IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 9 December 2022, accepted 8 January 2023, date of publication 12 January 2023, date of current version 19 January 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3236504

RESEARCH ARTICLE

Personal Learning Environments: Modeling Students' Self-Regulation Enhancement Through a Learning Management System Platform

SARAH ALSERHAN[1], TURKI MESFER ALQAHTANI[2], NORAFFANDY YAHAYA[1], WALEED MUGAHED AL-RAHMI[1], AND HASSAN ABUHASSNA[1]

[1]Faculty of Social Sciences and Humanities, School of Education, Universiti Teknologi Malaysia (UTM), Skudai, Johor 81310, Malaysia
[2]Department of Instructional Technology, Jazan University, Jazan 45142, Saudi Arabia

Corresponding author: Sarah Alserhan (sarah.alsarhan@hotmail.com)

ABSTRACT A personal learning environment (PLE) is known as a crucial support for educators who lead learners through the process of collection, creation, and organization of personalized learning tools. In this manner, the learner can interpret a variety of new tools in their own interest, which makes the learning process easier. The PLE approach represents a considerable movement away from traditional learning, where learners are considered consumers of information through isolated channels, particularly learning management systems (LMSs), to a model where learners draw significant connections from numerous resources that they choose. Thus, educational settings have implemented LMSs fully into their respective learning contexts. In this sense, LMS is identified as a learning platform that helps learners and educators submit assignments, share ideas, and communicate through web-based systems with numerous benefits. Under these circumstances, self-regulation is addressed as a significant component that explains how learners build and manage PLEs and come up with more choices; they take ownership of their own learning and enhance self-regulated learning (SRL) practices. On this occasion, there is a belief that teachers can utilize LMSs to shift from passive to active learning and to improve self-reflection (SR). Therefore, considering all the above issues, the current study examines integrating a third-generation LMS to enhance learners' SR. This study considered PLEs by utilizing Zimmerman's SRL model to investigate the integration of the third-generation LMS. SR is applied in this study in the form of a pretest and posttest following the involvement of the PLE course, which was designed and applied during the COVID-19 pandemic. Finally, the experimental findings of the current study formulated a model of SR factors in PLEs through the LMS platform with partial least squares structural equation modeling (SEM) before and after the intervention.

INDEX TERMS Personal learning environments, learning management systems, self-regulated learning, partial least squares structural equation modeling.

I. INTRODUCTION

The enhancement of modern learning techniques has been developed by adopting information and communication technologies in the education system [1]. In this manner, the adoption of information has distorted the limitations of formal, informal, and nonformal teaching techniques and face-to-face and online education systems. Through the swift development of technologies and learning management systems (LMSs), it is gradually moving toward personalized-based learning that seeks to improve self-regulated learning (SRL). This clearly shows that personal learning (PL) is a crucial approach to enhancing a learner's capability to benefit from SRL. In this decade, the role of technology, particularly LMSs, has changed. An LMS serves various purposes, such as the organization of organizations, online learning and teaching techniques, and desired results. Moreover, it is critical to mention that an LMS is an individual aspect, as every learner

The associate editor coordinating the review of this manuscript and approving it for publication was Chin-Feng Lai.

is unique and has different capabilities, interests, and limitations. Therefore, it is obvious that learners need their own processes to seek knowledge. This process leads to the development of personal learning environments (PLEs) and SRL enhancement, which is the major purpose of this paper.

A. PROBLEM STATEMENT

The general concept of a learning management system (LMS) is recognized as an institutional platform that focuses only on learners [2]. From the perspective of [3], an LMS helps to extend the diversity of functionalities in a user-oriented context. On this occasion, several researchers claim that an LMS includes the combination of numerous services from a variety of sources to develop a customized learning experience in which the integration of a more personalized LMS tool is necessary [2], [4], [5]. Fueled by the significance of an LMS to offer personalized tools, Conde et al. believed that there are several issues with LMSs that provide an open environment in personalized learning, such as learners' information techniques, idea and experience sharing networks, information sharing through management systems and identity techniques integrated via organizations, which are utilized in learning settings [2].

Apart from the considered components, although an LMS balances the learner's ability to acquire both formal and informal learning contexts [6], [7], educators face difficulties in tracking, adapting, and evaluating LMS effectiveness, along with adapting to various new personalized tools. In the same vein, Shaikh and Khoja consider that a lack of support for PLEs makes learning environments ineffective [8]. Therefore, driven by the significant role of PLEs and LMSs, educators must be the most knowledgeable party, which is crucial for learners to develop a strong and multifunctional association between themselves and PLEs.

PLEs play a crucial role in assisting educators in guiding learners by gathering, making, and organizing personalized learning tools. Similarly, Moreillon believes that learners can understand and interpret fresh tools in their own interest to thus make the learning process easier [9]. However, learners may face several difficulties in the PLE context, such as managing the information presented to them due to a lack of customization of learning materials [10]. In this manner, a study conducted by Hartley shows that learners face issues when articulating or discussing complex issues, which PLEs may use to attract learners as a significant learning component [10]. Fueled by the crucial role of PLEs, several researchers have employed Zimmerman's SRL in technologically assisted learning, such as Web.2, social media applications, and LMSs, to transform institution-centered environments into learner-centered environments [3], [4]. In line with the significant role of PLEs, Dabbagh and Kitsantas hold that PLEs are a highly promising pedagogical theory for learning through using social media and learners' self-regulating themselves [4]. In this context, several educators lack in one or both of these areas. A study by Schaffert and Hilzensauer reveals that many teachers are not comfortable working with technology-driven equipment [11]. Therefore, this is a problematic issue because if educators are not privy to the skills needed to facilitate PLEs, then their students will not receive the maximum number of benefits. Thus, considering all the above issues, the current study examines integrating a third-generation LMS into PLEs to enhance learners' self-regulation.

II. LITERATURE REVIEW

The development and utilization of technologies in the information and communication sectors in educational contexts have led to various changes in the employed tools for teaching and learning progress [1]. In this context, LMSs play a crucial role by focusing on higher institutions. According to Wesch, learners should not learn only in informal environments, in particular in thematic courses with tools that are not prepared and controlled by the institutions [12]. Therefore, to recognize these methods of learning, including the personalization features that are unique to our new digital age, PLEs have been announced. PLEs are defined as ways to make people learn for the rest of their lives. However, what occurs in them must be utilized with a consideration of the institution [13]. Conde et al. believe that PLEs facilitate learners' learning progress by guiding learners to employ the significant tools that they require and not collecting them for a specific institutional context as an LMS does [2]. As a result, interactions in the eventual environment have a great effect on learning outcomes and student academic performance.

From the perspective of Dabbagh and Kitsantas, the development of PLEs in the e-learning context through addressing learning control and personalization problems is regularly ignored in institutional LMSs [4]. An LMS is known as the most crucial method and has significant impacts on different purposes, such as the organization's objectives, online training strategy, and desired outcomes [14]. As stated by Martindale and Dowdy, the LMS is considerably presented as a vital element to emphasize that learning has an individual aspect, as they believe that every learner is unique and has different capabilities, interests, and limitations [15]. Therefore, it is obvious that learners need their own process of acquiring knowledge, which leads to the development of PLEs and the enhancement of SRL. Although LMSs were initially framed to offer a flexible framework for advanced learning pedagogies [15], it has been considered that LMSs focus on institutional broadcasting tools over learner learning tools. Under these circumstances, Dabbagh and Kitsantas state that SRL is recognized as a skill in which learners must comprehend how to set goals, determine what is important to reach the goals, and how to utilize the reached goals [4].

A. PERSONAL LEARNING ENVIRONMENTS

PL is identified as one of the means of lifelong learning, which addresses the fact that students obtain information in different ways [16]. According to Schwartz, learners should be provided with the flexibility to enhance their various skills to critically analyze information [16]. In this manner, the idea of PLEs was initially examined by Olivier and Liber, who address PLEs as a crucial resource for e-learning and interactive learning environments (ILEs) [14]. In the same vein, Kulathuramaiyer and Maurer portray PLEs as a great help in managing information and the cognitive overload that comes with it [17]. Lifelong learners have been defined as having a persistent user interface to meet their needs of with the purpose of managing their learning career [14]. According to Taraghi and Ebner and Alalwan et al., in an environment where learners can integrate distributed resources, applications, and tools into a single platform, this can provide individual learners with an acceptable circumstance to develop their specific needs in a study environment that allows people to interact within collaborative and distributed environments [18], [19]. In this situation, PLEs are known as an instructive approach that allows students to employ social media to obtain an experience of enhancing self-motivated learning in both formal and informal pedagogical contexts [4]. Many researchers have conducted different studies and found that the PLE concept has implications for open-access online learning, learner-based guidance, self-direction, and self-direction issues [8], [20].

Counted as the major point of PLE research, Buchem et al. believe that the creation of customized platforms is not the purpose of the research conducted by focusing on obtaining the learners' activities in terms of their employment of technology for supporting their learning process [21]. In addition, Van Harmelen considers that PLE plays a significant role as a system that assists learners in managing and taking control over the method of learning by setting their targets and communicating with other learners to fulfil their objectives [22]. This explanation, in the perspective of Panagiotidis, is identified as a particularly designed system that covers many external tools and resources for developing a customized learning experience that can be accessed individually [23], which is consistent with the perspective of several researchers who believe that PLEs enable learners to engage with their peers, resources, and services in a broad context [24]. Apart from the significant role of PLEs in learning and engaging learners, PLEs have been challenging the traditional (LMSs. According to Ullrich et al., an LMS should be recognized as a suitable solution for institutions [24]. In this sense, PLEs should ideally aim to enhance learners' cognitive abilities, redefine the pedagogical process, and integrate third-generation LMSs to design technology-enhanced practices and opportunities [11]. Therefore, Hicks and Sinkinson indicate that it is crucial to enhance PLEs, particularly because digital information is being developed. Thus, learners will be able to develop their own self-reflective and learning environments [25]; they will then need to develop and manage their PLEs through the required tools [26], [27]. According to Schwartz and Al-Rahmi et al., since components such as learning progress, technology, and resources are provided to help all learners and premiums, the outcome will be even more interesting to students, which prompts deeper responsibility and improves the results [16], [28].

B. PLES AND LMSS

PLEs help the educator guide learners via the progress of gathering, making, and organizing personalized learning tools [9]. In this context, Hicks and Sinkinson claim that PLEs enable learners to utilize and customize their reasonable individual objectives to cover their learning through the management of the tools that they integrate, and they enable communication among learners [25]. The combination of all of these aspects creates a very successful learning process. However, learners face some difficulties managing the information presented to them, which may be due to a lack of customization of the learning materials [10]. Yilmaz suggests that PLEs play a significant role as an efficient approach because they easily manage the learning process [29]. In addition, PLEs enable learners to hold their own personal, educational records, in which the tool will grant mobility of educational records by empowering learners to maintain their learning space [25]. From the perspective of Ragupathi, PLEs make it possible to promote peer and independent learning [30]. Although education is driven by the role of PLEs, there are still many challenges and obstacles that educators must overcome when implementing PLEs in the classroom setting. Not all of the obstacles are equally shared among educators, but some trends persist throughout the educational environment. A study conducted by Schaffert and Hilzensauer reveals that many teachers are not comfortable working with technology-driven equipment [11]. Burns claims that teachers can develop a positive, inspiring, and imaginative influence on learners by personalizing their teaching skills [31].

Learning LMSs originated in the 1960s. During this time. A learning system named PLATO was developed at the University of Illinois. According to Mott, the system offered computer-based learning instruction [33]. Traditionally, LMSs were created to provide, manage, cover, and examine learning tasks in a formal learning context. According to Mott [33], a new wave of systems is evolving to promote teaching and learning through new modes of collaboration, information sharing, and social networking services. All of the developments in the educational and training ecosystem have exposed the conventional LMS to an increasing range of challenges. From the perspective of Westphal, the learning environment has been a transforming outcome of technology development and resource accessibility [34]. An LMS desires to cover itself to make the environment transformation and developmental necessities of learners and teachers more open, individualized, social, updated, analytical, and accessible. Thus, in this sense, Broderick argues that to enable learners to complete prepared tasks, one must employ the instructional design factor to create a conducive instructional environment for learners [35]. Thus, according to Ellis, LMSs cover the following six key objectives that are in line with the objectives of this paper: i) centralize and automate administration; ii) utilize self-service tools; iii) sharply set and transform learning content; iv) develop teaching techniques in a scalable web-based context; v) guide and lead portability; and vi) personalize content and accessible knowledge sharing [36].

Exploring ever-larger amounts of data from educational contexts, such as LMSs, and creating computational techniques to better comprehend students' actions and learning environments are the main goals of educational data mining. Numerous studies have been conducted on the learning process of students, and as a result, many widely used frameworks and theories that describe students' learning behaviors have been developed. However, the most recent focus of study states that it is necessary to create effective models with ideas that can be put into practice to understand student learning practices and to influence students' academic performance. By analyzing fine-grained data samples gathered by LMSs at the student level, existing studies examine various individual, emotional, and social factors related to student learning behaviors, but they do not take into account the dynamics of learning behaviors and do not look at the full picture of students' learning lives. For instance, the majority of studies on student learning behavior concentrate on particular courses and associated academic achievement but do not consider the fact that students usually attend many courses at once. Therefore, it may be difficult to develop effective teaching methods for students by using the implications and knowledge from a static understanding of students' learning behavior in a single isolated course [37].

A useful approach for discovering the links buried in educational data and forecasting students' academic success is educational data mining (EDM). EDM is the use of conventional DM techniques to address the issues that pertain to education. EDM refers to the application of DM techniques to educational data, such as student data, academic records, exam results, participation in class, and the frequency of questions raised by students. EDM has developed into a useful tool in recent years for predicting academic success, finding hidden patterns in educational data, and enhancing the learning and teaching environment [38].

In order to improve the performance of the prediction algorithms in dynamic conditions, Khan et al. added a new learning to the prediction model. They have put forth a novel technique called ''learning to alpha-beta filter'' that is based on the alpha-beta filter and the deep extreme learning machine (DELM) algorithm. The prediction unit and the learning unit are the two key parts of the suggested methodology. In the prediction unit, we used an alpha-beta filter, and a DELM is used in the learning unit. The primary issue with the traditional alpha-beta filter is that the values are often chosen through the method of trial and error. The results demonstrated that the proposed model outperforms the traditional alpha-beta filter in terms of results [39].

In addition, Khan et al. suggested a new prediction learning model to boost the alpha-beta filter algorithm's dynamic performance. The suggested model consists of two main parts: (1) the main prediction module, which is the alpha-beta filter algorithm, and (2) the learning module, which is a feed-forward artificial neural network (FF-ANN). Additionally, a prediction method is employed in the model to forecast actual sensor values from noisy sensor readings. The model takes two inputs, temperature sensor and humidity sensor data. By incorporating the feed-forward backpropagation neural network into the innovative technique, prediction accuracy is greatly increased, and the root mean square error (RMSE) and mean absolute error are also decreased (MAE). The standard alpha-beta filter method and other algorithms, such as the Kalman filter, were used to assess the performance of the suggested model. The RMSE was 38.2%, while the MAE ranged from 35.1% to better forecast accuracy. When compared to conventional methods, the final proposed model's performance results demonstrated improved performance [40].

Furthermore, Khan et al. introduced a novel Multiple learning to prediction algorithm model that employed three distinct combinations of machine-learning techniques to raise the accuracy of the - filter algorithm. Instead of static settings, the parameters of and were optimized in dynamic situations. The deep extreme learning machine (DELM), the deep belief network (DBN), and the support vector machine (SVM) were chosen as the three different learning algorithms to be used in the suggested system. The final anticipated outcomes were then provided by these learned parameters after being taught using machine learning algorithms that were customized to the - filter method as a prediction module. The proposed approach produced results that were more accurate when compared to the standard alpha-beta filter algorithm [41].

C. LMSS IN PLES AND THE TREND TOWARDS SELF-REGULATED LEARNING

SRL is a philosophical paradigm to understand the cognitive, motivational, and emotional dimensions of learning [42]. According to Zimmerman [43], SRL has had a considerable influence on educational psychology since the relationship between SRL and metacognition began to be recognized. Since then, from the perspective of Sitzmann and Ely, various models of SRL have been addressed [42]. For instance, Puustinen and Pulkkinen published a theoretical analysis in 2001 that depicts the most important models developed by Boekaerts, Borkowski, Pintrich, Winne, and Zimmerman [44]. The fact that there are currently three meta-analyses of SRL results is a first indicator of the evolution of SRL models [37]. The second predictor is that in the area of educational psychology, there are already modern SRL models that did not exist in 2001 [45]. Finally, there is a recent handbook by Zimmerman [43] that illustrates a number of well-established approaches to analyze SRL. According to Ernesto Panadero, PLEs should ideally aim to improve learners' cognitive and metacognitive abilities, redefine the pedagogical process, and integrate third-generation LMSs [46] to design technology-enhanced practices and opportunities [11]. Therefore, from the perspective of Hicks and Sinkinson [25], it is crucial to enhance PLEs, particularly because digital information is being developed. Thus, learners will be able to develop their own self-reflective and learning environments and then need to develop and manage their PLEs through the required tools [26]. Several studies have evaluated the association between PLEs and SRL experimentally. For instance, in a study conducted by Cho et al., PLE-based learning is presented as the self-regulating setting of learners who can predict their social presence [47]. Similarly, Türker and Zingel conducted a study and organized learning resources accessible to PLEs into comprehensible learning tasks to reach setting objectives to be stated as a performance of instructional form to the forethought phase considered by Zimmerman's SRL model [48]. This explanation was also considered by Mott [33]. In this sense, Dabbagh and Kitsantas developed a three-phase system for using social media to promote SRL in PLEs, including personal knowledge management, social networking and communication, and information aggregation and management [4]. As Dabbagh and Kitsantas point out, engaging learners in personal information management practices through blogs and wikis can enable them to participate in a self-regulated forethought learning process [4].

III. RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

This research used Zimmerman's model [49]. The model was used as a self-regulatory learning process system in three stages, namely, forethought, performance, and self-reflection (SR) [50]. Zimmerman considered that the forethought stage process is used in PL for learning efforts (LEs) and is meant to boost learning. He also identified the performance phase process that is used to help in the self-monitoring (SM) of one's performance during LEs [49]. Finally, in Zimmerman, the SR phase process occurs after making an attempt to learn and is supposed to enhance a person's responses to his or her results [49]. In particular, these SRs shape forethought mechanisms and assumptions about future LEs. Finally, a self-regulatory cycle was completed. Prior studies provide different evidence of the relationship among the SRL factors. However, this suggests that a theoretical explanation of this relationship has been provided. Several studies provide many examples of evidence for the relationship between these factors in the learning environment [50], [51]. Given the complexity of SRL, such an explanation would necessitate the inclusion of multiple variables. In this manner, structural equation modeling (SEM) is an appropriate statistical analysis procedure for confirming indirect and direct relationships among many variables while also taking into account errors in measurement [52]. Following the utilization of SEM, path analysis models were developed in this study, including indirect and direct relationships among the observed variables. This method was utilized by Kormos and Csizér to examine a proposed model of the relationship among SRL factors [53]. See Figure 1.

A. SELF EFFICACY (SE)

SE is described as faith in one's ability to prepare and carry out the actions necessary to achieve clear goals [54]. It is a well-known motivational construct in educational psychology [55], and it is also a central motivational feature in most self-regulation models, such as [49]. SE is one of the motivating elements of the forethought process in Zimmerman's [49] self-regulation model [56]. As considered by Zimmerman, SE refers to learners' views about their abilities to fulfil a task, which has a key effect on personal processes [57]. In addition, Zimmerman considers SE as a central variable that influences SRL, which is also according to social cognitive theorists [57]. In a study conducted by Kurtz and Borkowski, the key aspects of students' SM were attributed to SE expectations [58]. Kurtz and Borkowski believed that high SE students demonstrated higher quality learning methods and more SM of their academic achievement than low SE students [58]. From the perspective of Bandaura, one of the motivating factors in the forethought process is SE [54]. However, notably, SE is not a stand-alone factor but rather one of the multiple factors considered during the self-regulation cycle [59]. Studies emphasize the beneficial impact of SE on self-regulation activities during forethought, performance, and SR and even on academic achievement [60], [61], [62]. It is indeed essential to note that SE is not only a condition for self-regulation but also a function of it. Diseth stated that the effects of SE can either directly affect learning strategies or indirectly affect learning strategies by its influence on other variables of motivation [63]. Self-motivation derives from student assumptions about learning, including SE perceptions about possessing a PL capacity and performance perceptions about the personal effects of learning [54]. As a result, Zimmerman suggests that students who feel self-efficient in learning to divide fractions and plan to use this ability to pass a college entrance exam are more driven to practice in a self-regulatory way [64]. A study by Moos indicates that significant monitoring and learning success are affected by SE [65]. In addition, the study shows that the association between SE and learning success is mediated by the monitoring factor. The findings are additionally confirmed by Moos and Azevedo, where the SE of learners is estimated as positive under these circumstances [65]. Under these circumstances, Moos and Azevedo believe that learners who have had little exposure to hypermedia learning can approximate the demands of the learning domain but not the demands of the learning community [65]. As a result, learners first overrate their knowledge and capacity. Self-efficiency also impacts self-assessment processes [66]. According to several researchers, SE is a strong indicator of academic performance [37], [64]. In addition, researchers consider that SE has beneficial effects on self-regulation processes during forethought, efficiency, and SR, along with learning achievement [37], [64]. Therefore, considering all the above explanations, this study proposes the following hypotheses to determine the relations.

Hypothesis 1 (H1): A significant relationship exists between SE and EF.

Hypothesis 2 (H2): A significant relationship exists between SE and EV.

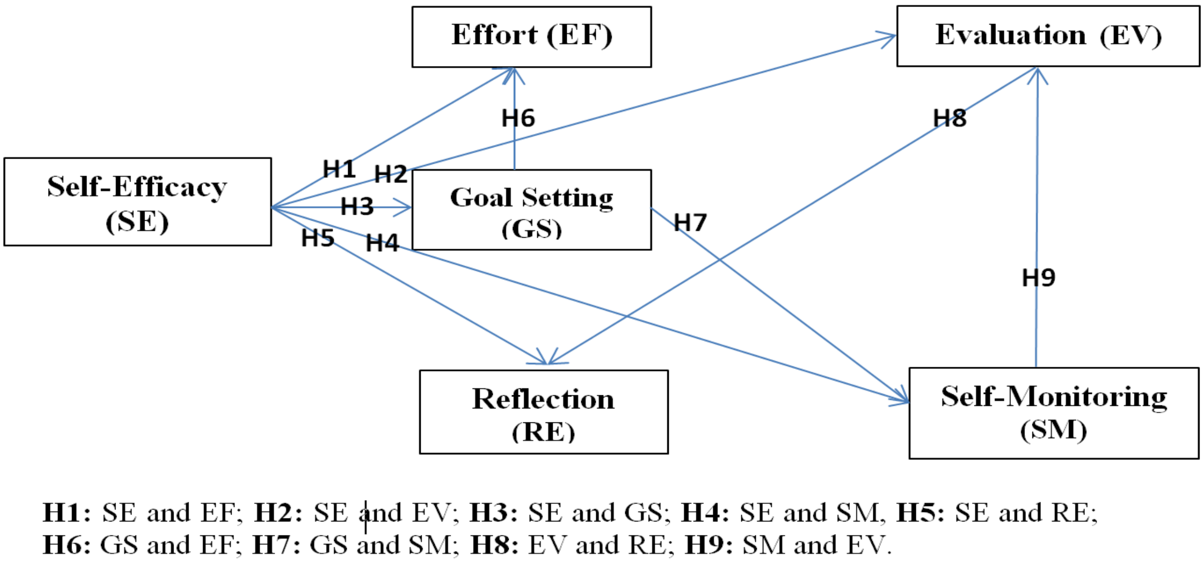

FIGURE 1. Research model.

Hypothesis 3 (H3): A significant relationship exists between SE and GS.

Hypothesis 4 (H4): A significant relationship exists between SE and SM.

Hypothesis 5 (H5): A significant relationship exists between SE and RE.

B. GOAL SETTING AND PLANNING (GS AND PL)

The forethought phase occurs before learning occurs, and it covers two main classes that include task analysis and self-motivation [50]. From Zimmerman's perspective, at this stage, learners analyze the learning activity and create particular objectives into covering this activity [57]. As considered by Pajares and Schunk [67], the PL phase helps learners self-regulate their learning prior to encouraging learning activities. The current study argues that GS and PL are complementary components because PL helps learners address well-thought-out objectives and techniques to reach the success step. According to Pajares and Schunk, objectives are significantly identified as desired end states to be obtained through a particular timeline [67]. Specifically, setting goals enhances the identification with the team's decision-making process, which impacts downstream adherence to the goals [68]. Hardin et al. find that teams are more dedicated to challenging, concrete goals than relatively difficult or idiosyncratically defined ''do-your-best'' goals [68]. That is, the accomplishment of difficult, participatory targets helps improve dedication to these goals [68]. At this stage, Pajares and Schunk indicate that PL takes place in three phases, namely, setting a learning task objective, determining strategies to achieve the goal, and defining how much time and what resources will be required to reach the goal [67]. Zumbrunn et al. consider teaching students to tackle educational exercises with a schedule as a feasible way of providing self-regulation and learning [69]. As stated by Hardin et al., the setting of goals progress develops productivity, fulfilment, inherent motivation, commitment in the face of challenges and employee behavior examination [68]. Therefore, this study proposes the following hypotheses.

Hypothesis 6 (H6): A significant relationship exists between GS and EF.

Hypothesis 7 (H7): A significant relationship exists between GS and SM.

C. SELF EVALUATION (SE)

Learners who can evaluate their own learning independently of teacher-centered summative assessments are more likely to become self-regulated students [69]. According to Zimmerman [57], teachers may empower students to assess themselves in the classroom by aiding them in monitoring their learning objectives and strategies and then making improvements to certain priorities and strategies based on learning performance. During the reflecting on results process, students measure their performance on the learning challenge in terms of the usefulness of the strategies that they choose [69]. Zumbrunn believes that throughout this process, students must monitor their feelings about the learning experience's outcomes. Students' future PL and aspirations are influenced by these SRs, which clearly shows the relation between SE with GS and PL [69]. Therefore, it can be concluded that self-assessment refers to measures of self-assessment results against some standard, such as previous performance, the performance of another person, or a total performance standard. Therefore, this study proposes another hypothesis as follows.

Hypothesis 8 (H8): A significant relationship exists between EV and RE.

D. SELF MONITORING (SM)

In the monitoring phase, students utilize multiple techniques to make progress on the learning activity and SM the efficacy of such strategies and their incentive to keep progressing toward the goals defined for the task [70], [71]. Furthermore, according to Kistner et al. if students need to be strategic, then they must take responsibility for their learning and performance outcomes, which self-regulated learners accomplish by measuring their progress against learning objectives [72]. Many of the above techniques are used in the SM phase [58]. A learner must set their own learning objectives, schedule accordingly, individually encourage themselves to achieve their goals, concentrate their energy on the task at hand, and use learning techniques to promote their comprehension of knowledge to self-monitor their success [58], which clearly addresses the relation between SM and both SGs and PL. Similarly, monitoring covers metacognitive understanding, and monitoring cognition is a central feature of self-regulation information retrieval models [73]. Thus, Butler and Winne believe that internal feedback is provided by successful self-regulated learners as they track their interaction with learning experiences and assignments and measure their progress against goals [74]. Students evaluate their self-monitored results to an absolute baseline or previous performance during this SE [57]. Therefore, the following hypothesis is proposed.

Hypothesis 9 (H9): A significant relationship exists between SM and EV.

E. EFFORT (EF)

Several self-regulation experiments have presented the EF variable as one of the essential aspects of motivation or as a separate variable [73]. Self-regulated learners, according to Zimmerman, not only report SE and intrinsic motivation but also bring forward exceptional EF and perseverance while learning [59]. This explanation clearly addresses the correlation between EF and SE. Zimmerman also illustrates the relationship between initiative and SE in which SE beliefs influence motivation by defining how individuals set goals and strategies for themselves, how much work they put forward, and how long they persevere in the face of hardship [73]. Their goals are often proposed as a means to encourage human action and inspire people to produce desired results [65]. Therefore, it clearly considers the significant relationship between EF and goals, as it influences performance through several mechanisms as stated by Bandura [75]. First, goals inspire people to perform more both cognitively and behaviorally. Goals also ensure commitment in reaching end states, which is especially important when goals are difficult to attain. Finally, targets implicitly boost job efficiency by encouraging individuals to check and apply applicable information and techniques.

F. SELF-REFLECTION (SR)

Reflection (RE) is recognized as the reflective thought that involves critiquing deeply held beliefs of what is learned, i.e., the higher-order processing aspect of reflective learning that relates to comprehending course material [76]. RE is also recognized as a move beyond material understanding to more involved participation in learning that elicits prior information and experience, includes challenging what has been learned, and can require a search for alternate meanings. In addition, RE from the perspective of Peltier et al. is covered by two main conditions, namely, student-to-student and instructor-to-student interactions. According to Peltier et al., the combination of these two conditions addresses the ultimate success of the educational process [77]. Under this condition, all members of the learning community are inspired by and in harmony with their teachers and fellow students and encourage them to experiment with new ideas. This model is selected by the current study, as shown in the relationships in Figure 1.

IV. RESEARCH METHODOLOGY

A pre-experimental design (one-group pretest-posttest design) is utilized in this study. A one-group pretest-posttest design is known as a type of research method that is most often utilized by behavioral researchers to examine the effect of a treatment or intervention on a given sample [78]. In this study, one experimental group was involved as the pretested (O1) group, which was exposed to the PLE-based course model as the treatment (X1). After conducting the pretest, the same group was selected for utilizing the posttest (O2) to examine the proposed model. This study was conducted in a particular time period (eight weeks) as follows. In the first week, the PLE course model was introduced to the teacher, followed in the second week by the introduction of the PLE course model to the students. This was followed by the third week when the pretest was conducted on the students. Afterwards, the applied PLE course-based model was conducted during week four. The PLE course model was continued until week seven. Finally, the posttest was performed during week eight to evaluate the students' self-regulation.

A. SAMPLE SIZE

The designed survey in this study was conducted on total. Previous literature has provided recommendations for the minimum sample size required to perform certain analyses. Thus, this study followed [79]. It is recommended that PLSSEM users who are not methodological researchers use the inverse square root method for the minimum sample size estimation in the early stages of their research design. These researchers will generate estimates that are both reasonably precise and safe by using both normal and nonnormal data. According to [80]'s analyses, their estimates will always be slightly larger than the true minimum sample sizes needed but not by much, which puts light demands on data collection beyond what is needed. As a result, in accordance with [80], the sample size of this study was kept small to be simpler (by relying on a simple equation), is also fairly precise, which results in small overestimations and is "safe" in its slight imprecision; thus, the sample size of this study was seventeen students.

B. THE PARTICIPANTS AND DATA COLLECTION

The experiment was conducted on convenience samples because of their availability and easy accessibility. A non-purposing sample was utilized to select 17 participants out of the population of 8th-grade students in government secondary schools in Saudi Arabia in 2019. However, the progress of blended learning and face-to-face learning has faced some limitations because of COVID-19. For the purpose of this study, 17 pretests were distributed, all of which were answered under the teacher's supervision. In addition, all 150 students attended the PLE course-based program. After school was postponed due to the COVID-19 pandemic, only 17 students completed the posttest. Therefore, a manual analysis of the total of 17 pretests and posttests was completed, which is an acceptable sample size in PLSSEM according to Marcoulides and Saunders and Privitera and Delzell [81], [82].

C. INSTRUMENTATION

The self-regulation of learning self-report scale (SRL-SRS) was utilized by this study for different components, including PL, SM, assessment, meditation, EF, and SE [83]. This instrument was utilized to investigate the self-regulating processes of the learners. The current study investigated PLEs as a measure of self-regulation. The SRL-SRS was used in this research for PL, SM, assessment, RE, EF, and SE, all of which, according to Toering et al., are essential aspects of learning. The SRL-SRS helps to evaluate learners' self-regulating processes. In a study conducted by Toering et al., which utilized the SRL-SRS, the adoption of the instrument was guided by the components related to the six subscales of PL, SM, EV, RE, EF, and SE [83]. The instrument was first translated into Arabic and then reverse-translated [84]. The items were translated by two bilingual translators from English into Arabic. Two independent translators who were fluent in both languages translated these interpretations from Arabic to English without using the original scale.

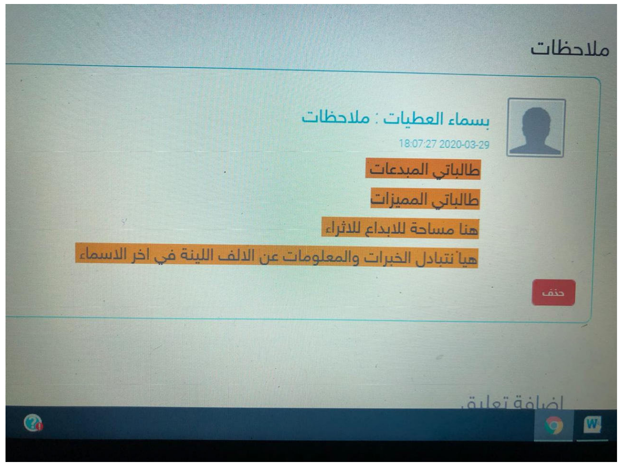

FIGURE 2. Goal setting tasks.

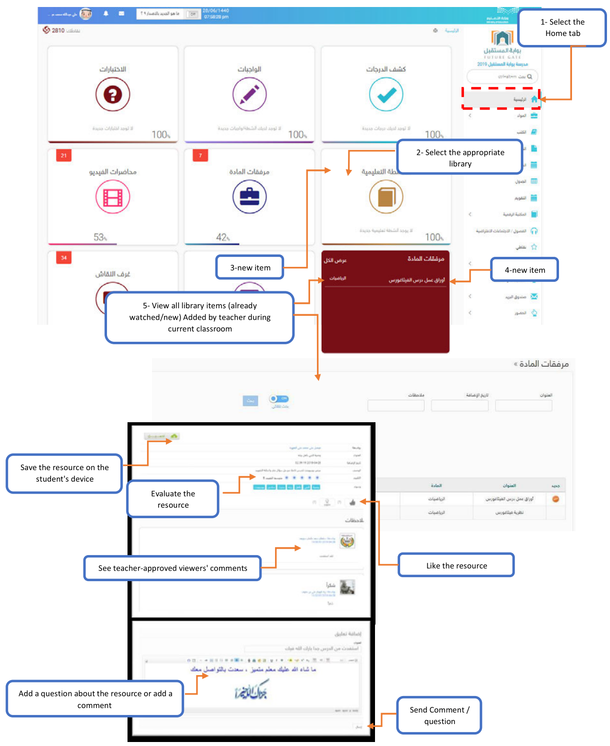

FIGURE 3. Selecting the main library.

V. THE PLE-BASED COURSE

A. THE CONTEXT OF THE TREATMENT

The intervention of this study was based on the PLE-based course. First, self-efficacy in goal-setting tasks was applied by encouraging the students to set the goals and strategy instruction and the contents for the first lesson for each unit (see Figures 2 and 3).

In this research, the context of the PLE-based course involved the experimental distance group, where the students in the experimental group were introduced to the PLE-based course during the 2nd semester of 2020. The researcher applied a systematic instructional system design approach called ADDIE. ADDIE is a sequence of five stages that must be followed logically for each phase to provide input for the following phase [85]. ADDIE provides a strategy to create and design instructional courses in education. In the process, each phase is informed by rapid prototyping to obtain the instructors', students', and any targeted users' feedback needed for the next phase [86]. First, in the analysis phase, as the first and most significant phase, a needs analysis should be implemented at the start of any development effort to decide whether the course is required to fill a gap in the audience knowledge skills and to determine whether the course design is the best way to deliver the course. In this regard, the researcher collected the data from the first phase of the study (assessment phase), topic content, learning outcomes, and student background. A target audience analysis is considered to be a crucial step.

FIGURE 4. Browsing the public library.

B. THE COURSE DESIGN AND DELIVERY OF THE PLE

The course design and delivery of the PLE course are influenced by the outcomes of the students' characteristics and their learning context and access to technology regarding the platform that was implemented in the study, which is Future Gate (FG). The second is the implementation phase, where the developed course is put into action, and the final product is presented to the target audience. The implementation phase consisted of two main steps according to Watson: installation and the distribution and management learning activities [87]. This study took place during the COVID-19 pandemic. Thus, all classes were conducted online. The instructor met with the learner online by using ZOOM software a few times before conducting the experiment. Before and during the actual online course, online meetings were put into action to introduce the learning system to ensure that the learners were well prepared and familiar with the learning system. Moreover, the learners were asked to create and sign up for the FG platform during these online meetings with an assistant from the lab technician to ensure that all learners had an accepted account to participate in the FG platform. Third, in the design phase, the researcher prepared the course outlines, user interface, menus, and guidelines by referring to the Curriculum book of the Arabic course according to the topics mentioned in the book. Thus, in this section, the researcher elaborated on the interface and all menus needed for both students and teachers who used the FG platform. Additionally, a proper framework was chosen to design the PLE-based course. The main menu of the Future Gate platform is shown in Figure 5.

C. THE THEORETICAL BASE OF THE COURSE

The theoretical base of the course focused on enhancing self-regulated learning through PLEs. The theoretical framework of the study was based on the following three theories: i) the theory of constructivism originated by Savery and Duffy [88]; ii) the theory of PLE originated by Schaffert and Hilzensauer [11]; and iii) the theory of self-regulation originated by Zimmerman [54]. Central to the theory was the responsibility of the learner to determine the contents, goals, and evaluation decisions of the learning program. Fourth, the development phase was the actual production and assembly of the materials of the planned system from the design phase. This phase began once the design phase was completed. The researcher transformed all products from both the analysis and design phases into the learning system. In this stage, the content was produced. The content varied considerably, depending on the available resources. For example, some of the content consisted of only simpler materials (i.e., those with little or no interactivity or multimedia, such as structured PDF documents), which can be combined with other materials (e.g., audio or video files), assignments and tests. In this situation, storyboard development and the development of media and electronic interactions would not be conducted. Finally, in the evaluation (EV) phase, the online courses could be evaluated for specific EV purposes. These evaluations might be to evaluate the learners' reactions, the achievement of learning objectives, the transfer of job-related knowledge and skills, and the impact of the project on the organization. According to Watson, EV is a constant process that starts from the beginning of the project until the end. Accordingly, feedback from the learners through post questionnaires was gathered in this phase [87].

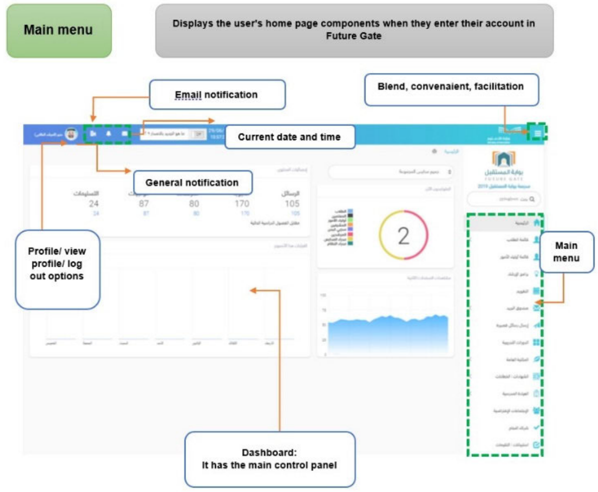

FIGURE 5. Main menu of the future gate platform.

VI. RESULT AND ANALYSIS (BEFORE INTERVENTION MODEL ANALYSIS)

A. MEASUREMENT MODEL (BEFORE INTERVENTION)

The Cronbach's alpha (CA) reliability coefficient was utilized in this study to evaluate the reliability of the factors that influenced SRL without the intervention of the PLE course based on three conditions. As stated by Hair et al., the variable indices must be less than 0.80, and the validity outcome in this study was found to be 0.7 [89], [90]. In addition, as claimed by Fornell and Larcker, each construct's average variance extracted (AVE) must be equal to or greater than 0.5 [91]. They also claimed that each construct's AVE square root must be greater than the interconstruct correlations (IC) for a factor. Therefore, a report by Fornell and Larcker stated that the construct must be greater than the standard of 0.5 [91]. Regarding the explanation, the factor loadings in this study are defined

TABLE 1. Outer loadings.

Factors	Items	EF	EV	GS	RE	SE	SM
Effort	EF1	0.800985	0.518276	0.599775	0.707875	0.723815	0.640725
	EF2	0.959625	0.802856	0.789227	0.901867	0.866722	0.895795
	EF3	0.725941	0.670875	0.718893	0.449104	0.607523	0.555703
	EF4	0.885275	0.793846	0.748634	0.715904	0.794344	0.874246
	EF5	0.942575	0.779727	0.814160	0.841997	0.802827	0.848198
Evaluation	EV1	0.521993	0.792585	0.672382	0.616684	0.605910	0.691969
	EV2	0.642797	0.799780	0.583178	0.732337	0.690542	0.728809
	EV3	0.696050	0.906890	0.890849	0.799429	0.851884	0.818068
	EV4	0.940761	0.925273	0.958369	0.879590	0.913674	0.918190
	EV5	0.598841	0.812293	0.762620	0.534898	0.709629	0.642775
	EV6	0.771239	0.885711	0.850828	0.878955	0.838978	0.841479
Goal Setting	GS1	0.696050	0.906890	0.890849	0.799429	0.851884	0.818068
	GS2	0.636016	0.805882	0.868583	0.655899	0.694290	0.691969
	GS3	0.805262	0.835910	0.935202	0.686033	0.779189	0.720198
	GS4	0.693393	0.714648	0.839911	0.710209	0.662154	0.675184
	GS5	0.918171	0.868008	0.923597	0.921276	0.885832	0.884673
Reflection	RE1	0.614856	0.560072	0.649327	0.823919	0.597172	0.601042
	RE2	0.779267	0.911162	0.812742	0.948560	0.914039	0.894114
	RE3	0.871943	0.857995	0.833674	0.936551	0.863950	0.954057
Self-efficacy	SE1	0.616595	0.868914	0.790749	0.885937	0.837143	0.828757
	SE2	0.765048	0.798452	0.751719	0.587276	0.755783	0.727287
	SE3	0.843527	0.717650	0.723287	0.855035	0.895425	0.817679
	SE4	0.770197	0.719159	0.783996	0.716109	0.831442	0.777536
	SE5	0.515746	0.504452	0.393642	0.488935	0.701277	0.469047
Self-monitoring	SM1	0.825273	0.867039	0.776706	0.961695	0.874602	0.940483
	SM2	0.754738	0.833528	0.781561	0.661087	0.800908	0.864825
	SM3	0.859915	0.802856	0.789227	0.901867	0.834933	0.933378

*Note. EF = effort, EV = evaluation, GS = goal setting, RE = reflection. SE = Self-efficacy, SM= Self-monitoring

TABLE 2. Construct reliability.

Factors	Items	Factors Loading	AVE	CR	CA	R-Square
Effort	EF1	0.381726	0.597101	0.873585	0.817948	0.454146
	EF2	0.715093				
	EF3	0.949307				
	EF4	0.904524				
	EF5	0.780440				
Evaluation	EV1	0.519764	0.526903	0.863688	0.807014	0.833274
	EV2	0.740307				
	EV3	0.769936				
	EV4	0.900505				
	EV5	0.454116				
	EV6	0.856316				
Goal Setting	GS1	0.626803	0.429566	0.780206	0.655386	0.477049
	GS2	0.636606				
	GS3	0.766781				
	GS4	0.353889				
	GS5	0.797804				
Reflection	RE1	0.873943	0.601480	0.814966	0.673951	0.701417
	RE2	0.835611				
	RE3	0.585164				
Self-efficacy	SE1	0.344163	0.407916	0.755978	0.619293	0.000000
	SE2	0.883961				
	SE3	0.401802				
	SE4	0.713335				
	SE5	0.685165				
Self-Monitoring	SM1	0.867113	0.775066	0.911663	0.857261	0.728028
	SM2	0.928204				
	SM3	0.843654				

*Note. CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average variance extracted.

according to Table 1. In addition, the measurement model is portrayed in Figure 2.

1) CONSTRUCT RELIABILITY

As suggested by Fornell and Larcker regarding factor checking, this study examined the composite reliability (CR) [91]. The findings of this study presented values that were considered greater than the standard value (0.7 for CR and 0.5 for AVE), as illustrated in Table 2. However, based on [91], to increase the CR, indicators with outer loadings between 0.40 and 0.70 were removed from the scale.

2) DISCRIMINANT VALIDITY

Discriminant validity (DV) is explained to present the differences among sets of concepts and their indicators. From the perspective of [87], the entire constructs' DV was considered

TABLE 3. Latent variable correlations.

	Effort	Evaluation	Goal Setting	Reflection	Self-Monitoring	Self-efficacy
Effort	1.000000					
Evaluation	0.633314	1.000000				
Goal Setting	0.614279	0.697502	1.000000			
Reflection	0.656478	0.822964	0.575932	1.000000		
Self-Monitoring	0.638338	0.671476	0.852866	0.690034	1.000000	
Self-efficacy	0.624691	0.890989	0.690688	0.662700	0.570655	1.000000

TABLE 4. Hypothesis testing.

Relationships	Hypotheses Number	Path Coefficient	Standard Error	T. Value	Result
Evaluation -> Reflection	H9	1.127907	0.044808	25.171960	Accepted
Goal Setting -> Effort	H6	0.349579	0.036329	9.622667	Accepted
Goal Setting -> Self-Monitoring	H7	0.877179	0.031882	27.513317	Accepted
Self-Monitoring -> Evaluation	H8	0.241756	0.017421	13.876869	Accepted
Self-efficacy -> Effort	H1	0.383241	0.035319	10.850994	Accepted
Self-efficacy -> Evaluation	H2	0.753029	0.015563	48.384930	Accepted
Self-efficacy -> Goal Setting	H3	0.690688	0.031191	22.144073	Accepted
Self-efficacy -> Reflection	H5	-0.342253	0.050009	6.843869	Accepted
Self-efficacy -> Self-Monitoring	H4	-0.035201	0.034753	1.012900	Rejected

to have values greater than 0.50 and to be significant at $p = 0.001$. Furthermore, [88] stated that the AVE square root as presented by a single construct's items must be less than the correlations between the items in the two constructs. According to this explanation, the outcomes of DV are presented in Table 3.

3) STRUCTURAL MODEL (BEFORE INTERVENTION)

After conducting the first phase, this study utilized the bootstrapping method with the aim of examining the normality of the data in the second phase. In this process, a large number of subsamples ($n = 5{,}000$) were taken from the original sample with the purpose of checking for errors. As illustrated in Figure 3, the findings offer the path coefficient values and the T values to present the importance of the measurement model, as illustrated in Figure 4.

According to the presented information in Table 4, the findings of this study addressed the first hypothesis (H1) through a positive and significant relationship between SE and EF ($\beta = 1.12$, $t = 25.17$, $p < 0.001$). Therefore, the findings show that students' SE significantly affects their EF.

To address the second hypothesis (H2) in this study, the findings portrayed the relationship between SE and EV ($\beta = 0.75$, $t = 48.38$, $p < 0.001$).

To present the findings according to the third hypothesis, a positive and significant relationship between SE and GS was presented. The analysis findings were $\beta = 0.69$, $t = 22.144$, and $p < 0.001$.

The fourth hypothesis proposed in this study was rejected based on the results of $\beta = -0.03$ $t = 1.01$, and $p > 0.001$. The fifth hypothesis was predicted to show a significant and direct effect between SE and RE. The findings showed $\beta = -0.34$, $t = 6.84$, and $p < 0.001$, which supports hypothesis (H5) and states that SE influenced students' RE.

The sixth hypothesis (H6) proposed in this study presented a direct and significant relationship between GS and EF through the results that supported this relationship ($\beta = 0.349$, $t = 9.633$, $p < 0.001$).

The proposed seventh hypothesis presented a direct relationship between GS and SM as the findings considered $\beta = 0.877$, $t = 27.51$, $p < 0.001$.

The eighth hypothesis (H8) showed a significant and positive relationship with SM ($\beta = 0.241$, $t = 13.876$, $p < 0.001$).

Furthermore, the ninth hypothesis showed a positive and significant relationship between EV and RE according to the findings ($\beta = 1.12$, $t = 25.171$, $p < 0.001$), which supported the hypothesis.

B. AFTER INTERVENTION MODEL ANALYSIS

The reliability of the factors that affect SRL with the PLE course-based intervention was examined via the same techniques as before the intervention. The construct was above the standard of 0.5. The factor loadings are shown in Table 5. Figure 5 illustrates the measurement model.

1) CONSTRUCT RELIABILITY

The research then went on to the next phase, which looked at the CR via the same model that was utilized before the intervention. According to the results, Table 6 shows that the values were higher than the normal value (0.7 for CR and 0.5 for AVE).

2) DISCRIMINANT VALIDITY

After examining the CR and AVE, this study evaluated the DV. The DV in this study portrayed the square root of the AVE with each hidden variable in the addressed model. In addition, as shown in Table 7, the latent variable correlations are presented to verify the normality of the DV.

3) STRUCTURAL MODEL (AFTER INTERVENTION)

This study utilized bootstrapping to evaluate the normality of the data. Thus, a large number of subsamples ($n = 5{,}000$) were taken from the original sample for error checking. The findings addressed the path coefficients in Figure 6, and the T values are defined in Figure 7.

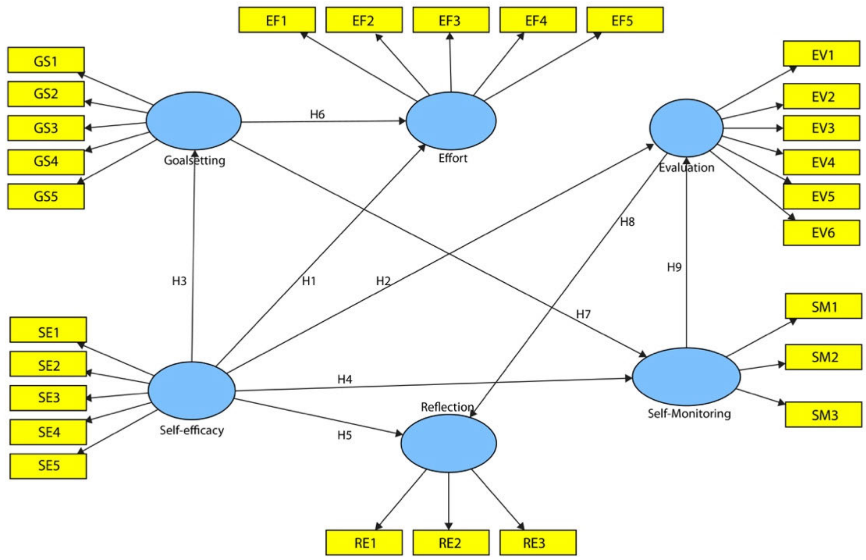

FIGURE 6. Before intervention measurement model.

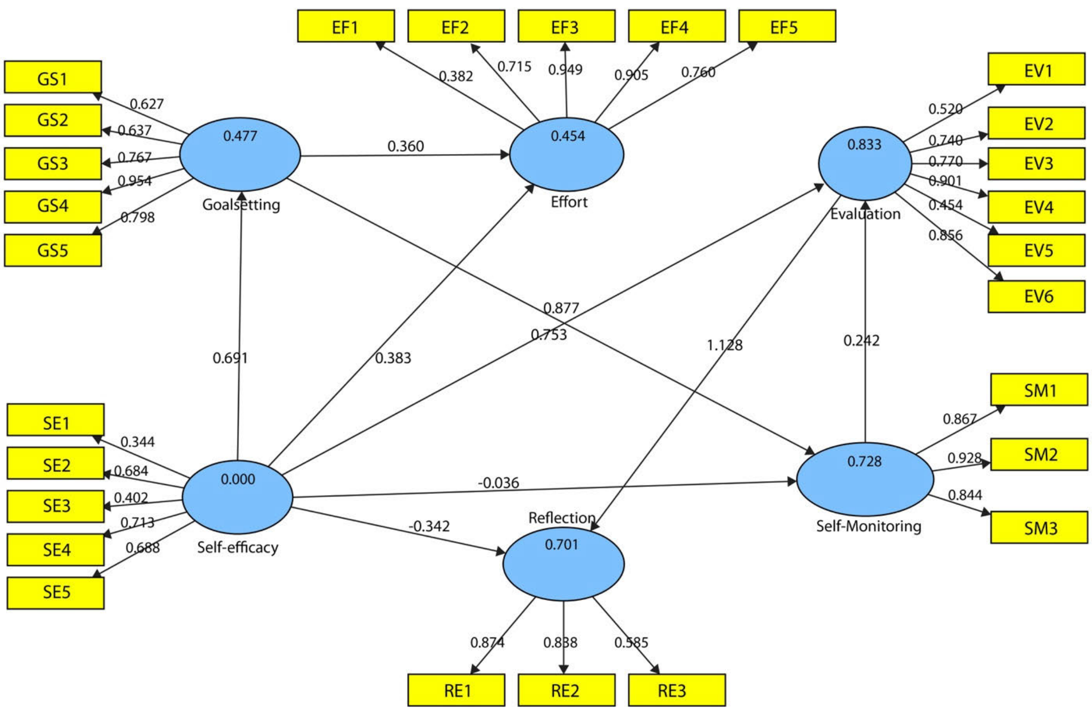

FIGURE 7. Path coefficient results.

The findings based on the proposed first hypothesis (H1) considered a positive and significant relationship between SE and EF ($\beta = 0.588$, $t = 16.503$, $p < 0.001$). Therefore, the students' SE significantly affects their EF.

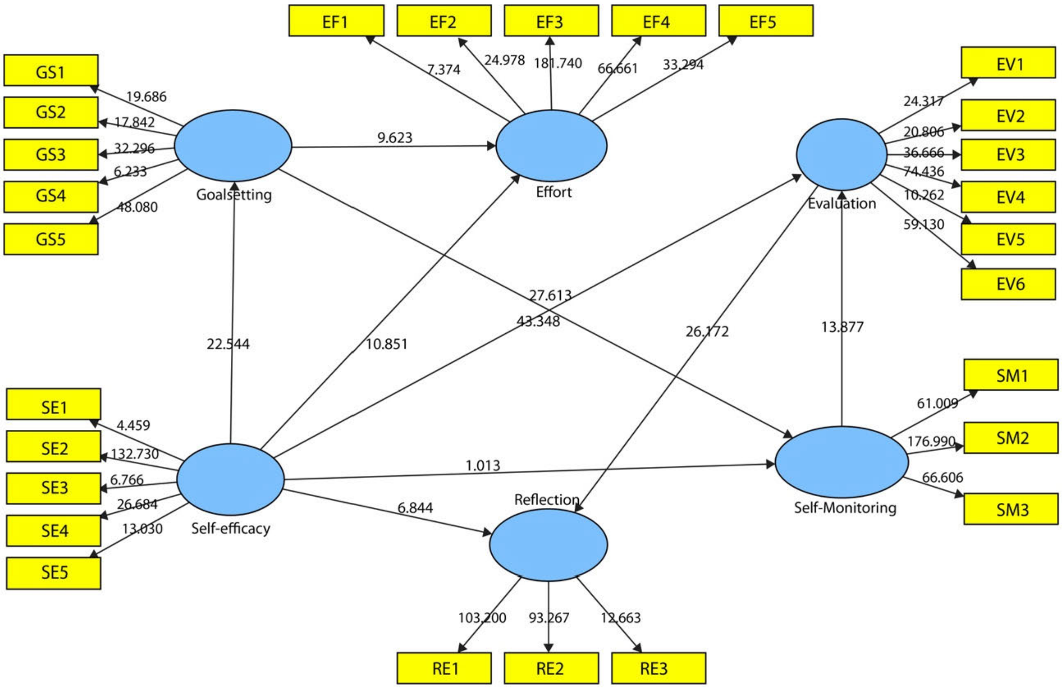

FIGURE 8. Path coefficient T values.

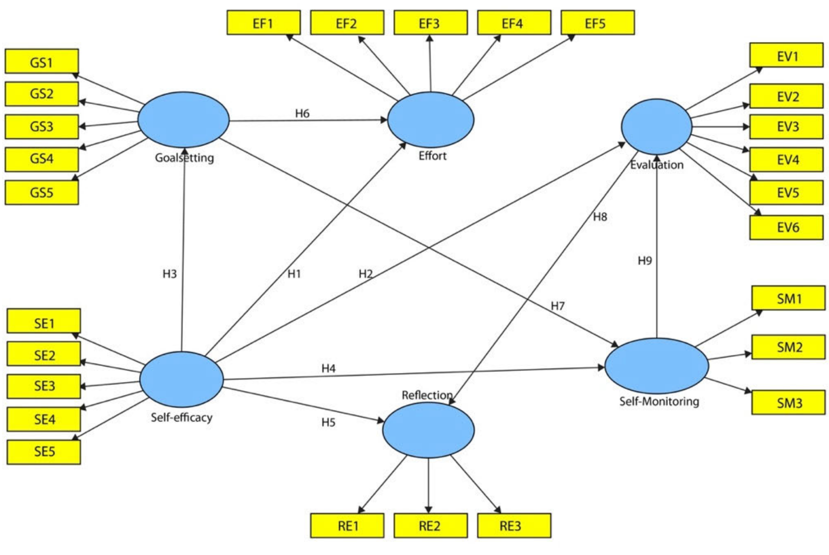

FIGURE 9. After intervention measurement model.

The findings to address the second proposed hypothesis (H2) supported the relationship between SE and EV ($\beta = 0.44$, t = 10.94, p < 0.001).

The third hypothesis proposed that SE and GS have a direct and significant relationship, as the results showed that $\beta = 0.87$, t = 92.68, and p < 0.001.

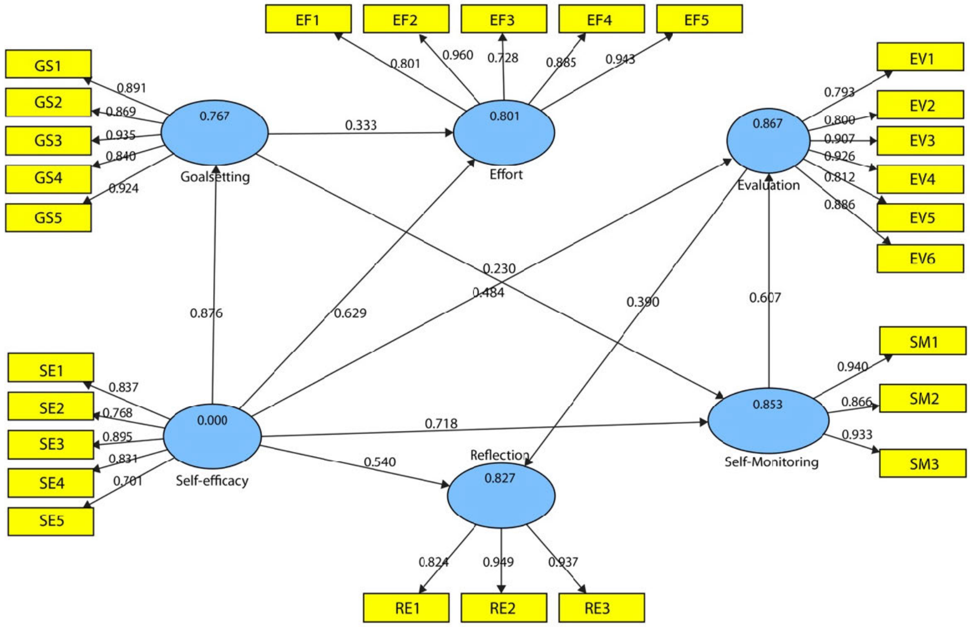

FIGURE 10. Path coefficients results.

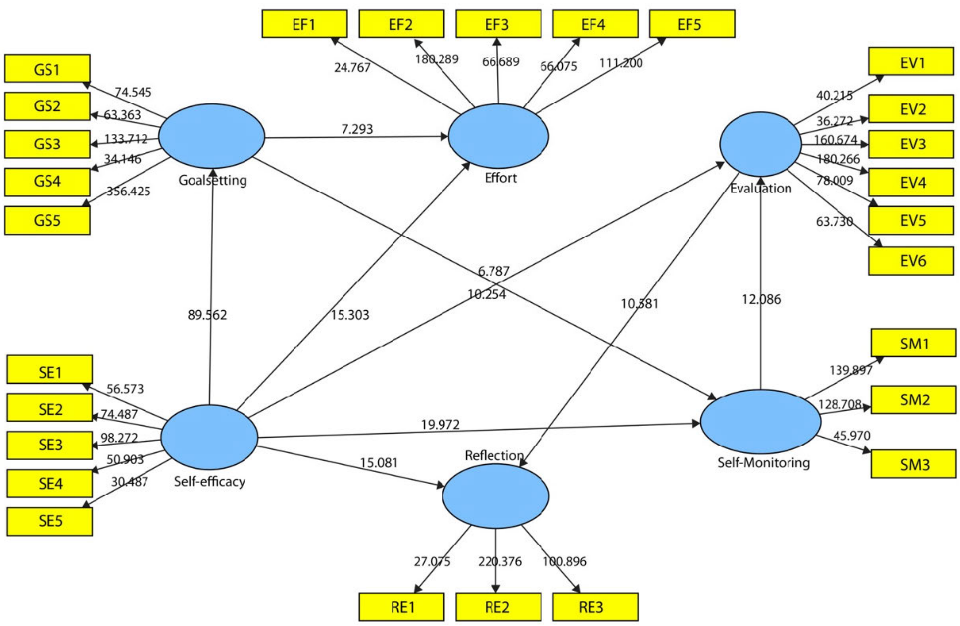

FIGURE 11. Path coefficients T values.

The fourth proposed hypothesis addressed a direct and significant relationship between SE and SM, as the results showed that $\beta = 0.7$ t $= 19.24$, and $p > 0.001$.

The fifth hypothesis addressed a direct effect between SE and RE because the results showed that $\beta = -0.540$, t $= 13.766$, and $p < 0.001$.

TABLE 5. Outer loadings.

Factors	Items	EF	EV	GS	RE	SE	SM
Effort	EF1	0.800985	0.518276	0.599775	0.707875	0.723815	0.640725
	EF2	0.959625	0.802856	0.789227	0.901867	0.866722	0.895795
	EF3	0.725941	0.670875	0.718893	0.449104	0.607523	0.555703
	EF4	0.885275	0.793846	0.748634	0.715904	0.794344	0.874246
	EF5	0.942575	0.779727	0.814160	0.841997	0.802827	0.848198
Evaluation	EV1	0.521993	0.792585	0.672382	0.616684	0.605910	0.691969
	EV2	0.642797	0.799780	0.583178	0.732337	0.690542	0.728809
	EV3	0.696050	0.906890	0.890849	0.799429	0.851884	0.818068
	EV4	0.940761	0.925273	0.958369	0.879590	0.913674	0.918190
	EV5	0.598841	0.812293	0.762620	0.534898	0.709629	0.642775
	EV6	0.771239	0.885711	0.850828	0.878955	0.838978	0.841479
Goal Setting	GS1	0.696050	0.906890	0.890849	0.799429	0.851884	0.818068
	GS2	0.636016	0.805882	0.868583	0.655899	0.694290	0.691969
	GS3	0.805262	0.835910	0.935202	0.686033	0.779189	0.720198
	GS4	0.693393	0.714648	0.839911	0.710209	0.662154	0.675184
	GS5	0.918171	0.868008	0.923597	0.921276	0.885832	0.884673
Reflection	RE1	0.614856	0.560072	0.649327	0.823919	0.597172	0.601042
	RE2	0.779267	0.911162	0.812742	0.948560	0.914039	0.894114
	RE3	0.871943	0.857995	0.833674	0.936551	0.863950	0.954057
Self-efficacy	SE1	0.616595	0.868914	0.790749	0.885937	0.837143	0.828757
	SE2	0.765048	0.798452	0.751719	0.587276	0.755783	0.727287
	SE3	0.843527	0.717650	0.723287	0.855035	0.895425	0.817679
	SE4	0.770197	0.719159	0.783996	0.716109	0.831442	0.777536
	SE5	0.515746	0.504452	0.393642	0.488935	0.701277	0.469047
Self-monitoring	SM1	0.825273	0.867039	0.776706	0.961695	0.874602	0.940483
	SM2	0.754738	0.833528	0.781561	0.661087	0.800908	0.864825
	SM3	0.859915	0.802856	0.789227	0.901867	0.834933	0.933378

*Note. EF = effort, EV = evaluation, GS = goal setting, RE = relief. SE = Self-efficacy, SM= Self-monitoring.

TABLE 6. Construct reliability.

Factors	Items	Factors Loading	AVE	CR	CA	R-Square
Effort	EF1	0.800985	0.752321	0.937620	0.914454	0.801154
	EF2	0.959625				
	EF3	0.725941				
	EF4	0.885275				
	EF5	0.942575				
Evaluation	EV1	0.792585	0.731787	0.942215	0.926016	0.867338
	EV2	0.799780				
	EV3	0.906890				
	EV4	0.925273				
	EV5	0.812293				
	EV6	0.885711				
Goal Setting	GS1	0.890849	0.796226	0.951236	0.935760	0.767244
	GS2	0.868583				
	GS3	0.935202				
	GS4	0.839911				
	GS5	0.923597				
Reflection	RE1	0.823919	0.818579	0.930958	0.889978	0.827472
	RE2	0.948560				
	RE3	0.936551				
Self-efficacy	SE1	0.837143	0.651377	0.902685	0.865382	0.000000
	SE2	0.755783				
	SE3	0.895425				
	SE4	0.831442				
	SE5	0.701277				
Self-monitoring	SM1	0.940483	0.834542	0.937928	0.900059	0.853001
	SM2	0.864825				
	SM3	0.933378				

*Note. CA = Cronbach's alpha, CR = Composite reliability, AVE = Average variance extracted.

The sixth proposed hypothesis showed a direct and significant relationship between GS and EF ($\beta = 0.33$, t = 7.9, $p < 0.001$).

The findings of this study to address the seventh hypothesis proposed a direct relationship between GS and SM, as the results showed ($\beta = 0.22$, t = 5.71, $p < 0.001$).

The relationship between SM and EV according to the eighth hypothesis was proposed to be significant and direct because the results showed that $\beta = 0.506$, t = 12.70, and $p < 0.001$). Finally, the ninth hypothesis showed a positive and significant relationship between EV and RE according to the addressed results ($\beta = 0.39$, t = 9.63, $p < 0.001$).

C. FINDINGS AND DISCUSSION

This study provided two significant contributions to PLEs through the LMS platform and modeled the relations between

TABLE 7. Latent variable correlations.

	Effort	Evaluation	Goal Setting	Reflection	Self-Monitoring	Self-efficacy
Effort	1.000000					
Evaluation	0.828151	1.000000				
Goal Setting	0.848844	0.929342	1.000000			
Reflection	0.845815	0.881375	0.854012	1.000000		
Self-monitoring	0.890653	0.914263	0.856592	0.923673	1.000000	
Self-efficacy	0.880507	0.909087	0.875925	0.895006	0.916912	1.000000

TABLE 8. Hypothesis testing.

Relationships	Hypotheses Number	Path Coefficient	Standard Error	T. Value	Result
Evaluation -> Reflection	H9	0.390272	0.040495	9.637533	Accepted
Goal Setting -> Effort	H6	0.333338	0.042149	7.908631	Accepted
Goal Setting -> Self-monitoring	H7	0.229622	0.040186	5.713943	Accepted
Self-monitoring -> Evaluation	H8	0.506739	0.039899	12.700668	Accepted
Self-efficacy -> Effort	H1	0.588527	0.035662	16.503001	Accepted
Self-efficacy -> Evaluation	H2	0.444453	0.040611	10.944211	Accepted
Self-efficacy -> Goal Setting	H3	0.875925	0.009451	92.682747	Accepted
Self-efficacy -> Reflection	H5	0.540215	0.039242	13.766186	Accepted
Self-efficacy -> Self-monitoring	H4	0.715780	0.037201	19.241019	Accepted

the SRL factors after a PLE intervention. The findings of this study confirmed that PLEs have a positive effect on students' SRL skills. The findings were in line with the perspective of Mott [33], who suggested that enhancing PLEs as learner-created and administered resource matrices can help learners develop their metacognition and self-regulation, which results in more positive learning experiences for learners. In addition, the findings of this study are consistent with the perspectives of several researchers that have addressed a positive and significant impact among the SRL factors [43], [47], [57], [60], [61], [64].

However, some of the relationships were confirmed after the intervention of PLEs. Accordingly, this study indicates that applying the 3rd generation LMS as a platform in PLEs develops students' SRL skills. According to Zimmerman [44], SE is not an isolated factor in the forethought phase; rather, it impacts a wide variety of factors in the self-regulation phases. In the same vein, the findings of this study portrayed SE as a key variable that affects SRL. In addition, several studies outline the beneficial impact of SE on self-regulation, including forethought (GS), performance (SM, ring SE), ion), and SR (reflection). In line with the perspective of Zimmerman [43], the findings of this research also indicated that SE shows a positive and significant impact on goal setting, EF, SE, and RE. This is in contrast with the findings of this study that demonstrated the effect of SE on SM to be insignificant, although after the intervention PLEs, the findings improved and showed a positive impact, which is also in line with a study conducted by Kurtz and Borkowski who found that students' perceptions of self-efficiency have proven to be associated with students' SM [58]. In addition, according to Kurtz and Borkowski, students with high SE demonstrate a greater SM of their academic achievement than students with low SE [58]. Furthermore, the findings of this study are consistent with the findings of a study conducted by Moos and Azevedo, who showed that the relationship between SE and learning performance is mediated by monitoring [65]. The findings further suggest that GS and preparation are related processes, with PL aiding learners in creating well-thought-out goals and plans for progress. This explanation has been supported by several researchers [63], [64]. More specifically, the findings of this study proved that goals to stimulate human activity and inspire people to attain successful results are recommended, which is in line with the perspective of Hardin et al. [68]. Under these circumstances, this study showed a positive impact of GS on performance phase factors, which are covered by SM and EF.

According to the findings of several studies, successful learning is based on self-regulation balancing with educational PL [59], [67], [68]. Furthermore, when they monitor their interactions with learning experiences and assignments and evaluate progress toward goals, successful self-regulated learners produce internal feedback [69]. Students' self-monitored performance was compared to an absolute baseline or previous performance during this SE [60]. Similarly, in the current study, the findings indicate that SM has a positive effect on SE. In addition, the findings portrayed the positive impact of SE on students' RE, which is similar to the perspective of Hadwin and Winne who argued that learners are eager to be self-regulated when they can assess their own learning [71].

VII. CONCLUSION AND RECOMMENDATIONS FOR FURTHER STUDIES

Therefore, according to the findings and discussion, this study claimed that enhancing SRL skills by using PLEs would be crucial in the education system. Furthermore, regarding the findings of this study, it can be considered that all the stated hypotheses were accepted after the intervention of PLEs. Therefore, the contributions of this study are as follows.

- The impact of SRL factors before and after PLEs intervention should be modeled.
- The use of PLEs in a learning context should enhance students' SRL skills. In addition, this can improve components such as goal-setting skills, EF, self-monitoring, SE, and RE

and can emphasize the effect on SE improvement and effect, among other factors.

• Educational institutions are advised to integrate the 3rd generation as a PLE platform.

Although this study offered several significant points, it also has its own limitations, which may offer some significant recommendations for further studies to be conducted. The first limitation refers to the sample size, which was limited due to the COVID-19 pandemic. This study recommends that further studies work on a larger sample to obtain generalizable findings. Second, the current research was restricted to a single country. It is recommended that further studies be conducted on several learners from different regions and societies to overcome the limitations and expand the reach of new findings. Finally, the findings of this study suggest that further studies could work in the vast context of PLEs. For instance, further studies may be conducted on the LMS as a PLE platform. Further studies could also focus on the implementation of PLE platforms to enhance learners' self-regulation skills to obtain more generalizable findings.

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SARAH ALSERHAN received the master's degree in educational technology from King Saud University, Saudi Arabia. She is currently pursuing the Ph.D. degree with the College of Education, Universiti Teknologi Malaysia, Johor. Her research interests include educational technology, instructional design, personalize learning, and virtual environment.

TURKI MESFER ALQAHTANI received the B.S. degree in computer science from King Khalid University, Abha, Saudi Arabia, and the master's degree in information technology from Griffith University, Australia.

He is currently a Lecturer with the Department of Instructional Technology, Jazan University, Saudi Arabia. He is also an expert in data analysis using IBM SPSS and SmartPLS. He had experience around nine years of teaching instructional design principles course and technology-based learning tools and applications. He also focuses on the flipped classroom and online anxiety. His research interests include flipped classroom, blend learning, and blockchain. He was a Committee Member of the Jury in the Final Selection of the National Olympiad for Scientific Creativity "Ibdaa," under the supervision of King Abdulaziz and his Companions Foundation for Giftedness and Creativity (Mawhiba) for several years in Riyadh, Saudi Arabia.

NORAFFANDY YAHAYA received the Ph.D. degree in computer-based learning from the University of Leeds, U.K.

He has been an Associate Professor with the Faculty of Education, Universiti Teknologi Malaysia, since 2013. He was the Head of the Department of Educational Science, Mathematics, and Creative Multimedia, for nine years. He conducted studies on students' interaction in online learning environment, learning analytics, and massive open online courses (MOOCs). He has published more than 70 papers in journals and conferences proceedings in the research area of online learning, ICT in education, and the use of technology in teaching and learning. He has been a supervisor to more than 25 completed master's degree students and seven completed Ph.D. students in the area of educational technology, online learning, and ICT in education. He had also been appointed as an external examiner for universities in Malaysia and Australia for doctoral theses and had been an assessor for master's dissertation for university in New Zealand. His research interests include multimedia in education, online learning, and ICT in education.

WALEED MUGAHED AL-RAHMI received the Ph.D. degree from the Faculty of Computing-Information Systems, Universiti Teknologi Malaysia (UTM).

He had eight years of teaching experience at the Department of Computer Science, Hodeidah University, and a Teaching Assistant with the Faculty of Computing, UTM, for a period of two and half years. Moreover, he was a Postdoctoral Researcher with the Faculty of Information and Communication Technology, International Islamic University, Malaysia; and the Faculty of Science, UTM. Currently, he is a Postdoctoral Researcher with the Faculty of Education, UTM. His research interests include information system management, information technology management, human–computer interaction, implementation process, technology acceptance model (TAM), communication and constructivism theories, impact of social media networks, collaborative learning, e-learning, knowledge management, massive open online course (MOOCs), and statistical data analysis (IBM SPSS, AMOS, NVIVO, and SmartPLS). He received the Best Student Award, the Doctor of Philosophy (Faculty of Computing-Information System), the Excellent Academic Achievement in Conjunction with the 56th Convocation Ceremony, UTM, in 2016.

HASSAN ABUHASSNA received the master's degree in instructional technology and the Ph.D. degree (Hons.) in education technology.

He worked at Universiti Teknologi Malaysia (UTM), as a Postdoctoral Fellow for six months, a part-time Lecturer for two months, and a Research Assistant for three years. He is currently an Assistant Professor with UTM. He has many recent publications in WOS and Scopus indexed. He has more than six years of experience working in the field of education and multimedia training. His current research interests include MOOC, multimedia in education, online learning, and e-learning.