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INVESTIGATING SELF-REGULATED LEARNING STRATEGIES FOR DIGITAL LEARNING RELEVANCY

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ABSTRACT

Purpose - The rise of digital learning and the prevalence of affordable devices are convenient for young adults who are accustomed to using their digital devices for almost everything such as communication, collaboration, and accessing multiple sources of information for solutions. However, the lack of ability to self-regulate learning processes has led to poor learning performance among undergraduates. Therefore, this study examined the effects of self-regulated learning strategies (SRLS) on learning performance among Malaysian IT undergraduates.

Methodology - A sample of IT undergraduates from private higher education institutions in Malaysia participated in the study. Quantitative data from a total of 563 respondents was collected through questionnaire surveys and analysed using PLS-SEM. The common method variance was utilized in this paper.

Findings - The findings of this study constitute essential results that three out of four SRLS domains (cognitive engagement, resource management, and motivational beliefs) positively influenced the students' perception of learning performance.

Significance - This study provides insight into the best SRLS to excel in digital learning for deeper learning particularly in the Malaysian context. Implications of the findings on higher education institutions as well as recommendations for future research are discussed.

Keywords: Self-regulated learning strategies, digital learning, higher education, learning performance, subjective learning outcomes.

INTRODUCTION

Digital technology has changed the student approach to learning. It has become a necessity and an integral part of their lives. The confident emergence of digital learning can be attributed to the rapid and continuous innovation in educational technology in this digital era (Benson & Kolsaker, 2015). Students are accustomed to using their digital devices for almost everything such as communication, collaboration, and accessing multiple sources of information for solutions. Creating a digital learning environment in higher education is not just about convenience, it is about preparing undergraduates for the future, as digital evolution is the new approach to learning and teaching as reported in the Future of Jobs Report (World Economic Forum, 2018). Additionally, with the current Covid-19 global pandemic, the adoption of digital learning will continue to persist in being the new norm for most universities. Thus, with this situation, the need for students to develop self-regulated skills and digital literacy skills is even more urgent. The rise of blended learning and the prevalence of affordable devices have laid the foundation for digital learning. Blended learning occurs any time a student learns, at least in part, at a supervised brick-and-mortar location away from home and at least in part, through digital delivery with some element of student control over the time, place, path, and/or pace of learning (Tang & Chaw, 2016; Anthonysamy, Ah-Choo, & Soon-Hin, 2020).

Notwithstanding the many benefits of digital learning, literature has revealed that self-regulated learning strategies such as setting academic goals, planning, monitoring, and controlling the learning process are poorly utilized among undergraduates (Balapumi, 2015; Stewart, Stott, & Nuttall, 2015). Time management issues (Stewart et al., 2015; Hafizah, Norhana, Badariah & Noorfazila, 2016) are also a major concern, aside from the lack of critical thinking skills to correctly analyze and efficiently use online resources among others (Hafizah et al., 2016). Findings from one study revealed that Malaysian undergraduates obtained low ratings on self-regulated abilities as they were still not comfortable with digital learning and preferred traditional learning (Adams, Sumintono, Mohamed, & Noor, 2018; Anthonysamy, Ah-Choo, & Soon-Hin, 2019). This has led to poor learning performance in digital learning (Hu & Li, 2017; Terras & Ramsay, 2015; Moreno-Marcos, Muñoz-Merino, Maldonado-Mahauad, Pérez-Sanagustín, Alario-Hoyos, & Delgado Kloos, 2019). Learning performance is a measure of subjective outcomes, which relates to non-academic outcomes (Soderstrom & Bjork, 2015). Conversely, academic performance measures student achievement through objective measures such as Grade Point Average (GPA), examination results, and final course grades (Honicke & Broadbent, 2016; Yang et al., 2016; Vo et al., 2017).

Self-regulated Learning Strategies (SRLS) are used to assist students to learn efficiently. Examples of SRLS are rehearsal, organization, time management, peer learning, and effort regulation. These involve the use of cognition, metacognition, motivation, environmental, and behavioral components derived from social cognitive theory (Bandura, 1986). SRLS comprises four domains, which are cognitive engagement, metacognitive knowledge, resource management, and motivational beliefs (Zimmerman & Martinez-Pons, 1986; Pintrich, 1999). In digital learning, it is necessary to acquire self-regulated learning strategies because students are expected to have self-management skills as they pursue their academic goals independently. Thus, to learn effectively and successfully in digital learning, students need to equip themselves with self-regulation abilities (Greene, Copeland, Deekens, & Yu, 2018; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Phillips, Turnbull, & He, 2015).

While many researchers have investigated the impact of SRLS upon academic performance and academic outcomes (Broadbent & Poon, 2015), there is a dearth of research about the effects of SRLS use on learning performance (non-academic outcomes) in digital learning within a blended learning environment in higher education. This is a problematic state of affairs as such digital learning is essential in assisting university students' learning progression (Li, Ye, Tang, Zhou, & Hu, 2018). Facilitating the student learning process is one of the key challenges encountered in blended learning environments (Boelens, De Wever, & Voet, 2017). Therefore, instead of investing heavily in computer infrastructure, increasing learner control should be the main focus and top priority of higher educational institutions. Hence, more research is needed to examine how SRLS can enhance students' learning performance in digital learning within blended learning environments (Zhu, Au & Yates, 2016; Broadbent, 2017). Likewise, a more detailed investigation is needed to look into the possible relationship between SRLS and learning performance (Garcia, Falkner, & Vivian, 2018; Cho, Kim & Choi, 2017) since digital learning requires self-regulation abilities (Greene et al., 2018). Furthermore, examining how SRLS can enhance students' learning performance in the context of non-academic measures in blended learning environments are essential (Zhu et al., 2016; Yamada, Goda, Matsuda, Saito, Kato & Miyagawa, 2016). By addressing this gap, a study will be able to reveal valuable information on how self-regulated learning strategies can enhance learning performance for undergraduates (Zhu et al., 2016).

The study reported in this paper, therefore aims to examine the effects of self-regulated learning strategies on learning performance in digital learning within blended learning environments in Malaysian higher education institutions. The following section presents the literature review on digital learning, self-regulated learning strategies, and learning performance. The method, data analysis, and findings are discussed in Sections 3, 4, and 5. This is followed by Section 6 which presents the limitation of the study and suggestions for future research. Finally, Section 7 presents the overall conclusions of the study.

LITERATURE REVIEW

Digital Learning

Digital learning is learning of any kind which makes use of technology effectively. Digital learning tools offer personalization and flexibility for each student to plan, gather, manage, analyze, and report information. It is a matter of attaining the same goal using different pathways of learning. For example, a student may take a set a learning goal and take photos to self-reflect as well as track their progress. Another student might use an app to set goals and track their goals through the app. Alternatively, a student might log their goals in digital calendars.

Blended learning is defined as the adoption of educational web-based technology or online learning (Broadbent, 2017). Blended learning is a term that describes traditional classroom learning and digital learning as methods used to create a student-centered, self-paced, and flexible approach to student learning (Anthonysamy et al., 2020). Thai, De Wever and Valcke (2017) stressed that the blended learning environment had a positive impact on students' perception and produced high levels of student engagement because it offered a richer learning experience (Thai et al., 2017). This was probably because the online support activities could increase students' attention and focus, thus enabling them to utilize higher-order thinking skills that fostered meaningful learning experiences (Rahmi, Azrul, & Adri, 2019). Therefore, the ongoing infusion of web-based technologies into the learning process tended to create an optimal environment for enhancing student engagement (Ibrahim & Nat, 2019). Generally, it become clear that for learners to actively engage in the learning process, they need to acquire some measure of self-regulated skills to structure their learning beyond the classroom.

Self-Regulated Learning Strategies

Self-regulation is the capacity of an individual to personally monitor, control, and manage their behavior, emotions, or thoughts to reach a goal. Self-regulation is not a person's behavior or characteristic. Instead, it is a skill that can be developed and mastered. Self-regulated learning (SRL) is based on the belief that students use cognitive, metacognitive, behavioral (Zimmerman, 1986) and motivational components (Pintrich, 1999) to manage their learning processes. Self-regulated learning strategies (SRLS) are used by students to self-observe their progress and to identify the strengths of the used learning strategies as well as gain awareness of any weaknesses throughout their learning process. Current literature has clearly stated that for students to learn successfully via digital learning, students need to equip themselves with self-regulated learning strategies (SRLS) (Greene et al., 2018). SRLS are relevant to students learning performance in both online and blended contexts according to the existing literature because these strategies assist students to become aware of their thought processes and actively participate in their learning process in all study contexts.

Scholars (Zimmerman & Martinez-Pons, 1986) have revealed fourteen categories of self-regulated learning strategies (SRLS) derived from social cognitive theory. Broadly, these SRLS can be classified into four domains, namely (1) cognitive engagement, (2) metacognitive knowledge, and (3) resource management (Zimmerman & Martinez-Pons, 1986) and (4) motivational belief (Pintrich, 1999) (refer to Table 1, on p.5). Cognitive engagement involves mental strength as well as the willingness to attain, retrieve, and observe new knowledge. Metacognitive knowledge is about what, how, and when to apply a particular strategy in a specific task. For example, if a student is unable to understand the online material, he or she will go back and forth to figure out the material. Students who are mindful of their metacognition knowledge, will, therefore, be able to make better use of their knowledge and skills in their learning journey. Next, resource management comprises behavioral and environmental components. This strategy involves using the available resources wisely; these include time management, peer learning, help-seeking, and environmental structuring. Lastly, motivational beliefs consist of motivational and emotional strategies that help students observe and reach learning goals with technological self-efficacy beliefs, goal orientation, and task value belief strategies. The purpose of these different forms of strategies is to help students improve the way they regulate their learning from the aspects of personal functioning, academic behavioral performance, and learning environment. For example, strategies that students may use to optimize cognitive engagement include organizing, rehearsal, elaboration, and several others.

Previous research has found self-regulated learning to be a significant predictor in learning and performance (Haron, Harun, Ali, Salim, & Hussain, 2015). The literature has shown that SRLS plays a role in distinguishing high scorers from low scorers, based on academic tasks which are focused on understanding instead of acquisition (Greene et al., 2018). Likewise, previous research has revealed that students performed better with the use of self-regulated learning strategies as opposed to students who did not (Haron et al., 2015). Thus, it is clear that self-regulated learning strategies are necessary for the higher education sector to improve students' learning and performance.

Learning Performance

Learning performance is defined as a permanent change in the behavior of student understanding and abilities that supports long-term retention and transfer of knowledge, where learning performance is measured through non-academic outcomes (Soderstrom & Bjork, 2015). Non-academic outcomes are measures that quantify students' overall attitude towards learning, using subjective measures such as student satisfaction, student engagement, and attitude towards learning (Yang et al., 2016; Vo et al., 2017; Li et al., 2018).

The performance of students in digital learning is emerging as a crucial factor in the evaluation of blended learning environments. In a blended learning setting, learning performance is measured by both objective measures and subjective measures (Yang et al., 2016; Vo et al., 2017), whereby the academic performance of a student is measured through objebctive measures, and the learning performance of a student is measured through subjective measures. Subjective measures that relate to non-academic outcomes are a good way to quantify the overall attitude of a student towards learning. Relying solely on objective measures such as grades, marks and attendance may not reflect the full picture of student performance (Bowyer, 2017) and oftentimes, short term fluctuations and changes in student behaviors may falsely result in an illusion of competence (Soderstrom & Bjork, 2015). Hence, objective measures alone may not reflect quality learning which enables learners to obtain knowledge that can be used in real situations.

Table 1

Self-regulated Learning Strategies

SRLS	Definition	Domain
Rehearsal	Rehearsal strategies are best for simple tasks and activation of information in working memory rather than acquiring new information in long term memory. Rehearsal helps learning through repetition.	Cognitive Engagement
Elaboration	Elaboration refers to the ability to connect prior knowledge with new information with the objective of remembering the new material.	
Organisation	Organisation refers to the ability of a learner to select the appropriate information and organise their thoughts during a learning process.	
Critical Thinking	Critical thinking refers to the ability of synthesizing and evaluating online material to make them more meaningful and memorable.	
Planning	Planning activities include skimming an online material before reading, doing a task analysis of the problem, planning the sequence, timing, and completion of activities directed at learning goals.	Metacognitive Knowledge
Monitoring	Monitoring activities of the learning process are in relation to defined learning goals.	
Regulating	Regulation strategies care closely linked to monitoring strategies. As students monitor their learning progress, it needs some fine-tuning and continuous adjustments to bring back academic behavior in line with goal-attainment.	
Time and Study Environment	Time management refers to the capability to manage one's own study time and tasks.	Resource Management
Peer learning	Peer learning can be referred to as the collaboration with other students or peers in order to aid in the learning process.	
Help Seeking	Help seeking refers to asking other people for help, such as the instructor or one's peers, or consulting external help and resources	
Effort Regulation	Effort regulation is the ability for an individual to have perseverance when faced with academic challenges.	

(continued)

SRLS	Definition	Domain
Technological Self-Efficacy	Technological self-efficacy involves the capability of a student to confidently navigate through online materials and produce a positive outcome.	Motivational Beliefs
Task Value Beliefs	An individual's beliefs about value of doing the task, and comprises of the sum of the components of attainment value, the utility value, and the intrinsic value, minus the cost value component.	
Goal Orientation	Goal orientation refers to the general goals formulate by a learner to a course as whole. Goal orientation focuses on three general orientations which are mastery, extrinsic and relative ability.	

Source: Zimmerman and Martinez-Pons (1986); Pintrich (1999).

Assessment of Perceived Learning Performance

Bowyer recommended that the evaluation criteria of perceived learning performance should include student engagement, perceived learning outcomes, and student satisfaction in a blended learning environment (Bowyer, 2017). On the other hand, Yang and associates suggested that learning performance can be measured through learning outcomes, interaction, and engagement as well as satisfaction (Yang et al., 2016). Another researcher echoed that students' learning performance can be assessed mainly through the student learning experience, the learning context, and the learning outcomes (Zhu, 2012).

A learning outcome is a change in a student's learning experience and it is reflective of the quality of learning (Choy, Yim, & Tan, 2017). In other words, a learning outcome is what a student can perform now, something that they could not previously do. Learning outcomes are the expected achievements of students as mapped against specific program learning outcomes and specific learning experiences. Perceived learning outcomes are among the widely accepted measures of the effectiveness of online educational systems and it is as valued as the learning experience of students (Eom, Wen, & Ashill, 2006). Students' perceived learning outcomes were found to be more important as compared to the quality of the teaching staff (Teng & Baum, 2013). Since learning can involve cognitive, affective, and psychomotor components, it is essential to measure all three domains to measure perceived learning (Whiting, 2011).

Social interactivity refered to a situation in which individuals were able to interact with other people and technology (Gauld, Lewis, White, & Watson, 2016). Trowler (2010) defined engagement as involvement in activities that required cognitive activities and feelings which would result in measurable outcomes. Moreover, stimulating student interaction was a critical interactive element in the blended learning environment (Boelens et al., 2017). Digital learning tends to motivate students to interact among themselves or with their instructors. Although university students are assumed to continually improve their skills and knowledge in a digital environment, the knowledge, facilitation, and feedback from educators are vital in empowering students to perform better online. Many researchers have reported that a higher level of interaction with peers and instructors led to better performance among students (Siemens, Gašević & Dawson, 2015). Student engagement could be divided into three interrelated factors, namely behavioral, emotional, and cognitive (Bloom, 1956). Behavioral engagement was a reference to student participation, whether positively or negatively with online technologies. Emotional engagement addresses the positive or negative affective reactions of students, such as enjoyment and interest, towards learning online. The cognitive aspect of student engagement assesses whether students use surface or deep learning approaches in their use of technology. Promoting student engagement in digital learning, particularly in blended learning environments has been regarded as crucial (Chuah & Hong, 2014); research findings have shown student engagement to be significantly positively correlated with learning performance (Hu & Li, 2017).

Student satisfaction has been defined as how students perceive their learning experience of education in an institution (Bowyer, 2017). Student satisfaction is an important course outcome that cannot be measured through course evaluations and attendance. The degree of learning satisfaction in a digital environment was seen as playing a vital role in a blended learning setting (Zhu, 2012). Student satisfaction in a blended learning environment was associated with satisfying student attitudes towards the overall course, the perceived teaching quality from the aspect of the student experience in the blended environment (Bowyer, 2017), performance expectations (Sun, Tsai, Finger, Chen, & Yeh, 2008) which was similar to perceived usefulness (Davis, 1989), and the quality of online content (Bowyer, 2017). Zhou and fellow researchers found a significant positive relationship between the use of self-regulated learning strategies and learning satisfaction (Zhou, Lee, & Sin, 2017).

From the foregoing literature review, it can be seen that perceived learning performance can be measured through learning outcomes, student interactive engagement, and student satisfaction.

Hypothesis Development

Cognitive engagement. Cognitive engagement incorporates basic and multifaceted strategies for gaining knowledge as well as retaining and retrieving of information. Cognitive engagement comprises four strategies, which are rehearsal, elaboration, organization, and critical thinking.

Broadbent and Poon (2015) mentioned that researchers should not assume that the same strategies would work in both traditional and online settings as the findings show otherwise. In a digital learning environment, certain constructs may not apply. In recent years, some aspects of cognitive engagement do not suit a higher education online environment. Okaz (2015) emphasized that digital learning did develop students' cognitive engagement (Okaz, 2015). Furthermore, one study found a positive relationship between organizational strategies and learning outcomes (Cacciamani, Cesareni, Martini, Ferrini, & Fujita, 2012). Another study also found a positive relationship between critical thinking strategies and academic outcomes (Goradia & Bugarcic, 2017). However, Broadbent and Poon (2015) reported that the cognitive strategies of rehearsal, elaboration, and organization were no longer related or useful to students' learning performance in the higher education digital learning environment. Similar results were recorded by other scholars, for example, in Goradia and Bugarcic (2017) it was revealed that the strategies of elaboration, rehearsal, and organization had the least empirical support towards learning performance.

Since the findings of cognitive engagement appear to be paradoxical, it is important to investigate how and the extent to which cognitive strategies impact perceived learning performance among Malaysian undergraduates. Hence, the cognitive engagement construct is tested in this study because cognition is an important aspect of SRL (Pintrich, 1999). An investigation into the relationship between this construct and learning performance is researched empirically. There is a lack of studies that link self-regulated learning strategies with perceived learning performance, especially in the Malaysian education setting. Therefore, there is a need to test the following hypotheses.

Hypothesis 1 (H_1) : *There is a positive relationship between cognitive engagement (CE) and perceived learning performance (PLP)*

Metacognitive Knowledge

Metacognitive knowledge is an inner guide that enables an individual to plan, monitor, and regulate his or her cognition process to attain a goal. Metacognitive strategies include planning, monitoring, and regulating (Zimmerman & Martinez-Pons, 1986). This internal guide can assume various forms such as creating awareness, self-explanation, refocusing attention, and realizing an action that needs to take place. Metacognitive knowledge increases the mental strength of students as this skill helps them to be more aware of their cognitive abilities and thus be more capable of taking control of their learning.

For example, a study conducted by Goda and fellow researchers reported that concerning timely assignment submission, students with metacognitive skills managed their time better and hence achieved better learning performance (Goda et al., 2014).

Other research findings have revealed that metacognitive knowledge is positively correlated with learning performance (Broadbent & Poon, 2015; Goradia & Bugarcic, 2017; Cacciamani et al., 2012; Dumford et al., 2018; Pellas, 2014; Kuo et al., 2013). Higher performers are significantly better at goal setting compared to lower performers (Lawanto, Santoso, Lawanto & Goodridge, 2014; Lai & Hwang, 2016). However, in contrast, several studies have instead claimed that metacognitive knowledge weaken regulation in a digital learning (Ackerman & Goldsmith, 2011; Ackerman & Lauterman, 2012; Lauterman & Ackerman 2014). Despite prevalent belief about the importance of metacognitive strategies in digital learning, Azevedo and his associates have discovered that students frequently used ineffective metacognitive strategies within the online learning environment (Azevedo, Moos, Greene, Winters, & Cromley, 2008). Furthermore, Hashemyolia reported that Malaysian university students had very poor usage of metacognitive strategies (Hashemyolia, Asmuni, Ayub, Daud, & Shah, 2015).

There is a lack of studies that link metacognitive learning strategies with learning performance, especially in the Malaysian education setting. Therefore, there is a need to test the following hypothesis.

Hypothesis 2 (H_2) : *There is a positive relationship between metacognitive knowledge (MK) and perceived learning performance (PLP).*

Resource Management

Resource management consists of adaptive approaches that encourage students to meet their needs and achieve their goals (Pintrich, 1999). Resource management components include time and study management, effort regulation, peer learning, and help-seeking strategies. Accordingly, resource management strategies help students navigate their learning environment and external sources. Past studies have reported positive relationships between resource management strategies and learning performance among students (Cacciamani et al., 2012; Dumford et al., 2018; Wichadee, 2018; Mikum, Suksakulchai, Chaisanit, & Murphy, 2018; Noh & Kim, 2019; Goda et al., 2014).

This is because students develop effective cognitive learning strategies through social interactions (Zhu, 2012). Lehmann and associates suggested that external resources and support helped enhance the learning performance of individuals (Lehmann, Hähnlein, & Ifenthaler, 2014). Although different learning environments might utilize different strategies to promote learning performance in students, some researchers reported that the learning environment did not influence students' learning behaviors and outcomes (Spanjers et al., 2015). Additionally, the self-regulated learning strategies that were initially developed by Zimmerman and Martinez-Pons (1986) focused on the physical environment and it involved school-going students. In contrast, the study reported here concentrated on digital learning. Hence, it was was deemed timely to test this construct as the resource management strategy had been one of the least researched self-regulating strategies (Garcia, Falkner, & Vivian, 2018). In addition to that, in digital learning, the importance of resource management strategies might change in higher education institutions (Garcia et al., 2018). Hence, further research is needed to gain more empirical evidence as to the strengths and weaknesses of different resource management strategies. Therefore, the following hypothesis is proposed:

Hypothesis 3 (H_3) : *There is a positive relationship between resource management (RM) and perceived learning performance (PLP).*

Motivational Beliefs

Motivation is the factor that drives a student towards completing a task. Motivation is needed to help students observe their behaviors and reach learning goals (Panadero, 2017). Pintrich (1999) concentrated on three general motivational strategies, which included technological self-efficacy, task value beliefs, and goal orientation. In learning, managing emotional factors apart from cognitive processes are equally important. This is because motivation also acts like a psychological supportive tool in the learning processes of students. Motivational problems can result in students dropping out of an online learning environment more easily (Fryer & Bovee, 2016).

Past studies have found a positive relationship between motivational belief strategies and learning performance (Kuo et al., 2013; Mikum et al., 2017; Yamada et al., 2016; Fanguy, Costley, Lange, Baldwin, & Han, 2018). Conversely, there were also some studies which found that technological self-efficacy did not significantly correlate with learning performance (Puzziferro, 2006; Rodriguez Robles, 2006). Similarly, self-efficacy did not show any correlation with learning performance (Sun & Rueda, 2012). In addition to that, one study reported a negative relationship between goal orientation and students' learning performance (Pintrich, 1999). Even though previous studies have shown the importance of motivational beliefs in digital learning towards learning performance (Hatlevik & Christophersen, 2013; Senkbeil et al., 2013; van Deursen & van Dijk, 2014), there is still a need to provide more empirical evidence to examine motivational belief as a key predictor of students' learning performance. Only a few studies have investigated the relationship between technological self-efficacy and students' perceived learning performance (Kuo, Walker, Schroder & Belland, 2014). Therefore, the following hypothesis is proposed:

Hypothesis 4 (H_4) : *There is a positive relationship between motivational beliefs (MB) and perceived learning performance (PLP).*

In light of the research problem and literature review, a research model was developed for the study. It is as shown in Figure 1.

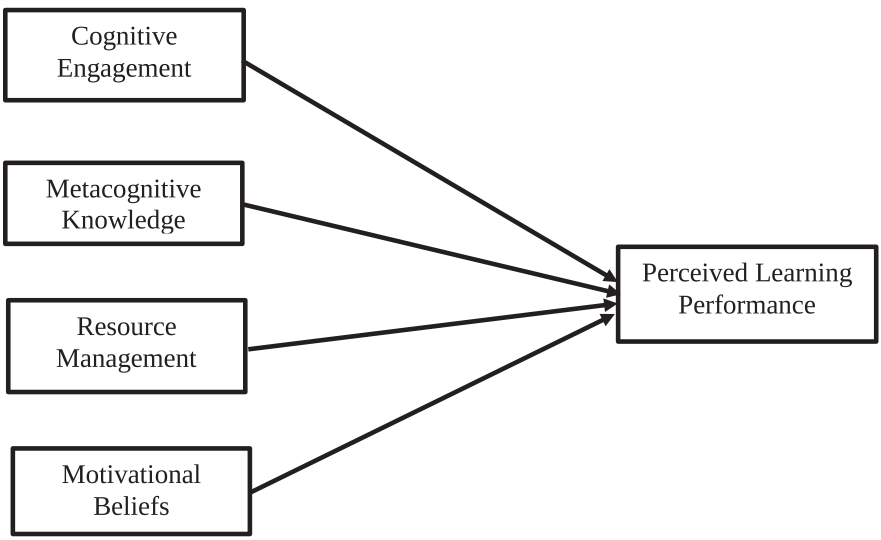

Figure 1. *The proposed research model.*

METHODOLOGY

Design

A quantitative cross-sectional design was employed in this study to investigate the relationships between self-regulated learning strategies and perceived learning performance. In Malaysia, there are 6 regions in Peninsular Malaysia and East Malaysia: (1) Northern region (2) Central region (3) Eastern region (4) Southern region (5) Sabah and (6) Sarawak. Figure 2 illustrates the distribution of private higher education institutions in Malaysia. Out of a total of 78 universities, 53 universities (equivalent to 68%) are located in the central region. Hence, universities located in the central region were chosen for our study. Subsequently, through informal interviews and website searches, eight private higher education institutions were identified and chosen because they had implemented blended learning for their undergraduate programs. The respondents for the questionnaire were undergraduates from IT or Multimedia degree programs. They were chosen purposively because these students had taken at least one blended learning subject.

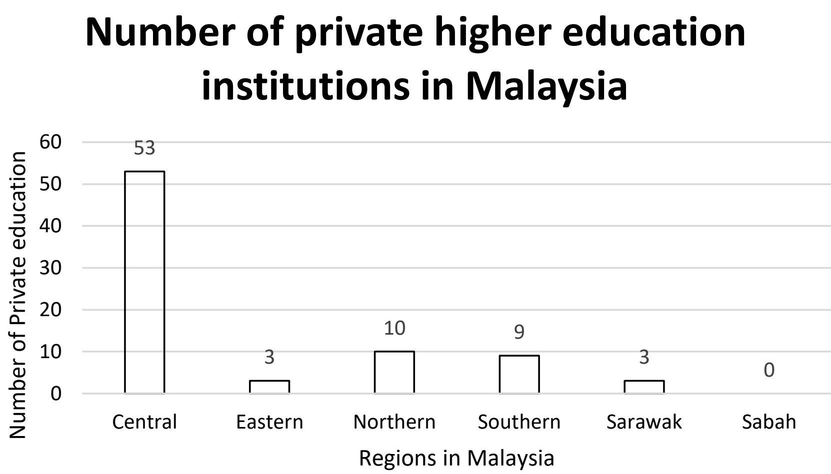

Figure 2. *Number of private higher education institutions in Malaysia (Malaysian Qualifications Register, 2018)*

Sample Size

The sample size was calculated with G power software (v 3.1) using a significance level of 0.05, an effect size of 0.15, and four predictors (exogenous variables). The confidence level of 95 percent with a 5 percent margin of error is accepted widely for most social science research (Sekaran & Bougie, 2013). G Power software which is based on the complexity of the model/ framework, suggested a minimum sample size of 129 for this study. In total, 770 questionnaires were distributed and 726 questionnaires were returned, with 563 questionnaires that were completed and usable in this study.

Instrument

The main instrument for this study is a questionnaire. To develop the self-reported instrument, several prior relevant studies were reviewed to ensure that a comprehensive list of measures would be included in our locally adapted questionnaire. The Motivated Strategies for Learning Questionnaire (MSLQ) was adapted because it has been widely used to assess the self-regulatory behaviors of students (Pintrich, Smith, Garcia, & McKeachie, 1991) in an online environment (Zhu et al., 2016) that involved undergraduates (Broadbent, 2017). To measure perceived learning within the cognitive, affective, and psychomotor domains, the Cognitive Affective Psychomotor (CAP) Perceived Learning Scale was used. This scale is a valid and reliable instrument used within a blended learning environment in higher education (Rovai, Wighting, Baker, and Grooms, 2009). Other resources were also used to design the questionnaire (Eom et al., 2006; Trowler, 2010; Yang et al., 2016; Sun et al., 2008; Wu et al., 2010).

Common Method Variance

The Common Method Variance (CMV) is mainly caused by biasness from the instrument rather than the respondent. The CMV needs to be examined when data collection is done using a single instrument at the same time (Podsakoff & Podsakoff, 2012; Williams and McGonagle, 2016) via self-reported questionnaires. It is particularly important when the same person is answering both predictor and criterion variable questions.

Harman's Single Factor Analysis was used to estimate the CMV. Harman's analysis evaluates the number of biases inherent in the variance proportion distribution of items. This is obtained by considering all items in an exploratory factor analysis where the unrotated 1st factor should be less than 50 percent (Podsakoff & Podsakoff, 2012). Harman's single factor score was used to test the CMV whereby all the latent variables were loaded into one common factor (see Table 2). If the total variance for a single factor is less than 50 percent, it suggests that the CMV does not affect the data, hence the results. For this study, the total variance extracted from Initial Eigenvalues showed that the extraction sum of loadings on the first factor was 22.07 percent. Since this value is less than 50 percent, it can be concluded that this data set does not suffer from common method bias (Podsakoff & Podsakoff, 2012).

Table 2

Harman's Single Factor Analysis: Total Variance Explained

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**13.98**	**23.30**	**23.30**	**13.24**	**22.07**	**22.07**
2	3.89	6.49	29.80			
3	2.71	4.51	34.32			
4	1.88	3.13	37.45			
5	1.68	2.80	40.26			
6	1.51	2.52	42.79			
7	1.43	2.39	45.18			

Data Analysis Method

SPSS and Structured Equation Modeling (SEM) using partial least squares were employed in this study. SPSS, a first-generation software, was used to key in each respondent's response as well as perform data cleaning to prepare for data analysis. Descriptive statistics were also generated with the aid of SPSS. First-generation statistical software is suitable for simple and straight forward research models. Moreover, it is only able to analyze single relationships at a time between the independent and dependent constructs.

Structured Equation Modeling (SEM) is a second-generation multivariate statistical approach that analyses measurement models and structural relationships in the same data analysis (Hair et al., 2010). This type of testing is relevant to this study's objective in testing the relationship between self-regulated learning strategies and learning performance. It also enables measurement errors to be analysed and factor analysis to be combined with hypotheses testing.

There are two types of SEM: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM is primarily used to confirm or reject theories (i.e., a set of systematic relationships between multiple variables that can be tested empirically). It determines how well the proposed theoretical model can estimate the covariance matrix for a sample data set. On the other hand, PLS-SEM is used to maximize the explained variance of the dependent variables (Hair, Hult, Ringle, & Sarstedt, 2017). The PLS-SEM approach is more applicable in this study because the main objective for PLS-SEM analysis is to estimate the coefficient that maximizes the R^2 values of the target endogenous construct. This feature achieves prediction ability that matches the objective of this study, which is to identify the extent to which self-regulated learning strategies influence learning performance. Furthermore, PLS-SEM supports reflective and formative measures in estimating the measurement model and the structural model. Hence, PLS-SEM was the preferred choice for the data analysis technique.

Normality

The SPSS (v.25) was used to test for normality. Data were tested for normality through kurtosis and skewness values, and was considered to be normal if skewness was between +-1 and kurtosis was between +-7 (Hair et al., 2017). The results of the data collected in this study suggest that the data did not meet multivariate normality. Thus, the data distribution is not normal. Thus, the PLS approach is more appropriate for this study because PLS-SEM is a nonparametric tool.

RESULTS

Descriptive Statistics

The sample for the final analysis consisted of 563 questionnaires as mentioned earlier. The response rate was more than 70 percent of the total number of questionnaires distributed. The final data set used for analysis comprised mostly males (70.3%) with the remaining being females (29.7%). Almost half of the respondents fell in the age group of 21 to 22 years of age (49.9%), followed by respondents aged 19 to 20 years old (45.1%), and the remaining 5 percent fell in the age group of 23 to 24 years old. As noted in Table 3, the year of study for the IT undergraduates was mainly first-year students (37.7%), followed by second-year students (34.5%) and third-year students (25.7%). The vast majority of respondents were Malaysians (85.1%).

Table 3

Demographic Profile of Respondents

	n	(%)		n	(%)
Gender			***Age***		
Male	396	70.30	19 – 20 years old	254	45.10
Female	167	29.70	21-22 years old	281	49.90
Total	563	100.0	23-24 years old	28	5.0
Nationality			**Total**	563	100.0
Malaysian	479	85.1	***Year of Study***		
Non-Malaysian	84	14.9	Year 1	212	37.70
Total	563	100.0	Year 2	201	34.50
			Year 3	150	25.70
			Total	563	97.9

Validity and Reliability

Internal consistency is a measure of reliability, where reliability measures the consistency of an instrument to be reproduced. Cronbach's alpha is the traditional method of measuring reliability and it assumes factor loading to be the same for all items. The generally accepted Cronbach's alpha value is 0.7 (Sharma, 2016).

Table 4

Indicator Reliability Analysis

Constructs	Number of items	Cronbach Alpha	Composite Reliability	AVE	VIF
Self-regulated learning Strategies					
Cognitive Engagement	7	0.67	0.78	0.72	1.05
Metacognitive Knowledge	6	0.70	0.80	0.69	1.20
Resource Management	9	0.67	0.77	0.67	1.16
Motivational Beliefs	7	0.78	0.84	0.72	1.43
Perceived Learning Performance					
Perceived Learning Outcome	6	0.84	0.88	0.55	0.55
Social Interactive Engagement	5	0.81	0.87	0.57	0.57
Student Satisfaction	5	0.82	0.88	0.65	0.65

Since the constructs of this study were both unidimensional and multidimensional, the low alpha value obtained reflected the multidimensionality of the constructs as the constructs consisted of clusters of items, each measuring a distinct factor (Hair et al., 2017). Composite reliability is the internal consistency evaluation of a set of indicators. Composite reliability also examines the relationship between the latent variable and its indicators. Although composite reliability measures internal consistency similar to Cronbach's alpha, it is more superior as it also takes into account the indicator loadings (Hair et al., 2017). Composite reliability takes into consideration the varying factor loading for each item. Values between 0.70 and 0.90 are good to assess composite reliability (Hair et al., 2019). Based on the findings shown inTable 4, Cronbach's alpha and composite reliability values denoted that the constructs were reliable. The Average Variance Extracted (AVE) represents the degree to which a latent construct explains the variance of its indicator. Satisfactory values scores of higher than 0.5 are needed to achieve adequate convergent reliability.

To ensure that the constructs were truly distinct from one another, discriminant validity was assessed using cross-loading criterion, Fornell, and Larcker's criterion, and HTMT (heterotrait—montrait ratio), (Hair et al., 2019). The Cross-loading criterion, which checks the item loads on respective variables, fulfills the assumption of discriminant validity. Fornell and Larcker's criterion suggests that a latent variable will better explain the variance of its indicators than the variance of other latent variables. Fornell and Larcker's criterion were also found to have satisfactory values. HTMT ratios were also tested where values must be greater than 0.85 (Kline, 2011) or greater than 0.9 (Gold, Malhotra & Segars, 2001). Table 5 confirmed that the study has no issue with discriminant validity. Thus, this indicates that discriminant validity has been completely ascertained.

Table 5

Discriminant Validity Assessment

	CE	MK	RM	MB	PLO	SII	SS
Cognitive Engagement. Item 1	0.54	0.30	0.19	0.33	0.31	0.24	0.23
Cognitive Engagement. Item 2	0.67	0.31	0.30	0.27	0.23	0.25	0.15
Cognitive Engagement. Item 3	0.55	0.32	0.18	0.27	0.26	0.24	0.19

(continued)

	CE	MK	RM	MB	PLO	SII	SS
Cognitive Engagement. Item 4	0.62	0.25	0.23	0.25	0.25	0.25	0.20
Cognitive Engagement. Item 5	0.62	0.32	0.30	0.30	0.25	0.24	0.14
Cognitive Engagement. Item 6	0.49	0.29	0.29	0.22	0.20	0.16	0.10
Cognitive Engagement. Item 7	0.54	0.34	0.27	0.32	0.28	0.25	0.14
Metacognitive Knowledge. Item 1	0.28	0.71	0.36	0.34	0.25	0.21	0.18
Metacognitive Knowledge. Item 2	0.41	0.73	0.34	0.40	0.30	0.21	0.19
Metacognitive Knowledge. Item 3	0.42	0.72	0.35	0.42	0.34	0.32	0.26
Metacognitive Knowledge. Item 4	0.32	0.38	0.24	0.26	0.17	0.22	0.16
Metacognitive Knowledge. Item 5	0.27	0.55	0.27	0.29	0.26	0.19	0.09
Metacognitive Knowledge. Item 6	0.32	0.68	0.43	0.33	0.29	0.32	0.17
Resource Management. Item 1	0.23	0.31	0.50	0.36	0.22	0.23	0.20
Resource Management. Item 2	0.25	0.30	0.61	0.35	0.30	0.21	0.18
Resource Management. Item 3	0.14	0.26	0.57	0.24	0.25	0.29	0.14
Resource Management. Item 4	0.33	0.31	0.57	0.31	0.29	0.31	0.21
Resource Management. Item 5	0.34	0.29	0.39	0.27	0.21	0.21	0.17
Resource Management. Item 6	0.26	0.30	0.51	0.24	0.21	0.23	0.17
Resource Management. Item 7	0.17	0.26	0.62	0.24	0.21	0.22	0.14
Resource Management. Item 8	0.23	0.29	0.58	0.36	0.25	0.24	0.22
Motivational Beliefs. Item 1	0.32	0.32	0.27	0.66	0.39	0.25	0.28
Motivational Beliefs. Item 2	0.36	0.39	0.38	0.72	0.45	0.34	0.32

(continued)

	CE	MK	RM	MB	PLO	SII	SS
Motivational Beliefs. Item 3	0.36	0.38	0.38	0.70	0.42	0.41	0.38
Motivational Beliefs. Item 4	0.35	0.38	0.38	0.72	0.46	0.40	0.45
Motivational Beliefs. Item 5	0.32	0.39	0.40	0.66	0.41	0.33	0.28
Motivational Beliefs. Item 6	0.20	0.23	0.29	0.54	0.33	0.28	0.30
Motivational Beliefs. Item 7	0.29	0.36	0.37	0.60	0.38	0.35	0.27
Perceived Learning Outcome. Item 1	0.39	0.41	0.37	0.49	0.73	0.54	0.51
Perceived Learning Outcome. Item 2	0.30	0.26	0.34	0.40	0.70	0.45	0.41
Perceived Learning Outcome. Item 3	0.31	0.31	0.31	0.50	0.77	0.51	0.50
Perceived Learning Outcome. Item 4	0.31	0.30	0.29	0.44	0.77	0.50	0.47
Perceived Learning Outcome. Item 5	0.33	0.33	0.35	0.45	0.74	0.51	0.38
Perceived Learning Outcome. Item 6	0.31	0.29	0.33	0.45	0.75	0.51	0.40
Student Interactive Engagement. Item 1	0.29	0.27	0.33	0.32	0.47	0.70	0.34
Student Interactive Engagement. Item 2	0.29	0.31	0.34	0.34	0.49	0.76	0.42
Student Interactive Engagement. Item 3	0.29	0.29	0.34	0.36	0.50	0.78	0.45
Student Interactive Engagement. Item 4	0.34	0.30	0.33	0.44	0.57	0.78	0.48
Student Interactive Engagement. Item 5	0.33	0.28	0.33	0.46	0.53	0.75	0.51
Student Satisfaction. Item 1	0.24	0.25	0.29	0.42	0.53	0.53	0.81
Student Satisfaction. Item 2	0.26	0.24	0.26	0.40	0.47	0.46	0.77
Student Satisfaction. Item 3	0.23	0.23	0.28	0.39	0.48	0.43	0.84
Student Satisfaction. Item 4	0.20	0.16	0.22	0.39	0.46	0.47	0.80

(continued)

Fornell-Larcker Criterion					
	CE	MB	MK	PLP	RM
Cognitive Engagement	**0.58**				
Motivational Beliefs	0.48	**0.66**			
Metacognitive Knowledge	0.52	0.53	**0.64**		
Perceived Learning Performance	0.44	0.63	0.43	**0.66**	
Resource Management	0.43	0.54	0.52	0.47	**0.55**
Heterotrait-Monotrait ratios					
	CE	MB	MK	PLP	RM
Cognitive Engagement					
Motivational Beliefs	0.66				
Metacognitive Knowledge	0.78	0.72			
Perceived Learning Performance	0.57	0.74	0.54		
Resource Management	0.67	0.75	0.78	0.61	

Note. CE: Cognitive Engagement; MK: Metacognitive Knowledge; RM: Resource Management; MB: Motivational Beliefs; PLO: Perceived Learning Outcome; SII: Student Interactive Engagement; SS: Student Satisfaction; PLP: Perceived Learning Performance

Path Analysis

Given that the study performed measurement model analysis in PLS-SEM to achieve reliability and validity of the studied constructs, the next stage involved structural model analysis. Based on the path coefficient (β) as shown in Table 6, it is evident that motivational belief (β=0.47) is the most important predictor, followed by resource management (β=0.14), cognitive engagement (β=0.140) and finally metacognitive knowledge (β=0.02). The R^2 for the four constructs (SRLS) on perceived learning performance (PLP) indicated a value of 0.270, which represented a substantial model (Cohen, 1988). The predictive relevance Q^2 of perceived learning performance (PLP) produced a value of 0.262, thus confirming that the model had sufficient predictive relevance (Hair et al., 2017).

The standardized beta (β), t-values, p-values, and effect size, f^2 are as displayed in Table 6. The predictors of cognitive engagement, resource management, and motivational beliefs were found to have t- value ≥ 1.645, with a 0.05 level of significance except for the metacognitive knowledge construct. Three out of the four tested hypotheses were significant and supported. Only one hypothesis (H2) was not supported and it was rejected. No relationship was found between metacognitive knowledge (MK) and perceived learning performance (PLP).

Table 6

Hypotheses Testing

	Hypotheses Relationship	Std Beta ,β	Std Error	t-value	p-value	Decision	f^2
H_1	Cognitive Engagement (CE) -> Perceived Learning Performance(PLP)	0.14	0.04	3.31**	0.001	Supported	0.02
H_2	Metacognitive Knowledge (MK) -> Perceived Learning Performance(PLP)	0.02	0.04	0.66	0.25	Not Supported	0.001
H_3	Resource Management (RM) -> Perceived Learning Performance(PLP)	0.14	0.04	3.47**	0	Supported	0.02
H_4	Motivational Beliefs (MB) -> Perceived Learning Performance(PLP)	0.47	0.04	12.10**	0	Supported	0.23

$^{**}p<0.05$

DISCUSSION

The study reported here was aimed at investigating the impact of self-regulated learning strategies on perceived learning performance in digital learning within blended learning environments. Higher education providers are concerned with providing high-quality education that caters to students' needs. Globally, the education system places constant emphasis on the importance of pedagogical innovation using the latest digital technology to create effective and meaningful digital learning. As digital learning has become a part of education, self-regulated learning is needed to help students self-manage their learning, navigate through online materials independently, apply relevant self-regulated learning strategies, monitor their progress, and reflect upon their learning (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Greene, Copeland, Deekens, & Yu, 2018; Phillips, Turnbull, & He, 2015). In this study, self-regulated learning strategies were found to have a positive effect on perceived learning performance among undergraduates.

Four domains of self-regulated learning strategies were identified, namely cognitive engagement, metacognitive knowledge, resource management, and motivational beliefs from literature (Zimmermn & Martinez-Pons, 1986; Pintrich, 1999). Then, four hypotheses were formulated which proposed that these strategies could have positive effects on perceived learning performance. The first hypothesis assessed the effect of cognitive engagement on learning performance perception in light of blended learning environments. The significantly positive outcome indicated that students who used the four strategies (rehearsal, elaboration, organization, and critical thinking) of the cognitive engagement domain experienced a positive impact on their learning performance. However, compared to the other domains of SRLS, cognitive engagement strategies were found to be the least significant. This seemed to suggest that students might still prefer face to face teaching for knowledge acquisition as cognitive strategies weret strategies that dealt with basic information processing (acquire, store, and use). Hence, all students needed to utilize cognitive engagement strategies to enhance knowledge acquisition. For example, organization strategies that involved students outlining notes while learning online, tabulating data to organize online information, generating concept mapping, or creating graphical data allowed them to structure their learning content visually, thus aiding in rememebering and understanding (Effeney, Caroll & Bhar, 2013). Elaboration strategies which included paraphrasing online materials to be learned, taking notes, reconnecting ideas, and explaining the ideas to another individual were required for digital learning as these strategies required deeper processing of information and were thought to be higher-level strategies (Broaddbent & Poon, 2015).

Specifically, it was pointed out that when students learn something through digital content, they connect the online information to what they knew. This would help learners build internal connections between prior knowledge and items to be learned, thus improving student engagement. Besides that, a rehearsal strategy has enabled students to acquire knowledge and retain information at a very basic level (Effeney et al., 2013). For example, a student who watches a video repeatedly to remember and understand the material may also achieve a better learning performance. Using software repeatedly might sharpen a student's skill in using that software. Moreover, a student who carefully examines an online material and reflects on it independently to make reasoned judgments is said to have utilized the critical thinking strategy of cognitive engagement. Overall, cognitive engagement findings in this study have positively indicated that IT undergraduates used these strategies to achieve success in their digital learning.

The second hypothesis revealed a negative relationship between metacognitive knowledge and students' views on learning performance. Metacognitive strategies are used to plan, monitor, and regulate the cognition process to attain a goal (Zimmerman & Martinez-Pons, 1986). Hence, a possible explanation for the insignificant relationship might be because metacognitive knowledge was used in strategies that help learners to become increasingly effective at learning to improve academic performance (e.g., grades, exams, tests) instead of learning performance. These findings also seemed to suggest that undergraduates were still lacking in self-awareness and understanding of their thought processes through self-reflection, and utilizing planning, monitoring as well as regulating strategies. Thus, metacognitive strategies were seen to be not affecting students' learning performance. Additionally, the results of this study might have also implied that compared to a knowledgeable user of self-regulated strategies, students were unable to see the bigger picture of the task at hand through planning, monitoring, and regulating academic tasks online. This finding resonated with the findings of studies by Hashemyolia et al. and Anthonysamy et. al., both of which reported that Malaysian university students had shown a very low usage of metacognitive strategies (Hashemyolia et al., 2015; Anthonysamy et al., 2020). Metacognition is a tool that not only involves students in the process of learning, but also places their learning responsibilities on their own shoulders. Students with metacognitive abilities can deal with their learning and execution by handling thoughts, assessing learning, and evaluating the time required for study through the use of strategies. Although previous research has shown that students in higher education can monitor and reflect on their strategy use (Roth et al., 2016), this study has postulated that metacognitive knowledge was not strengthened in Malaysian students.

Therefore, students need to be mindful of their metacognitive knowledge, so that they will be able to optimize their focus and attention in their learning journey to acquire knowledge and skills. For example, before attempting an online task, the students are aware that they need to plan, monitor their progress as well as refine their task before submission. Besides that, academicians can teach metacognitive strategies in the classroom as a way to support student learning. Supervision and guidance from educators are necessary to encourage students to evaluate their learning and to reflect on their learning actions. Even though metacognitive strategies did not affect students' learning performance, it could possibly drive a positive relationship with perceived learning via intervention by a mediator.

The third hypothesis assessed the effect of resource management on students' perception of learning performance in blended learning environments. This strategy domain has a positive and significant effect on learning performance. It is clear that resource management strategies facilitate student learning by enabling students to manage their time and study environment, seek help, engage in peer learning, and regulate their effort. Thus, these findings suggest that the environment plays a very important role in enhancing digital literacy and learning performance as has been reported in the literature (Pintrich, Smith, Garcia, & Mckeachie, 1991). Hence, students need to leverage the resources around them to achieve success in digital learning. Educators play a crucial role in the digital learning environment in supporting and shaping students' metacognitive awareness. Metacognitive awareness and skills are shaped by students' learning experiences and these experiences come from educators and the learning environment.

The fourth hypothesis measured the effect of motivational beliefs prevailing in the students' learning performance within blended learning environments. Essentially, the findings indicated a positive and significant effect of motivational beliefs on perceived learning performance. The inclusion of motivational beliefs as the fourth domain of self-regulated learning strategies by Pintrich (1999) has also proven to be enlightening as findings revealed that motivational beliefs had the strongest relationship with perceived learning performance compared to other SRLS domains. This is consistent with the findings of Stark (2019) in which motivational variables play a larger role in predicting student success in online courses compared to the other learning strategies. Thus, this suggests that motivation significantly enables students to excel in their studies. Students should learn to identify ways to self-motivate to minimize problems they may face throughout their studies. For example, technology training may help increase students' confidence in performing online tasks required by the course. Students who are motivated to reach a certain goal will engage in self-regulatory activities that they feel will help them achieve that goal. From the findings of our study, it is clear that motivation plays a huge role in students' learning progress and subsequently learning performance. Thus, academicians should not limit their focus to teaching and delivering information and imparting knowledge to students, they should also teach students about motivational strategies. This will guide students to use motivational learning strategies to improve their digital literacy and learning performance.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This study has several limitations. The first limitation concerns the study context whereby only private universities in Malaysia that had adopted blended learning approaches were selected. Hence, this study was unable to incorporate data from other study contexts such as public universities or universities from the Sabah/Sarawak Zone. Due to cultural differences within the same country, students from different areas might have different educational perspectives. Hence, it is recommended that future researchers should include a more comprehensive area coverage in their sample. Secondly, the instrument used in this study was a questionnaire. Although self-reporting is widely considered to be the most important way to assess learning strategies in higher education (Rovai et al., 2009), the limitation of using a self-reported instrument to measure a student's view of learning strategies and learning performance is that it might not be very accurate; self-reported instruments essentially require a respondent to provide an account of his/her attitude or feelings toward the use of learning strategies and its impact on their learning performance. Therefore, it is difficult to gauge the true attitude or feelings of students towards learning or the use of learning strategies. Nevertheless, it is recommended that for future studies there is the need ton use triangulation methods such as observation or interviews to collect data to validate the findings. Thirdly, this study did not assess the extent to which the students engaged in self-regulated learning strategies throughout the course. For future research, an experimental design can be used as this method may be able to better capture an understanding of the extent of self-regulated learning strategy use in digital learning.

CONCLUSION

The study reported here investigated the effects of self-regulated learning strategies on learning performance in digital learning within blended learning environments in higher education institutions. Overall, the results obtained confirmed the existence of a positive relationship between cognitive engagement, resource management, and motivational beliefs domains of self-regulated learning strategies and learning performance. As such, self-regulated learning strategies did contribute positively to digital learning success in blended learning environments in private higher education institutions in Malaysia.

This research study has addressed a substantial number of prevailing concerns found in the literature regarding self-regulated learning strategies and learning performance. Overall, a deeper understanding has been gained on the effects of the studied constructs on learning performance. The academic growth of students is the utmost concern for any university and a vital factor affecting the overall performance of a university. Hence, the utilization of self-regulated learning strategies has enabled students to achieve better learning performance in a blended learning environment.

The outcomes of this study offer practical understanding for higher education institutions in their quest to provide high-quality education that caters to the needs of their students. The outcome of this research may be useful for educators to establish guidelines to effectively use self-regulated learning strategies in digital learning. Teaching staff can help students to become aware of alternative ways to approach learning situations through self-regulated learning strategies. This guidance will enable students to reflect on and develop their learning strategies and thus enhance their performance. Well-regulated students will undeniably enhance their learning performance in digital learning as they become capable of managing their learning environment and progress.

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