Journal of Asian Scientific Research
ISSN(e): 2223-1331
ISSN(p): 2226-5724
DOI: 10.55493/5003.v13i4.4953
Vol. 13, No. 4, 195-208.

URL: www.aessweb.com

Factors influencing effective smart learning environment in Malaysian universities

Erlane Ghani[1]
Kamaruzzaman Muhammad[2+]
Mazurina Mohd Ali[3]
Razana Juhaida Johari[4]
Citra Sukmadilaga[5]

[1,2,3,4]*Faculty of Accountancy, Universiti Teknologi MARA Cawangan Selangor, Puncak Alam, Selangor, Malaysia.*
[1]*Email: erlanekg@uitm.edu.my*
[2]*Email: kamaruzzaman@uitm.edu.my*
[3]*Email: mazurina@uitm.edu.my*
[4]*Email: razana@uitm.edu.my*
[5]*Department of Economics and Business, Universitas Padjadjaran, Bandung, Indonesia.*
[5]*Email: citra.sukmadliaga@unpad.ac.id*

(+ Corresponding author)

Article History
Received: 27 September 2023
Revised: 1 December 2023
Accepted: 18 December 2023
Published: 29 December 2023

Keywords
Attitude
Environment
Malaysia
Smart learning tools
Smart learning
Students.

ABSTRACT

This study aims to examine the factors influencing an effective smart learning environment in the universities in Malaysia from the perspective of the students. Specifically, this study examines three key factors: students' attitudes towards smart learning, their perception of smart learning tools, and the impact of course design in the smart learning environment. This study utilized a quantitative approach using a questionnaire survey that was administered to a sample of 386 students enrolled in both private and public institutions without regard to their academic year. This study demonstrates that there exists a positive and statistically significant correlation between all three parameters and the efficacy of smart learning environments. These results suggest that institutions should consider the viewpoint of students when developing a smart learning environment. Ultimately, this has the potential to enhance their educational experience. This study's findings offer additional insights into the various factors that can impact the efficacy of smart learning environments. These insights can aid universities in formulating strategies to optimize the content, activities, and assessments within such environments, thereby enhancing their overall effectiveness.

Contribution/ Originality: This study contributes to the existing literature by being the first to examine students' attitudes, smart learning tools, and course design in a smart learning environment in both public and private universities in Malaysia.

1. INTRODUCTION

Higher education systems globally have undergone significant transformations and reorganization to adapt to the increasing impact of the information and communication revolution and the rising demand for knowledge [1, 2]. Therefore, the use of technology can be a vital means of implementing technological strategies to improve the quality of exchange experiences by easing the transmission of advanced knowledge to learners [3]. The integration of technology into educational environments serves to promote and enhance collaborative interactions between students and academics. This platform facilitates collaboration among students from diverse geographical locations on a shared project. Additionally, it enables educators to engage in communication and provide assistance to students [4]. Undoubtedly, technology has emerged as an indelible catalyst for revolutionising traditional pedagogical methods throughout many tiers of the global education system. Within the higher education system, educational institutions have integrated and used a variety of technologies, including artificial intelligence, big data, learning analytics, and the cloud [5].

In light of this, researchers in the field of education have initiated inquiries into the integration of these technologies into conventional pedagogical methods, aiming to augment students' learning experience and efficacy. Smart learning is an emerging technological advancement that, when integrated with diverse pedagogical strategies, has the potential to provide an innovative educational setting aimed at enhancing students' educational encounters and knowledge acquisition [6]. Smart learning refers to the use of technology to enhance the process of teaching and learning. It has the potential to revolutionise traditional educational practices by creating a conducive learning environment that caters to the individual needs of students. This is achieved through the incorporation of interactive and visual tools, with the ultimate goal of enhancing education in a more intelligent and efficient manner [7]. Nevertheless, the veracity of this proposition in the context of Malaysian universities, renowned for their size and sustainability, has to be confirmed. The first stage in assessing the effectiveness of a smart learning environment as a platform for teaching and learning involves examining the factors contributing to an effective smart learning environment.

This study investigates the factors that contribute to the establishment of an effective smart learning environment inside Malaysian universities. This study focuses on investigating the impact of university students' attitudes towards smart learning, their perceived efficacy of smart learning, and the design of courses in a smart learning environment on the effectiveness of smart learning environments. The results of this study can aid universities and scholars in devising efficient, smart learning environments at Malaysian universities. Section 2, which follows, consists of a thorough literature review. Section 3 provides a detailed explanation of the study design, while Section 4 includes the findings and subsequent discussion. The study ends in the final portion, section 5.

2. LITERATURE REVIEW

According to Razinkina, et al. [8], students' satisfaction with the curriculum on offer at their respective universities has traditionally been a prerequisite for the achievement of educational objectives. The assessment of students' educational experiences, known as educational satisfaction, is a crucial factor to consider when examining the teaching and learning process in the field of education [9]. According to Elliott and Healy [10], the concept of students' satisfaction pertains to a transient attitude that emerges from the evaluation of a student's educational encounters. Through the assessment of feedback on student satisfaction, which serves as a measure of success for institutions of higher education [11], one may ascertain a comprehensive evaluation and emotional reaction to educational services. The term "student satisfaction feedback" refers to the collection of data from students about the services they use while enrolled in school. Razinkina, et al. [8] discuss several aspects of the educational process, including opinions on its arrangement, learning support resources, and the learning environment. The assessment of student satisfaction upon completion of their education is widely acknowledged as a crucial factor in the evaluation of educational outcomes and performance, as well as in the process of modifying or enhancing educational material [12]. Nevertheless, it is important to include the satisfaction of university academics in the realm of educational happiness, given their active involvement in the teaching and learning process.

The proliferation of educational concepts and technological advancements has presented universities with a range of challenges. These include the exploration of pedagogical approaches [13], the implementation of personalised adaptive learning [14], and the utilisation of learning data [15, 16]. Previous research has emphasised the challenges faced by universities in relation to the incorporation of both formal and informal learning [6] as well as the implementation of assessment approaches Picciano [17]. Ertmer, et al. [18] identified a lack of professional development and training as the predominant factors contributing to the limited integration of technology in educational settings. According to the National Education Association [19], one of their policy recommendations is to promote the improvement of professional development in the field of technology. The NEA reported in 2008 that educators are experiencing a growing sense of proficiency in integrating technology into their classrooms, including operating software and navigating the internet. In light of ongoing technological advancements, it has become more crucial for educators to maintain and enhance their proficiency in technical competencies. The introduction of smart learning was a direct response to these aforementioned concerns.

Smart learning is defined as the use of technological tools and resources to augment conventional approaches to teaching and learning. The objective of this method is to provide an educational setting that is favourable to learning and addresses the unique requirements of students via the integration of interactive and visual aids. The primary objective of smart learning is to augment education by using intelligent and streamlined methods [7]. The incorporation of both formal and informal learning within the context of smart learning enables the establishment of a versatile educational environment that provides students with prompt and uninterrupted learning opportunities. According to Gros [6] and Cheung, et al. [5], the concept of smart learning encompasses several dimensions, including flexibility, effectiveness, efficiency, engagement, adaptivity, and reflectiveness. According to Zhu, et al. [3], a comprehensive and universally accepted definition of smart learning remains elusive. The topic under consideration has been a subject of ongoing discussion among scholars and professionals in several fields within the field of education.

Numerous definitions can be found in the bulk of academic literature that highlight various facets and attributes of intelligent learning. The subject matter at hand is now a subject of continuing discourse among researchers and practitioners across several disciplines within the realm of education. Multiple definitions may be found in the majority of academic literature, emphasising different aspects and characteristics of intelligent learning. However, scholars in this field have reached a consensus, emphasising certain basic and essential elements. The first argument underscores the need to include two separate classifications of technology, namely smart devices and intelligent technologies, in the context of smart learning. Smart gadgets include a class of artefacts that exhibit certain characteristics often associated with ubiquitous computing, perhaps including artificial intelligence. Smart devices include a wide range of technological artefacts, including those embedded within the Internet of Things (IoT) framework and wearable technology. The latter category encompasses various items such as glasses, backpacks, and clothing, all of which have integrated smart capabilities. The use of intelligent technologies, including cloud computing, learning analytics, and big data, revolves around the collection, examination, and application of educational data to improve the practises of instruction and knowledge acquisition. Furthermore, these technologies contribute to the progression of personalised and adaptable learning [17].

A smart learning environment refers to a learning system that enables effective and personalised learning [14]. Furthermore, smart learning has emerged as a preferred educational platform due to its incorporation of many forms of media and information technology [20]. The use of intelligent learning environments extends beyond the mere utilisation of advanced technological solutions. A smart learning environment enables learners to conveniently access digital materials and actively participate with learning systems regardless of their location and time constraints. Furthermore, it provides proactive assistance by offering suitable educational advice, hints, helpful resources, or recommendations in the appropriate context, time, and style. According to Spector [21], a smart learning environment may be defined as one that has the qualities of being effective, efficient, and engaging. He also says that it is important to support combining technology and teaching methods in order to create a system that gives constant and immediate feedback on how knowledge is growing and encourages the development of skills that can be easily used in different learning settings [22].

Choi, et al. [23] conducted an early investigation into the field of smart learning. This study investigates students' perspectives on intelligent learning in the context of online higher education, with a focus on its conceptualization, functions, and significance. According to the findings of a questionnaire survey conducted among a sample of 1950 university students, smart learning exhibits greater levels of engagement, interactivity, and collaboration compared to conventional e-learning. This is attributed to the integration of students' own experiences into the learning process. Additionally, it was shown that individuals in the age range of 40s and 50s saw smart learning to be characterised by greater levels of personalisation, human-like interaction, active participation, enjoyment, consistency, familiarity, reduced stress, and enhanced practicality as compared to those in their 20s and 30s. According to Choi, et al. [23], the primary component of smart learning, as seen by students, is the consolidation of learner experiences. Previous research has investigated the concept of smart learning through the assessment of student satisfaction with smart learning experiences [24]. Additionally, the evaluation of smart classrooms has been explored by examining the effectiveness of integrating technological equipment with an advanced learning environment to facilitate successful learning outcomes [25]. A smart learning environment encompasses more than just a platform that enables learners to access materials and engage in interactions at their convenience. It also encompasses a system that offers timely learning ideas, guidance, and even supportive tools. According to the findings of Ha and Kim [26], the integration of smart technologies in education has been seen to enhance efficiency. However, it is crucial for both educators and students to exert substantial effort in order to effectively harness the potential of these smart tools towards achieving this objective.

The adoption of smart learning in Malaysia is seeing a steady increase in acceptability. The integration of wireless networks and smart devices, particularly in the context of online learning, has resulted in a unique platform that enhances and streamlines students' experiences and learning processes. According to Peters and Araya [27], the use of mobile phones will enable students to conveniently access digital resources, enhancing the comfort and convenience of learning. Based on research findings, the optimal realisation of smart learning within university settings may be achieved via the implementation of suitable interaction strategies between faculty members and students [28]. However, research has shown that these platforms were mostly used by themselves, which doesn't fit with the idea of authentic smart learning, which means using a single technological medium to create a better learning environment than what's currently available in higher education. Furthermore, there is a dearth of research investigating the many aspects that contribute to intelligent learning, specifically focusing on university students.

The attitudes of students towards smart learning may constitute a significant aspect that influences the quality of the smart learning environment. Several studies have been undertaken to examine the perspectives of students towards smart learning. In this instance, Adesanya and Odunola [29] undertook a survey-based investigation involving a cohort of 40 students in a senior secondary school inside Lagos State. The primary objective of this research was to evaluate the perspectives of these students about the implementation of smart classrooms. The researcher found that advanced technology, such as virtual reality, enables smart classrooms to engage with visual content. Additionally, these classrooms enhance the adaptability of teaching and learning methods while also enhancing the overall in-class experience for students. The author suggests that the use of smart classrooms by academics may facilitate the storage, collection, processing, and analysis of data, ultimately enabling the formulation of optimal pedagogical judgements. According to the research conducted by Hung, et al. [30], students' attitudes towards the utilisation of smart learning tools can be attributed to three key factors: their inclination towards the mode of material delivery during the instructional process, their reliance on electronic and Internet-based media to enhance their learning outcomes, and their ability to engage in independent or self-regulated learning. Nevertheless, there is a dearth of research on the correlation between students' attitudes and smart learning in the specific context of Malaysia. Consequently, this study formulates the first hypothesis:

H_1: There is a positive relationship between the Malaysian university students' attitudes towards smart learning and an effective smart learning environment.

Another factor that may influence the achievement of effective smart learning is the students' attitudes towards smart learning and an effective smart learning environment. Research findings indicate that the perception of students about the efficiency of smart learning has been shown to have an impact on their desire to study [31]. However, it should be noted that this influence does not necessarily guarantee a corresponding improvement in actual learning outcomes. Van De Bogart and Wichadee [31] conducted a study that revealed that students have a high perception of a smart learning environment. This perception is attributed to the ability of academics to use smart learning tools in order to produce novel pedagogical techniques for their instructional practices. As a result, this prompted the students to perceive that their learning experience would be more effective in a smart learning environment, in contrast to a conventional learning environment. This study posits that the attitudes shown by university students in Malaysia towards smart learning instruments have the potential to significantly impact the establishment and enhancement of an efficient smart learning environment. Hence, the following hypothesis is formulated:

H_2: There is a positive relationship between the Malaysian university student's perceived smart learning tools and an effective smart learning environment.

Existing literature in the field of education has put forward the notion that the manner in which courses are structured in the context of smart learning may have an impact on the overall smart learning environment. According to Gros [6], comprehending the pedagogical environment is crucial, particularly in terms of the course design's impact on student activities. Additionally, the identification of patterns in students' learning behaviours may be leveraged to enhance teaching and learning experiences in a more constructive manner. There exists a deficiency in instructors' understanding of how to connect the insights derived from learning analytics with the pedagogical strategies they use to facilitate intelligent learning. According to Gros [6], the discipline of learning design presents a potential solution to this issue by enabling educators to clearly explain the design and purpose of learning activities. This, in turn, may serve as a valuable framework for evaluating data derived from learning analytics. One may argue that the design of courses within a smart learning environment has significant importance in supporting effective teaching and learning [32]. Consequently, this study formulates the following hypothesis:

H_3: There is a positive relationship between the Malaysian university students' perceived course design and an effective smart learning environment.

3. RESEARCH METHODOLOGY

3.1. Sample Selection

This study selected students from both private and public institutions in Malaysia to participate in it. The selection of these respondents is based on their suitability since they are individuals who are situated in an intelligent educational setting. Therefore, these students have the potential to create an effective, smart learning environment. According to Statista [33], Malaysia is home to a total of 43 universities. Furthermore, it is projected that in the year 2020, the combined enrolment of students in both public and private universities in Malaysia will reach around 592,680. The sample size for this investigation was determined based on the aforementioned numerical value. The recommended sample size would be 384 when the population is 592,680, according to the study by Krejcie and Morgan Krejcie and Morgan [34].

3.2. Research Instrument

This study utilised a questionnaire as the primary research tool. A thorough analysis of the existing literature influenced the development of the questionnaire. The survey has six distinct components.

The first segment comprises demographic profile data about the participants, including gender, university affiliation, academic year, and cumulative grade point average (CGPA). The subsequent portion of the survey asks participants to provide feedback about their experience and level of satisfaction with the online learning platform.

Within the third portion, participants are requested to express their perspectives about online learning, including aspects such as its ease of use, interactivity, and ability to improve the learning experience.

Within the fourth section, participants are requested to express their viewpoint about the efficacy of the online learning system in terms of its organisation, flexibility, and overall functionality. Within the fifth section, participants are requested to provide responses pertaining to the design and structure of the online courses provided, which include aspects such as the visual appeal, accessibility, and variety of the courses. This study used a six-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree). Table 1 presents a concise overview of the content covered in sections two to five of the questionnaire.

Table 1. Questionnaire items.

Category	Code	Statement
Smart learning environment	Exp1	The smart learning experience encourages me to take a new smart learning course.
	Exp2	I recommend other people use smart learning systems.
	Exp3	I am satisfied with my decision to take this smart course.
	Exp4	I am satisfied with the performance of the smart learning system.
	Exp5	I look forward to the experience of using the smart learning system.
	Exp6	The smart learning course contributed to the success of my training.
	Exp7	The smart learning system helped me succeed.
Attitude towards smart learning	Att1	I find smart learning easy to use.
	Att2	Interacting with a smart learning system does not require a lot of mental effort from me.
	Att3	The smart learning system provides all the required features, which makes my learning task easy.
	Att4	The use of smart learning is useful for teaching and learning.
	Att5	The smart learning system has helped me increase my productivity.
	Att6	Using the smart learning system allows me to learn quickly.
	Att7	I have confidence in the security level of the smart learning system.
	Att8	I can rely on the system's level of security.
Perceived smart learning	Sys1	I am satisfied with the quality of the smart system.
	Sys2	The quality of the smart learning system influences my academic performance.
	Sys3	The smart learning system is well organised.
	Sys4	I can easily find the required information on the smart learning system.
	Sys5	The smart learning system uses all the presentation modalities I need for my learning (text, figures, audio, and video).
	Sys6	I have the possibility of using different devices to access the smart learning course (such as a computer, tablet, or smartphone).
	Sys7	The smart learning system provides the same functionality even if I use different devices.
Section 5-course design	Course1	The smart learning course design is nice.
	Course2	The design of the smart learning course is attractive.
	Course3	The courses offered by the smart learning system are rich in quantity.
	Course4	The smart learning system constantly updates the courses it offers.
	Course5	The courses offered by the smart learning system are available all the time.
	Course6	Courses offered by the smart learning system are available from anywhere.
	Course7	The smart learning system offers me different ways to access my learning (Quiz, written work, etc.).
	Course8	The diversity of evaluation allows me to obtain better results.

3.3. Data Collection and Data Analysis

The questionnaires were distributed to the student population of the colleges using a range of social media platforms, such as Facebook, WhatsApp, and Instagram. A total of 394 respondents completed the survey. However, a total of eight submissions were considered incomplete and were deleted from the dataset after passing a rigorous data screening approach aimed at identifying and removing outliers. As a result, a grand total of 386 questionnaires were successfully filled out and considered appropriate for further study. The data was subjected to input and assessment with partial least squares structural equation modelling (PLS-SEM). Hair Jr, et al. [35] suggest that, in the domain of partial least squares structural equation modelling (PLS-SEM), it is advisable to have a sample size that is at least 10 times larger than the number of arrows pointing towards a certain variable. The present research incorporates a set of four arrows to represent the variables inside the conceptual model. Hence, in order to meet the requirement for representativeness, a minimum of 40 valid surveys would be required. With a considerable number of 386 people included in this study, the sample size exceeds the minimal need for performing the present investigation.

4. RESULTS

4.1. Demographic Profile

The descriptive statistics for the sample used in the study are shown in Table 2. Table 2 shows that 64.8 percent of the respondents are female, with the remaining 35.2 percent being male. With regards to age, the results show that slightly more than half of the respondents came from public universities (51 percent), and the remaining 49 percent came from private universities. More than half of the students are in year 3, year 2 students make up 28 percent, year 4 and above students make up 10.3 percent, and year 1 students make up the remaining 10.1 percent. Table 2 also shows that 48.4 percent of the respondents have a CGPA of between 3.00 and 2.49, followed by respondents who have a CGPA of between 2.00 and 2.99 (24.4 percent), respondents with a CGPA of above 3.50 (23.6 percent), and the remaining 3.6 percent of the respondents have a CGPA below 2.00.

Table 2. Demographic profile.

Item	N	Percent
Gender		
Male	136	35.2
Female	250	64.8
University		
Private	189	49.0
Public	197	51.0
Year of study		
Year 1	39	10.1
Year 2	108	28.0
Year 3	199	51.6
Year 4 and above	40	10.3
CGPA		
Below 2.0	14	3.6
2.00 to 2.99	94	24.4
3.00 to 3.49	187	48.4
3.50 to 4.00	91	23.6

4.2. Smart Learning Tools Usage

Table 3 presents the results of the descriptive statistics of the smart learning tools experienced by the respondents. In this study, the respondents were asked to identify their most-used smart learning tools. The results show that most of the respondents use Webex as their smart learning tool, with a mean score of 2.83. Following this are respondents who used Google Meet, who received a mean score of 2.57, and zoom, who received a mean score of 2.25. Such results indicate that these three smart learning tools are the most commonly used by the respondents. However, it is quite surprising that even though Webex has the highest mean score, the number of respondents who have not used this tool is also high, with 208 respondents. The least used smart learning tools, according to Table 3, are EdPuzzle (77 percent) and Massive Open Online Courses (MOOC) (76 percent), with mean scores of 1.41 and 1.44, respectively. The respondents also did not frequently use Future (69 percent), Quill (73 percent), or any other tools. The features that these tools offer could be one reason.

This study shows that most of the respondents have used smart learning tools to have online meetings with them using Microsoft Teams (56 percent), Google Meet (49 percent), and Zoom (44 percent), as shown in Table 4. Table 4 also shows that the respondents have mostly used Google Classroom to conduct Learning Management System (LMS), followed by Ufuture (20 percent) and Powtoon (16 percent). 28 percent of the respondents have used Kahoot to conduct online tests, with Quill coming in second with 18 percent and EdPuzzle coming in third with 15 percent.

Table 3. Descriptive statistics of usage on smart learning tools.

Platform	Never	Sometimes	Often	Very often	Mean	Std. deviation
	Percent					
Google meet	18	32	24	26	2.57	1.063
Google classroom	49	15	20	16	2.03	1.151
Webex	62	15	13	10	1.71	1.037
Microsoft teams	14	30	15	40	2.83	1.109
Zoom	32	24	32	12	2.25	1.034
Powtoon	74	10	12	4	1.47	0.863
Kahoot	54	18	16	12	1.86	1.077
Quill	73	9	15	4	1.50	0.881
Edpuzzle	77	8	11	4	1.41	0.831
Ufuture	69	11	13	7	1.59	0.974
MOOC	76	9	11	4	1.44	0.858

Table 4. Purpose of smart learning tools usage.

Platform	Online meeting	LMS	Online quiz
Smart learning tools	Percent		
Microsoft teams	56		
Google meet	49		
Zoom	44		
Google classroom		36	
Kahoot			28
Webex	23		
Ufuture		20	
Quill			18
Powtoon		16	
MOOC		15	
EdPuzzle			15

4.3. Measurement Model Analysis

The present study conducted an analysis of the collected data in order to evaluate the validity and reliability of the constructs under investigation. Reliability pertains to the evaluation of the internal consistency of constructs, while validity pertains to the evaluation of whether a scale effectively measures the intended notion. During the preliminary analyses, the whole sample was evaluated, and items exhibiting outer loadings below the threshold of 0.4 were excluded from further analysis. The measurement model results are shown in Figure 1.

The reliability of the measurements in this study was evaluated using Cronbach's alpha and composite reliability (CR). The current study used the standards put forward by Hair Jr, et al. [36], wherein they advised that the thresholds for Cronbach's alpha and composite reliability (CR) should surpass 0.7 and 0.708, respectively. Convergent validity and discriminant validity measures were both used to assess concept validity. Convergent validity refers to the assessment of entities that are categorised under the same construct. Convergent validity refers to the degree to which an item used to assess a certain construct demonstrates a connection with other items used to measure the same construct. The measurement is performed using outer loading and average variance extracted (AVE).

According to the findings of Hair, et al. [37], it is recommended that the outer loading of each item attain a minimum value of 0.708. Nevertheless, in some circumstances, objects with an external loading value ranging from 0.4 to 0.7 may also be deemed to be kept, provided that the average variance extracted (AVE) attains a threshold of 0.5 or above. Based on the results in Table 5, the results for convergent validity (shown by outer loading and AVE) and internal consistency reliability (measured by Cronbach's alpha and CR) all meet the set threshold.

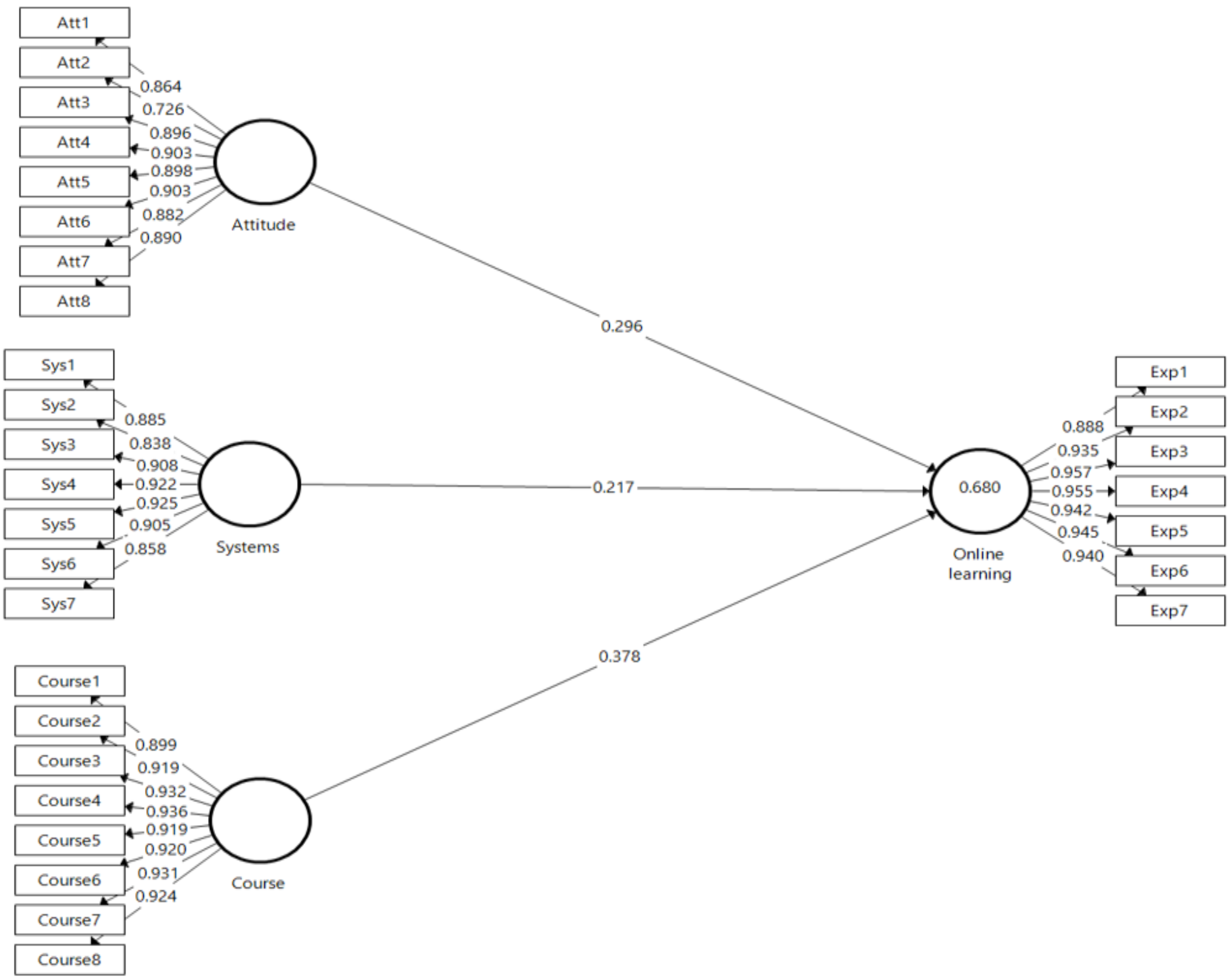

Figure 1. Measurement model.

Note: Attitude-attitudes towards smart learning, system-smart learning tools, course-course design.

Table 5. Measurement model.

Category	Code	Loading	Cronbach's alpha	CR	AVE
Smart learning	Exp1	0.89	0.98	0.98	0.88
	Exp2	0.94			
	Exp3	0.96			
	Exp4	0.96			
	Exp5	0.94			
	Exp6	0.95			
	Exp7	0.94			
Attitude towards smart learning	Att1	0.86	0.95	0.96	0.76
	Att2	0.73			
	Att3	0.90			
	Att4	0.90			
	Att5	0.90			

Category	Code	Loading	Cronbach's alpha	CR	AVE
	Att6	0.90			
	Att7	0.88			
	Att8	0.89			
Smart learning tools	Sys1	0.88	0.96	0.96	0.80
	Sys2	0.84			
	Sys3	0.91			
	Sys4	0.92			
	Sys5	0.93			
	Sys6	0.90			
	Sys7	0.86			
Course design	Course1	0.90	0.97	0.98	0.85
	Course2	0.92			
	Course3	0.93			
	Course4	0.94			
	Course5	0.92			
	Course6	0.92			
	Course7	0.93			
	Course8	0.92			

Discriminant validity, on the other hand, is established to ascertain whether an item that is designed to measure a particular construct does not correlate with items that are used to measure different constructs. In this study, the Fornell and Larcker criterion [38] and the heterotrait-monotrait (HTMT) were used, where the value should be below 0.90.

Table 6. Discriminant validity using Fornell & Larcker.

Variable	Attitude	Course design	Smart learning environment	Smart learning tools
Attitude	0.87			
Course design	0.74	0.92		
Smart learning environment	0.74	0.78	0.94	
Smart learning tools	0.75	0.85	0.76	0.89

The findings shown in Table 6 and Table 7 demonstrate that all values meet the necessary requirements, hence confirming the presence of discriminant validity. The results indicate that the participants had a comprehension of the unique nature of the variables, hence establishing the presence of discriminant validity.

Table 7. Discriminant validity using HTMT.

Variable	Attitude	Course design	Smart learning environment	Smart learning tools
Attitude	1.00			
Course design	0.76			
Smart learning environment	0.76	0.80		
Smart learning tools	0.79	0.88	0.78	1.00

4.4. Structural Model Analysis

Prior to conducting hypothesis testing, this study conducted a model fit test with two model fitting parameters, namely the standardised root means square residual (SRMR) and the normative fit index (NFI).

The SRMR is a statistical measure that quantifies the discrepancy between the actual correlation matrix and the correlation matrix predicted by the model. According to Hu and Bentler [39], an SRMR value below 0.08 is indicative of a satisfactory match. The NFI, on the other hand, which stands for Normed Fit Index, is a statistical metric that quantifies the goodness of fit of a given model by calculating the Chi-square value and comparing it to a relevant benchmark [40]. NFI values that exceed 0.9 often indicate a satisfactory level of fit. The saturation model yielded an SRMR value of 0.040 and an NFI value of 0.89, suggesting that the data adequately conforms to the model. The structural model of this study is shown in Figure 2.

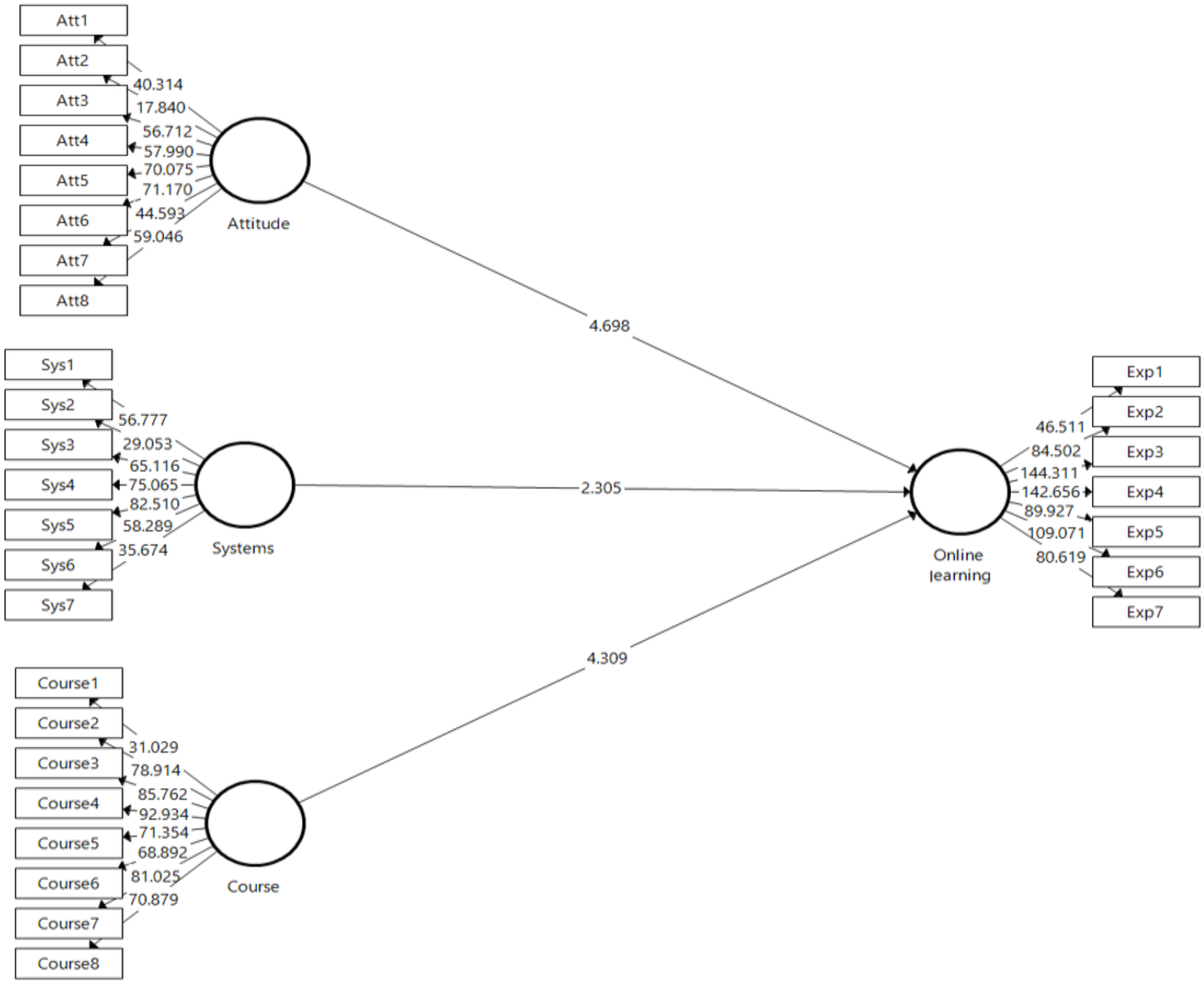

Figure 2. Structural model.

Note: Attitude-attitudes towards smart learning, system-smart learning tools, course-course design.

The subsequent phase of this study included evaluating the postulated correlations via the use of bootstrapping techniques. The study examined the direct links, and the findings are comprehensively provided in Table 8. The findings indicate that all hypotheses demonstrated favourable and statistically significant outcomes. The findings indicate that there is a positive and significant relationship between attitude and online learning (OL) ($\beta = 0.30$, $t = 4.698$, $p = 0.000$), course and OL ($\beta = 0.38$, $t = 4.309$, $p = 0.000$), and system and OL ($\beta = 0.22$, $t = 2.305$, $p = 0.020$). Therefore, hypotheses H1, H2, and H3 are deemed to be valid.

Table 8. Results of hypothesis testing.

H	Relationship	Beta	SD	t-value	p-value	Decision	VIF	f2
H1	Attitudes-> OL	0.30	0.06	4.698	0.00	Accepted	2.54	0.11
H2	Course design-> OL	0.38	0.09	4.309	0.00	Accepted	3.86	0.12
H3	Smart learning tools -> OL	0.22	0.09	2.305	0.02	Accepted	4.06	0.04

The model's development in this study is contingent upon the collective impact of the independent variables (namely, attitudes towards smart learning, smart learning tools, and course design) on the process of online learning. The adjusted R square value demonstrates the goal of this analysis, which is to evaluate the significance of the independent variables in this study. According to the findings shown in Table 9, it is evident that the collective impact of the independent factors accounts for 68% of the variance seen in online learning. The findings, as reported by Hair, et al. [37], are significant.

Table 9. Model development.

Variable	R square	Adjusted R square
Attitudes towards smart learning, smart learning tools, and course design > Smart learning	0.68	0.68

5. CONCLUSION

This study focuses on three factors that are believed to contribute to the effectiveness of smart learning environments. This study examines three factors: students' attitudes towards smart learning, their perception of smart learning technologies, and the design of courses in the smart learning environment. The present study used a questionnaire survey that was administered to a sample of 386 students enrolled in both private and public institutions, without regard to their academic year. This study demonstrates that there exists a positive and statistically significant correlation between all three parameters and the efficacy of smart learning environments. These results suggest that it is important for institutions to include the viewpoint of students while building a smart learning environment. Ultimately, this has the potential to enhance their educational experience.

This study is not without limitations. First, in 2020, the total number of students enrolled in both private and state institutions in Malaysia is projected to reach 592,680. The present research successfully obtained a total of 386 replies from the student participants. While the current sample size is adequate for representing the population, increasing the number of replies might provide more reliable and resilient conclusions. In addition, this research has selected three specific characteristics for the purpose of investigating their potential impact on the effectiveness of a smart learning environment. The present research's results indicate that the three parameters examined account for 68 percent of the effectiveness seen in a smart learning environment. However, it is important to note that there are other components that were not included in the scope of this study. The incorporation of additional variables may provide a more comprehensive comprehension of the determinants impacting the efficacy of a smart learning environment.

Funding: This study received no specific financial support.
Institutional Review Board Statement: The Ethical Committee of the Universiti Teknologi MARA, Malaysia has granted approval for this study on 25 April 2022 (Ref. No. REC/04/2022 (ST/MR/65)).
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

[1] J. Salmi, "Tertiary education in the 21st century: Challenges and opportunities," *Higher Education Management*, vol. 13, no. 2, pp. 105-130, 2001.

[2] R. Arambewela and J. Hall, "A comparative analysis of international education satisfaction using SERVQUAL," *Journal of Services Research*, vol. 6, no. S1, pp. S141-S141, 2006.

[3] Z.-T. Zhu, M.-H. Yu, and P. Riezebos, "A research framework of smart education," *Smart Learning Environments*, vol. 3, no. 4, pp. 1-17, 2016.

[4] J. Laru, P. Näykki, and S. Järvelä, "Four stages of research on the educational use of ubiquitous computing," *IEEE Transactions on Learning Technologies*, vol. 8, no. 1, pp. 69-82, 2014.

[5] S. K. Cheung, K. Phusavat, and H. H. Yang, "Shaping the future learning environments with smart elements: Challenges and opportunities," *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, pp. 1-9, 2021. https://doi.org/10.1186/s41239-021-00254-1

[6] B. Gros, "The design of smart educational environments," *Smart Learning Environments*, vol. 3, no. 15, pp. 1-11, 2016.

[7] A. D. Singh and M. Hassan, *In pursuit of smart learning environments for the 21st century. In: Current and critical issues in curriculum, learning and assessment, UNESCO International Bureau of Education*. Geneva: UNESC, 2017.

[8] E. Razinkina, L. Pankova, I. Trostinskaya, E. Pozdeeva, L. Evseeva, and A. Tanova, "Student satisfaction as an element of education quality monitoring in innovative higher education institution," presented at the E3S Web of Conferences, 2017.

[9] S.-M. Park and Y.-G. Kim, "A metaverse: Taxonomy, components, applications, and open challenges," *IEEE Access*, vol. 10, pp. 4209-4251, 2022. https://doi.org/10.1109/access.2021.3140175

[10] K. M. Elliott and M. A. Healy, "Key factors influencing student satisfaction related to recruitment and retention," *Journal of Marketing for Higher Education*, vol. 10, no. 4, pp. 1-11, 2001. https://doi.org/10.1300/j050v10n04_01

[11] M. Shah, C. Nair, and J. Richardson, *Measuring and enhancing the student experience*. Cambridge: Chandos Publishing, 2017.

[12] A. Athiyaman, "Linking student satisfaction and service quality perceptions: The case of university education," *European Journal of Marketing*, vol. 31, no. 7, pp. 528-540, 1997. https://doi.org/10.1108/03090569710176655

[13] M. A. Chatti, M. R. Agustiawan, M. Jarke, and M. Specht, "Toward a personal learning environment framework," *International Journal of Virtual and Personal Learning Environments*, vol. 1, no. 4, pp. 66-85, 2010. https://doi.org/10.4018/jvple.2010100105

[14] G.-J. Hwang and Q.-K. Fu, "Trends in the research design and application of mobile language learning: A review of 2007–2016 publications in selected SSCI journals," *Interactive Learning Environments*, vol. 27, no. 4, pp. 567-581, 2019. https://doi.org/10.1080/10494820.2018.1486861

[15] M. Kwet and P. Prinsloo, "The 'smart' classroom: A new frontier in the age of the smart university," *Teaching in Higher Education*, vol. 25, no. 4, pp. 510-526, 2020. https://doi.org/10.1080/13562517.2020.1734922

[16] R. D. Baking, F. P. Ibarra, and A. Mukminin, "Predictive analysis of cognitive skills achievements in mathematics along seven logical operations among elementary pre-service teachers," *Edelweiss Applied Science and Technology*, vol. 7, no. 1, pp. 28–37, 2023. https://doi.org/10.55214/25768484.v7i1.332

[17] A. G. Picciano, "The evolution of big data and learning analytics in American higher education," *Journal of Asynchronous Learning Networks*, vol. 16, no. 3, pp. 9-20, 2012. https://doi.org/10.24059/olj.v16i3.267

[18] P. A. Ertmer, A. T. Ottenbreit-Leftwich, O. Sadik, E. Sendurur, and P. Sendurur, "Teacher beliefs and technology integration practices: A critical relationship," *Computers & Education*, vol. 59, no. 2, pp. 423-435, 2012. https://doi.org/10.1016/j.compedu.2012.02.001

[19] National Education Association, *Technology in schools: The ongoing challenge of access, adequacy and equity*. Washington, DC: NEA Policy and Practice Department, 2008.

[20] C.-Y. Chang and G. Lee, "Major e-learning project to renovate science learning environment in Taiwan," *Turkish Online Journal of Educational Technology*, vol. 9, no. 1, pp. 7-12, 2010.

[21] J. M. Spector, "Conceptualizing the emerging field of smart learning environments," *Smart Learning Environments*, vol. 1, no. 1, pp. 1-10, 2014. https://doi.org/10.1186/s40561-014-0002-7

[22] P. Chen, X. Liu, W. Cheng, and R. Huang, "A review of using augmented reality in education from 2011 to 2016," *Innovations in Smart Learning*, pp. 13-18, 2017. https://doi.org/10.1007/978-981-10-2419-1_2

[23] H. Choi, Y. Woo, and H. Jung, "Students' perception of smart learning in distance higher education," *The Journal of the Korea Contents Association*, vol. 13, no. 10, pp. 584-593, 2013. https://doi.org/10.5392/jkca.2013.13.10.584

[24] Y. Safsouf, K. Mansouri, and F. Poirier, "Development of a measurement tool to evaluate the learning experience in an e-learning system," presented at the 14th International Conference e-Learning 2020, Zaghreb, Croatia, 2020.

[25] J. Yang, H. Pan, W. Zhou, and R. Huang, "Evaluation of smart classroom from the perspective of infusing technology into pedagogy," *Smart Learning Environments*, vol. 5, no. 1, pp. 1-11, 2018. https://doi.org/10.1186/s40561-018-0070-1

[26] I. Ha and C. Kim, "The research trends and the effectiveness of smart learning," *International Journal of Distributed Sensor Networks*, vol. 10, no. 5, pp. 537346-5373, 2014. https://doi.org/10.1155/2014/537346

[27] M. A. Peters and D. Araya, "Transforming American education: Learning powered by technology," *E-Learning and Digital Media*, vol. 8, no. 2, pp. 102-105, 2011. https://doi.org/10.2304/elea.2011.8.2.102

[28] A. N. Fayez, F. M. Ghabban, and O. Ameerbakhsh, "Advantages and challenges of smart learning in higher education institutions in Saudi Arabia," *Creative Education*, vol. 12, no. 5, pp. 974-982, 2021. https://doi.org/10.4236/ce.2021.125071

[29] O. O. Adesanya and O. O. Odunola, "E-learning participation among senior secondary students during COVID 91 pandemic lockdown in Epe local government area of Lagos State," *Library Philosophy and Practice*, pp. 1-14, 2023.

[30] M.-L. Hung, C. Chou, C.-H. Chen, and Z.-Y. Own, "Learner readiness for online learning: Scale development and student perceptions," *Computers & Education*, vol. 55, no. 3, pp. 1080-1090, 2010. https://doi.org/10.1016/j.compedu.2010.05.004

[31] W. Van De Bogart and S. Wichadee, "Students' perceived effectiveness of educational technologies and motivation in smart classroom," *TEM Journal*, vol. 5, no. 4, pp. 566-574, 2016.

[32] E. Durall and s. B. Gros, "Learning analytics as a metacognitive tool." Barcelona: CSEDU, 2014, pp. 380–384.

[33] Statista, "Number of students enrolled in public higher institutions in Malaysia from 2012 to 2020," Retrieved: https://www.statista.com/statistics/794845/students-in-public-higher-education-institutions-by-gender-malaysia. 2022.

[34] R. V. Krejcie and D. W. Morgan, "Determining sample size for research activities," *Educational and Psychological Measurement*, vol. 30, no. 3, pp. 607-610, 1970. https://doi.org/10.1177/001316447003000308

[35] J. F. Hair Jr, M. Sarstedt, L. Hopkins, and V. G. Kuppelwieser, "Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research," *European Business Review*, vol. 26, no. 2, pp. 106-121, 2014. https://doi.org/10.1108/ebr-10-2013-0128

[36] J. F. Hair Jr, M. C. Howard, and C. Nitzl, "Assessing measurement model quality in PLS-SEM using confirmatory composite analysis," *Journal of Business Research*, vol. 109, pp. 101-110, 2020.

[37] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*, 2nd ed. Thousand Oaks, CA: Sage Publications Inc, 2017.

[38] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39-50, 1981. https://doi.org/10.2307/3151312

[39] L.-t. Hu and P. M. Bentler, "Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification," *Psychological Methods*, vol. 3, no. 4, pp. 424-453, 1998. https://doi.org/10.1037/1082-989x.3.4.424

[40] P. M. Bentler and D. G. Bonett, "Significance tests and goodness of fit in the analysis of covariance structures," *Psychological Bulletin*, vol. 88, no. 3, pp. 588–606, 1980.