and Hui (2012) obtains an R^2 value of 0.22 in technology-mediated learning. This might be because the engagement constructs are a better indicator of the PLE separately. Interestingly, our results show that CEng is the predominant antecedent of PLE. This can be attributed to the fact that students who get involved at a cognitive level are motivated, put effort and use various strategies to learn, tend to perceive that e-learning is effective for them. Moreover, CEng also deals with going beyond the course requirements and seeking challenges to increase competence, which positively affects PLE.

The result shows that the ISE positively affects the behavioral, emotional and cognitive dimensions of engagement. We find that ISE positively impacts BEng (R^2 = 0.57, beta = 0.182), EEng (R^2 = 0.53, beta = 0.294), CEng (R^2 = 0.34, beta = 0.240). Our finding is aligned with the study by Pellas (2014), which finds that self-efficacy positively impacts EEng (R^2 = 0.55, beta = 0.36) and CEng (R^2 = 0.42, beta = 0.22) in the context of the virtual world.

The information, system and service quality parameters have a significant positive impact on behavioral, emotional and cognitive engagement. Interestingly, we find that the SerQ has a greater effect on all the dimensions of engagement compared to the information and system quality. This also confirms the findings of Almarashdeh (2016) that SerQ is one of the key factors in instructor satisfaction in distance learning. This can be attributed to the fact

Mediator	Standardized direct effect (bootstrap estimate)	Standardized indirect effect (bootstrap estimate)	95% confidence interval Lower limit	Upper limit	Comments
BEng	−0.003(ns)	0.021(0.010)	0.004	0.050	Full Mediation
EEng	−0.006(ns)	0.047(0.004)	0.016	0.091	Full Mediation
CEng	−0.014(ns)	0.106(0.001)	0.053	0.177	Full Mediation

Table 6. Mediation results: Preacher and Hayes approach (bootstrapping)

that when students are satisfied with the support and service administrative team, they tend to engage in terms of participation, affective reactions and psychological investments. The result implies that any shortfall in SerQ can have a significant effect on student engagement even with a good quality course content and delivery. Thus, we can conclude that SerQ is a critical factor in fostering student engagement in the e-learning context.

It is found that the PLE positively determines student marks. This confirms the findings of Agudo-Peregrina *et al.* (2014) and Renaud and Van Biljon (2008), which posits that the intention toward a behavior leads to the actual behavior. The result is also aligned to the findings of Kankanhalli *et al.* (2011), which obtain a positive correlation between the learning effectiveness and actual grades.

The result from Barron and Kenny (1986) approach and Preacher and Hayes (2004) method shows that all the dimensions of engagement fully mediate the positive relationship between ISE and PLE. This implies that self-efficacy affects PLE through engagement. Our study supports and extends the findings of Chen (2017) and Hu and Hui (2012). First, we explore the role of various dimensions of engagement as a mediator for the relationship between ISE and PLE. Second, we consider the independent variable as ISE as in an e-learning platform, students learn over the Internet. Wang *et al.* (2013) find that self-efficacy in using technology positively impacts grades with a regression coefficient of 0.187 and an R^2 value of 0.167. Literature, for example, Bandura (1986) suggests that self-efficacy is a psychological state of an individual that might not directly impact the academic outcome, rather a determining factor of the outcome. Therefore, our study through the mediating effect of various engagement dimensions determines PLE with an R^2 value of 0.45. This implies that ISE affects PLE through behavioral, emotional and cognitive engagements.

Theoretical and practical implications

The study has several theoretical implications. First, we have built and validated a model using personal and environmental factors to understand PLE through the theoretical lenses of the SCT framework. The research on the factors affecting PLE is limited. Hence, our model adds to the extant e-learning literature. Furthermore, the theory used for our study is validated, and it fits well in our research model.

Second, our paper extends the work of Hu and Hui (2012) in which they study the role of engagement on PLE. Although the multidimensional nature of engagement is well studied in the education literature (Fredricks *et al.*, 2004; Kuh, 2009), the role of behavioral, emotional and cognitive engagements on PLE in the e-learning context is underresearched. We find that the cognitive dimension of engagement is the predominant antecedent of PLE.

Third, although many studies have investigated the role of IS quality parameters on continuation intention (Almarashdeh, 2016; Mohammadi, 2015), and also the relationship between continuation intention and engagement (Hussein and Hassan, 2017), the study of the relationship between IS quality parameters and engagement is limited. Our study establishes a positive relationship between the IS quality parameters and engagement in e-learning. We also observe that the SerQ dimension is the primary predecessor of all the dimensions of engagement.

Fourth, the mediation effect of various dimensions of engagement is investigated, and it is found that all the dimensions fully mediate the positive relationship between ISE and PLE. This suggests that the students' belief in their ability to organize and execute Internet actions required to yield certain outcomes leads to PLE through various dimensions of engagement in terms of participation, enjoyment and strategy use.

Based on our empirical findings, the results can have several implications for the students and the e-learning provider organization. Since the findings show that ISE is a significant predecessor of all the dimensions of engagement, by giving it greater focus, the students can achieve a required level of PLE. Since enactive mastery (previous success in a task) is the primary source of self-efficacy (Van Dinther *et al.*, 2011), students should put effort and focus on the success in using the Internet to achieve higher PLE.

Additionally, the e-learning providing organizations can also benefit from the findings of the study to design e-learning systems such that an optimum learning outcome is achieved. First, since all the environmental factors – information, system and service quality are positively related to the engagement constructs, the e-learning organizations should focus on the IS quality parameters to achieve better student engagement. The faculties should design updated, relevant, required and sufficient course content. Additionally, the difficulty level should be set according to the knowledge level of e-learning users. The e-learning design team should design a system to present the course materials in multimedia and readable format with interactivity facilities with the instructor. In addition to it, the system should be fast, consistent and provide flexibility to the student such that the students have control over their learning activity. The support help desk should provide support for any issues related to software, hardware and connectivity. The administrative support team should respond in a reasonable amount of time to the student queries via calls or emails. Additionally, the faculty should resolve queries (if any) on the topic appropriately during or immediately after the session via chat and mail. Moreover, the stakeholders such as the admin and the support staff should be included to create an integrated network to facilitate a better learning experience and thus, better student engagement.

Second, the result shows that all dimensions of engagement are positively related to PLE, which further is positively related to student marks. Therefore, effort should be put from the organization's side to foster student engagement. There should be provision for monitoring the attendance, checking student homework and proctoring (artificial intelligence–based or manual) to monitor if the students are following the classroom rules in the software used to deliver the course content. The faculty should adopt strategies for students' participation, such as cold call, debate, voting and quiz on the topic discussed whenever required. To make the class effective, faculty should assign readings and exercises related to the topic and ask the students to submit the same prior to taking the same class (i.e. preparation before the class). The faculty should also provide supplementary online materials and keep formative assessments in the class so that students will revise the class materials to increase their engagement at the cognitive level.

Limitations

This study has a few limitations, which can be addressed in future research. First, in the environmental factors, only system characteristics with quality parameters are taken into account. Future studies can examine peer interactions on different dimensions of engagement. Second, we have conducted a cross-sectional survey. Future researchers are invited to perform longitudinal research for learning effectiveness. The longitudinal study can help in uncovering the dynamics of the relationship between the personal and environmental factors on various dimensions of engagement with time. For instance, ISE may change over time. Therefore, the dynamics of ISE and engagement construct can be studied over a span of time. Third, as the online survey is conducted using Indian students with postgraduation qualifications as respondents, the generalization of the results needs careful considerations.

Notes

1. United Nations Sustainable Development Goals: http://www.un.org/sustainabledevelopment/education/.
2. χ^2 Chi-square; df: degrees of freedom; RMR: Root Mean square Residual; TLI: Tucker–Lewis Index; CFI: Comparative Fit Index; RMSEA: Root Mean Square Error of Approximation.

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