



**MALAYSIAN JOURNAL OF LEARNING
AND INSTRUCTION**

<https://e-journal.uum.edu.my/index.php/mjli>

How to cite this article:

Ling Chai Wong, Ying Ying Tiong, Poh Kiong Tee & Benjamin Yin Fah Chan. (2023). Exploring a tricomponent attitude model for the application of “forced” online learning in the post-covid era. *Malaysian Journal of Learning and Instruction*, 20(2), 233-266. <https://doi.org/10.32890/mjli2023.20.2.2>

**EXPLORING A TRICOMPONENT ATTITUDE MODEL
FOR THE APPLICATION OF “FORCED” ONLINE
LEARNING IN THE POST-COVID ERA**

**¹Ling Chai Wong, ²Ying Ying Tiong, ³Poh Kiong Tee &
⁴Benjamin Yin Fah Chan**

^{1&3}School of Marketing and Management,
Asia Pacific University of Technology and Innovation
Kuala Lumpur, Malaysia

²Department of Management, Marketing, and Digital Business,
Faculty of Business, Curtin University Malaysia, Miri,
Sarawak, Malaysia

⁴Tun Razak Graduate School,
Universiti Tun Abdul Razak, Kuala Lumpur, Malaysia

¹*Corresponding author: lingchaiwong10@gmail.com*

Received: 13/12/2023 Revised: 6/5/2023 Accepted: 25/5/2023 Published: 31/7/2023

ABSTRACT

Purpose – The present study explores a tricomponent attitude model for “forced” online learning applied in the post-Covid era following the online learning transition. The study aims to provide a reference for future practitioners in the event a similar crisis results in the mandatory transition towards this study mode again.

Methodology – Following the guideline for judgmental sampling, a total of 156 valid responses were collected from Malaysian

undergraduate students via an online questionnaire from Google Forms. The respondents' profiles were computed using the Statistical Package for the Social Sciences (SPSS) version 21.0, while Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to validate the measurement model, structural model, and mediation model for hypothesis testing.

Findings – The findings demonstrate that perceived usefulness (PU) is insignificant when online learning is the only feasible learning strategy. Technical system quality (TSQ) was found to be positively related to perceived ease of use (PEU), attitude (ATT), and student satisfaction, while quality of content (QC) was found to be positively related to PEU and student satisfaction. The remaining hypotheses were rejected. These findings are expected to transform various student attitude, leading to the cognitive components of PEU and PU and ultimately contributing to student satisfaction. In line with the government's desire to transform digital education in higher education, TSQ and QC constitute a framework for shaping the affective components of students' attitude. Attitude, in turn, drives students' PEU and PU, which are two critical factors of the Technology Acceptance Model that serve as the main determinants of student satisfaction.

Significance – The study demonstrates that instructors can use a variety of strategies to increase student satisfaction with online education, which can be beneficial even in the post-Covid era. The findings can aid education providers in implementing necessary changes to improve online learning for their students in the future. In addition, the study reveals that through the pandemic, students have become more resilient and have begun to value online learning, highlighting the importance of considering the long-term effects of online learning on student satisfaction.

Keywords: Tricomponent attitude model, technical system quality, quality of content, attitude, perceived ease of use, perceived usefulness, student satisfaction.

INTRODUCTION

Online learning is a type of education that provides learners with on-demand access to learning resources via the internet (Wong et al.,

2023a). Embracing online learning offers several advantages for educational providers, including cost-effectiveness, standardization, flexibility, and scalability of the teaching curriculum (Jaffar et al., 2022). Prior to the Covid-19 pandemic, however, many Malaysian universities relied on face-to-face classes, making online learning expensive and difficult to implement (Coussement et al., 2020; Zalut et al., 2021).

Inevitably, the Covid-19 outbreak prompted Malaysian higher education institutions to use online learning to reduce human contact (Yiswaree, 2020). The pandemic thus hastened Malaysia's digital transformation in higher education, as outlined in the Malaysia Education Blueprint 2015–2025. It is also a strategy mentioned in Thrust Four of the MyDIGITAL initiative (Digital Transformation for Higher Education Post COVID-19, 2021). Nevertheless, due to the absence of prior experience and strong precedents, many institutions have struggled to shift their education services online. Teachers, students, parents, publishers, and educators were unprepared to adopt it, and the infrastructure was insufficient (Simamora, 2020; Yu & Kim, 2019). Fortunately, readily available solutions such as Microsoft Teams, Google Meet, Moodle, Blackboard, CN Networking, Canvas, and Zoom have helped many institutions overcome these challenges.

It is noteworthy that none of the tools aforementioned or learning systems were developed by Malaysian tertiary education service providers. This raises concern that in the absence of tailor-made and self-developed tools that fit the Malaysian tertiary education system, education service providers can only employ universal tools to address the sudden shift in learning mode caused by the Covid-19 pandemic. This gap between adopters and tools producers must be bridged by conceptualizing and developing an ideal online learning system that addresses users' expectations, needs, and obstacles.

Research has found that due to the Covid-19 pandemic, students have become more resilient and have come to value online learning (Lee et al., 2021). However, in the post-Covid era, there has been insufficient emphasis placed on the continuous use and forced execution of online learning in both asynchronous and synchronous learning environments. While the vast majority of most studies have examined students' attitude and satisfaction towards online learning, both before the pandemic and the abrupt transition to the online mode

during the pandemic (Lee et al., 2021; Tee et al., 2019; Wong et al., 2023; Hussein et al., 2020; Mo et al., 2021; Nam & Zellner, 2011; Peng et al., 2006), little is known about whether students' satisfaction is maintained or decreased as they grow more accustomed to it. This underscores the need for higher education institutions to understand if the online learning system is compatible with user requirements, and to use such feedback to improve their online learning system. Therefore, this study takes a different viewpoint and goes beyond mainstream research to examine students' satisfaction with online learning in the post-pandemic era, following the pandemic-enforced online learning transition.

Specifically, this study investigates students' actual experiences with the online learning system, which enables them to evaluate whether the system satisfies their needs and expectations. Despite the students having embraced and gained hands-on experience with online learning, their emerging feelings and cognitive assessment towards online learning have affective outcomes, which are driven by their current attitude. Firstly, this study examines students' perception of online learning's technical system quality (TSQ) and quality of content (QC) when using the online learning system, which encompasses the conation outcomes. Following that, TSQ and QC are posited as the bases for the formation of attitude, which stimulates the cognitive components: perceived ease of use (PEU) and perceived usefulness (PU) based on the Technology Acceptance Model (TAM) (Davis, 1989). Finally, the study focuses on PEU and PU as two critical TAM factors that serve as primary determinants of student satisfaction. Based on the preceding discussion, the research objectives of the current study can be summarized as follows:

1. To investigate the effect of TSQ on students' attitude, satisfaction, PEU, and PU.
2. To examine the effect of the QC on students' attitude, satisfaction, PEU, and PU.
3. To test the effect of students' attitude on their PEU and PU.
4. To explore the effect of students' PEU and PU on their satisfaction.

LITERATURE REVIEW

In explaining students' satisfaction with their online learning experience, this study is underpinned by Rosenberg and Hanland's

(1960) Tricomponent Attitude Model and Davis's (1989) TAM. The Tricomponent Attitude Model has three components: cognitive, affective, and conative. PEU, PU, and attitude, on the other hand, make up the TAM. Notably, the current study attempts to broaden the TAM by incorporating TSQ and QC.

Conative Outcomes

The actual push for online education in Malaysia is driven by government policy, which mandated higher education institutions' practices during the Covid-19 pandemic (Selvanathan et al., 2020). Specifically, the Malaysian government ordered the closure of educational institutions as a temporary measure to prevent the spread of the pandemic outbreak (Wang et al., 2020). As a result, more than 90 percent of students in the country were unable to attend classes upon being forced to stay at home. This led to the transition of education from in-person teaching to online learning to prevent any disruption to students' learning progress (Yiswaree, 2020). According to Datuk Parmjit Singh, President of the Malaysian Association of Private Colleges and Universities (MAPCU), most higher education institutions in Malaysia were well-equipped for the online learning transformation, and students have been overwhelmingly receptive (Tharanya, 2020).

Conation, an element of the Tricomponent Attitude Model, is concerned with an individual's likelihood of taking a particular action or behaving in a particular way concerning the attitude object (Mohsin & Ahmad, 2012; Tee et al., 2022). Given that students were obliged to participate in online learning whether they wanted to or not, the current study emphasizes TSQ and QC as conative "outcomes" rather than "components."

Technical System Quality

Technical System Quality (TSQ) refers to the technological advancement of an information-producing communication system that is accurate, efficient, dependable, fast loading, information is clearly organized and safe for users (Mobarra et al., 2022; Daghan & Akkoyunlu, 2016). As elucidated by Kim et al. (2013), system quality in the online learning context is evaluated by computer networking speed and e-learning reliability. Simultaneously, the e-learning

system must possess rich media capabilities, including audio, multimedia, animation, practical manuals, and assistance services. This corroborates Yu and Kim's (2019) findings that the e-learning system must show visuals, sound, and animation for both the educator and the student. Cheong and Park (2005) added that TSQ includes a user-friendly layout and interface design that enable users to search for information quickly. These features influence users' attitude and intention to use the system (Lin & Lu, 2000), which is in line with findings by Muthuprasad et al. (2021) on the positive attitude of students in India during the Covid-19 pandemic.

According to Jaffar et al. (2022), Chang and Tung (2008), and Mohammadi (2015), TSQ is also related to system "bugs", user interface functioning, user-friendliness, software quality, and program code consistency and maintenance. If existing users encounter security difficulties or curriculum disruptions while using the system, they are more likely to make mistakes. This phenomenon might lead to a decline in the e-learning system's perceived user-friendliness, consequently impacting users' attitude, behavioral intent to utilize the platform, and overall satisfaction (Tee et al., 2014). Based on the prior discussion, this study operationalized TSQ as an e-learning system that: does not take an excessive amount of time to log in; has a friendly layout and interface design; allows users to quickly search courses; ensures users are rarely disconnected and is safe to use. Limited research has investigated TSQ as a factor influencing undergraduate students' satisfaction with online learning from home, both during and after the Covid-19 pandemic. In extending previous research, the following hypotheses are proposed:

- H1: TSQ positively affects undergraduate students' attitude towards "forced" online learning in the post-Covid era.
- H2: TSQ positively affects undergraduate students' satisfaction with "forced" online learning in the post-Covid era.
- H3: TSQ positively affects undergraduate students' PEU of "forced" online learning in the post-Covid era.
- H4: TSQ positively affects undergraduate students' PU of "forced" online learning in the post-Covid era.

Quality of Content

Quality of content (QC) can be defined as the extent to which educational materials are tailored to the unique needs of students

and enable students to access a variety of valuable services and information (Cheong & Park, 2005; Calisir et al., 2014). Xin et al. (2022) expanded the prior definition of QC, stating that e-learning contents must be clear, concise, comprehensive, and accurate. The contents displayed in the online system must be communicated to the intended audience and ensure that both teachers and learners have a mutual understanding of the information flow (Cabrera et al., 2006). Kim et al. (2013) stated that the quality of e-learning contents must include being consistent with the learning objectives, incorporating both significant issues and references, covering advanced issues rather than basic ones, and being moderated to the level of learners. Furthermore, Yu and Kim (2019) emphasized that learning materials must contain precise audios, images, and animations to explain scientific phenomena or specific situations in the syllabus. Other researchers echoed that quality content must be shown to the user, clearly and precisely, which is compatible with digital therapy research findings that available content must be accurate, timely, and relevant (Kraft et al., 2008; Stawowy et al., 2021).

The current study defines QC as learning material published through an online learning system that is clear and understandable, provides an extensive and diverse range of learning materials, displays important announcements accurately, enables students to keep track of the syllabus, and enables the students to stay connected with the learning material via online platform (Zhou et al., 2019). Motivated by previous studies, this study incorporates QC as a predictor of students' satisfaction with home-based online learning satisfaction after the Covid-19 pandemic. Hence, the hypotheses below are suggested:

- H5: QC positively affects undergraduate students' attitude towards "forced" online learning in the post-Covid era.
- H6: QC positively affects undergraduate students' satisfaction with "forced" online learning in the post-Covid era.
- H7: QC positively affects undergraduate students' PEU of "forced" online learning in the post-Covid-era.
- H8: QC positively affects undergraduate students' PU of "forced" online learning in the post-Covid era.

Students' Attitude towards Online Learning

Students' attitude towards online learning has been a topic of interest since the proliferation of online learning decades ago (Mo et al., 2021;

Nam & Zellner, 2011; Peng et al., 2006; Masrom, 2007). During the Covid-19 pandemic, institutions were urged to promote students' positive attitude towards the continued use of online learning to prevent the spread of the disease through physical interaction in class (Nghah et al., 2021). Although students agree that time-and-cost efficiency, safety, convenience, pleasant, and a high participation rate were the benefits of online learning if compared with traditional face-to-face class amid the emergency change caused by the pandemic (Hussein et al., 2020; Lin, 2011) the shift to online learning was an abrupt change that occurred before they had time to adjust to it. As such, difficulties such as psychological, emotional, and financial preparation to attend online classes; distractions and reduced attention; technological challenges and internet access; and insufficient assistance from instructors and peers (Maqableh & Alia, 2021; Hussein et al., 2020) are expected to affect students' attitude toward online learning.

Unsurprisingly, students' attitude during and after the abrupt transition to online learning have yielded mixed results, with some students having positive, negative, or a combination of positive and negative attitude towards it (Ferrer et al., 2020; Hussein et al., 2020; Rafique et al., 2021). Previous studies showed that students were somewhat motivated to study through online learning and felt confident completing basic computer and internet operations during the pandemic (Rafique et al., 2021). Some of them praised their instructors' teaching capabilities and the quality of online courses as significant complements (Boca, 2021). However, students also reported that their online learning activities were not completely personalized or successful; furthermore, they considered online learning to be stressful even though they still preferred online assessments (Boca, 2021; Rafique et al., 2021).

The current study posits the importance of attitude towards online learning and postulates that students' mixed feelings are not country-specific, given that the earlier empirical studies were conducted in various countries. It has also been emphasized that the outcomes are heavily influenced by the availability of online resources and the degree of technical assistance. With these considerations in mind, the current study focuses on the influence of technology on attitude towards online learning after the pandemic, further emphasizing that students' attitude, in addition to technical factors, play a role in their acceptance of technology. The study thus proposes a relationship

between students' perception, cognition, and attitude regarding the PEU and PU of online learning. Although this notion is not commonly studied, it is plausible and supported by previous research. For instance, Mo et al. (2021) found that PEU and PU impact students' learning outcomes and attitude toward online learning. Correspondingly, the current study focuses on attitude as a driving force behind students' perception, given that online learning was not a choice but rather a requirement during the lockdown. Based on this, the following hypotheses are put forth:

H9: Attitude positively affects undergraduate students' PEU of "forced" online learning in the post-Covid era.

H10: Attitude positively affects undergraduate students' PU of "forced" online learning in the post-Covid era.

Cognitive Components

Despite voluminous evidence indicating that perception is distinct from cognition (Firestone & Scholl, 2016), establishing a boundary between the two has proven challenging. According to Efron (1969), perception is a person's cognitive contact with the surrounding world which is essential to his or her beliefs and thoughts about performing actions (Brown et al., 2011; Cahen & Tacca, 2013). A link between the two components suggests that knowledge created based on perception is sent to cognitive systems. Potter (2012) postulated that perception and cognition are continuous yet independent processing stages operating on the same representational format, with memory acting as their mediator. This became applicable a decade later when Nejati's (2021) experiment offered strong evidence on the relationship between perception and memory in characterizing the roles of perception and cognition. Brown et al. (2011) also expanded on the premise that attention mediates perception and proprioceptive inputs. Based on the prior notions of perception as the foundation of cognition, this study introduces PEU and PU as two components of students' cognition.

Davis (1989) incorporated PEU and PU as components of the TAM and argued that PEU and PU are key drivers of attitude, with PU being influenced by PEU and external factors. Taylor and Todd's (1995) Theory of Planned Behavior further divided attitude into PU and PEU. The current study differs from mainstream research in that it assumes that the two perception components are derived from attitude

towards online learning, as people's perception of online learning are influenced by their past and present experiences. Therefore, to change someone's perspective or expectations about online learning, it is necessary to modify their present and past references, which is the focus of the current study's recommendation of PEU and PU as the first references for students' attitude toward online learning (Zhao & Zhang, 2020).

Perceived Ease of Use

Perceived Ease of Use (PEU) is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). In the context of online learning, PEU is described as the degree to which a student believes that using an online learning system would be effortless, resulting in their readiness to embrace the system. When a student finds online learning easily accessible, their PEU improves and they accept the system, which positively influences their attitude. However, Venkatesh and Davis (1996) discovered that as users grow more familiar with a system (i.e., online learning system), this positive effect on the technology diminishes. Hence, continuous online learning may not be favorable for PEU, since students may become bored or more stressed with it. This is corroborated in empirical findings by Sugihartono et al. (2020) that PEU has little impact on the attitude toward usage, especially when the user's objective for utilizing a system is achieved. However, the current study's assumption of attitude as the main force behind PEU is expected to yield a different outcome.

Perceived Usefulness

Perceived Usefulness (PU) refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). According to Davis (1986), a person's decision to utilize a system is based on his or her own perception that the system will help him or her accomplish work more efficiently. It describes the user's perception of how much the technology will improve his or her work performance or simply the outcome of an experience (Davis et al., 1992). An online learning system's PU is crucial in measuring user acceptance and should be actively emphasized when introducing new technology to students coping with the abrupt transition (Goh & Wen, 2021). Accordingly,

acceptance of the online learning system in this study is recognized as a significant attitude that makes students adopt the online learning system based on the belief that it will be valuable to them during and after the pandemic.

Affective Outcome: Student's Satisfaction with Online Learning

Prior research on work satisfaction has defined it as an affective or emotional response stemming from the employee's comparison of actual outcomes with valued ones (Cranny et al., 1992; Locke, 1969). Accordingly, with this in mind, the current study defines students' satisfaction with online learning as the affective outcome based on the value of online learning they have received. Students' satisfaction with online learning has been extensively researched in the literature, and a variety of theoretical frameworks have been established in this respect (Finneran & Zhang, 2003). These studies have widely measured students' online learning satisfaction using TSQ and QC (Alqurashi, 2019). For example, Mohammadi (2015) found that TSQ and QC are the most critical factors impacting undergraduate students' intention and satisfaction toward online learning. Moreover, studies employing TAM (Davis & Bagozzi, 1992) reported PEU and PU as two major factors influencing students' satisfaction with online learning (Wu & Chen, 2017).

The current study concurs with Homburg et al. (2006) that satisfaction needs to be viewed dynamically. Adopting a different lens, this study sheds light on situations where online study is mandatory, the course content, instructors, and peers remain constant, and the learning system continues until it becomes a norm. In such cases, satisfaction levels may vary, and they may be driven by other factors such as the quality of the online course delivery system, the unchanged content quality, or the learner's perception of unplanned online learning. Indeed, Homburg et al. (2006) found that cognition has a significant impact on satisfaction in their experimental study. Meanwhile, Lee (2010) compared the perceptions of Korean and American students on online support systems and found perception to be a crucial factor in overall online learning satisfaction. Generally, previous research has discovered that independently, TSQ, QC, PU, and PEU all have a positive impact on students' satisfaction with online learning (Joo et al., 2011; Lee, 2010). However, few studies have simultaneously incorporated these variables as outcomes of students' conation and

cognition. Given the need for insight into these relationships in the Malaysian higher education context, the hypotheses below are drawn:

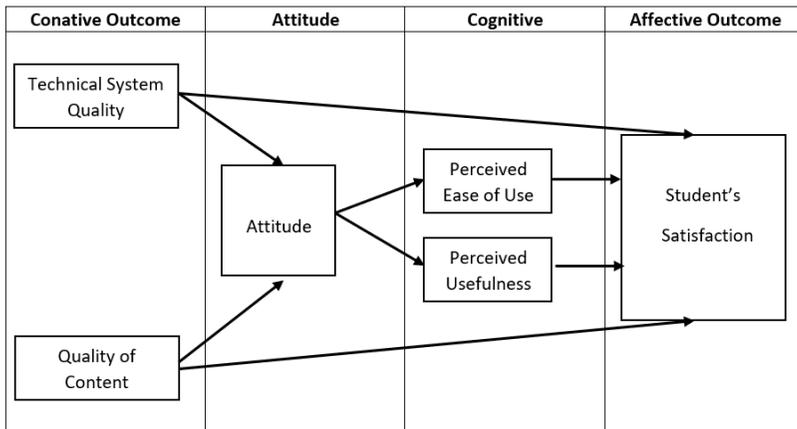
- H11: PEU positively affects undergraduate students’ satisfaction with “forced” online learning in the post-Covid era.
- H12: PU positively affects undergraduate students’ satisfaction with “forced” online learning in the post-Covid era.

Research Framework

The conceptual framework of this study starts with the conative component, which is evidenced by the government’s enforcement of online learning, leading to outcomes of TSQ and QC. The attitude component is next, which is shaped by TSQ and QC. This is followed by the cognitive component, represented by PEU and PU. Finally, student satisfaction represents the affective outcome of the tricomponent model. Figure 1 shows the research framework of the current study.

Figure 1

Research Framework



METHODOLOGY

In this section, the study’s population and sampling, measurement and scales, and data analysis are discussed.

Population and Sampling

Data was collected using judgmental sampling from undergraduate students in Malaysia via online questionnaire administered on the Google Forms platform (Fricker, 2008). This enabled the researchers to choose the sample based on their best judgement during and after the Covid-19 pandemic. To ensure a suitable sample, pre-screening questions were used to avoid respondent error issues. Specifically, respondents had to be active undergraduate students using the learning management system and to have at least one semester of experience with fully online learning systems. Universities' standard operating procedure (SOP) during the Covid-19 pandemic emphasizes social distancing and minimizing physical contact as much as possible to combat the virus spread (Jamaludin et al., 2020). Furthermore, due to the Personal Data Protection Act of 2010, the researchers were unable to obtain a complete list of active undergraduate students along with their contact information from the target universities, namely the Asia Pacific University of Technology and Innovation and Curtin University Malaysia. As a result, judgmental sampling method was the best option for data collection.

In terms of sample size, G*Power analysis was applied to ensure a minimum sample size of 100 participants for the current study (Wong et al., 2023). A total of 200 questionnaires were distributed online from 1 September 2020 to 30 September 2020. Out of these, 156 responses were deemed useful for data analysis, resulting in a valid response rate of 78 percent. The participants' involvement in the study was voluntary, which eliminated the possibility of response bias.

The respondents' profile showed that 63.5 percent were female, while 36.5 percent were male. The majority of the respondents were aged between 22 and 25 years (56.4%), followed by those between 18 and 21 years of age (34%) and those aged between 32 and 40 years (5.1%). The remaining 4.5% were between 26 and 30 years. In terms of academic level, 69.8 percent of the respondents were pursuing a bachelor's degree, while 30.1 percent were enrolled in a diploma program. Regarding the level of study, 31.4 percent were third-year students, 25 percent were in their second year, 23.1 percent were in their first year, and the remaining 20.5 percent were in year four and above.

Measurement and Scales

The survey used a five-point Likert scale ranging from ‘1 = strongly disagree’ to ‘5 = strongly agree’ to measure respondents’ perception in terms of TSQ, QC, ATT, PEU, PU, and student satisfaction toward online learning system. There are five indicators specifically designed to measure the TSQ construct. As shown in Table 1, the first two TSQ indicators were adapted from Daghan and Akkoyunlu (2016), the third and fourth indicators were adapted from Chang and Tung (2008), and the final TSQ indicator was adapted from Mohammadi (2015). This section is followed by five QC indicators adapted from Zhou et al. (2019). Next, the five indicators for PEU and PU were adapted from Davis (1989). The indicators for ATT were adapted from Masrom (2007) and Cheng (2012). Finally, five indicators from Alshare et al. (2019) were adapted to measure the satisfaction of students. Table 1 contains a sample of the indicators for each construct as follows.

Table 1
Measurement of the Constructs

Construct	Indicator	Scale	Source
Technical System Quality (TSQ)	1. The information on the screen of the online learning is clearly organized.	Five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).	Adapted from Daghan and Akkoyunlu (2016).
	2. I think online learning can optimize your response time.		Adapted from Daghan and Akkoyunlu (2016).
	3. The layout and user interface design of the online learning is friendly.		Adapted from Chang and Tung (2008).
	4. I can quickly search for courses via online learning applications.		Adapted from Chang and Tung (2008).
	5. I am rarely disconnected during online classes and tutorials.		Adapted from Mohammadi (2015).
Quality of Content (QC)	1. The learning material published via online learning system is clear.	Five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).	Adapted from Zhou et al. (2019)
	2. The online learning system offers a wide range of learning materials that meet my requirements.		Adapted from Zhou et al. (2019).
	3. The online learning system accurately displays important announcements such as exam dates, fees, and subject enrolment.		Adapted from Zhou et al. (2019).
	4. The online learning system allows the student to keep track of the syllabus.		Adapted from Zhou et al. (2019).
	5. The variety of learning materials provided by the online learning system is extensive, and it meets my requirements.		Adapted from Zhou et al. (2019).

(continued)

Construct	Indicator	Scale	Source
Perceived Ease of Use (PEU)	1. I find that online learning is easy to use.	Five-point	Adapted from Davis (1989).
	2. I can easily access the Internet whenever I need to study.	Likert scale from 1 (strongly disagree) to 5 (strongly agree).	Adapted from Davis (1989).
	3. I think online learning is easy to operate.		Adapted from Davis (1989).
	4. I think online learning is easy to understand.		Adapted from Davis (1989).
	5. Using online learning apps does not require a lot of mental effort.		Adapted from Davis (1989).
Perceived Usefulness (PU)	1. The output of online learning is the same as the classroom.	Five-point	Adapted from Davis (1989).
	2. I can effectively manage my study time through online learning.	Likert scale from 1 (strongly disagree) to 5 (strongly agree).	Adapted from Davis (1989).
	3. I can complete my assignments on time through online learning.		Adapted from Davis (1989).
	4. I can get a quick response from the teacher in the online class.		Adapted from Davis (1989).
	5. Online learning is a useful way of learning.		Adapted from Davis (1989).
	6. The use of online learning has improved my learning efficiency.		Adapted from Davis (1989).
Attitude (ATT)	1. I like to use online learning to study.	Five-point Likert scale from 1 (very unlikely) to 5 (very likely).	Adapted from Masrom (2007).
	2. I think online learning is a wise idea.		Adapted from Masrom (2007).
	3. I think it is convenient to use online learning.		Adapted from Lin (2011).
	4. I think online learning is pleasant.		Adapted from Cheng (2012).
	5. I think online learning is more interesting than conventional face-to-face class.		Adapted from Cheng (2012).

(continued)

Construct	Indicator	Scale	Source
Student Satisfaction	1. I think the online learning system was very helpful during the pandemic.	Five-point Likert scale	Alshare et al., (2011).
	2. Overall, I am satisfied with the online learning system.	from 1 (strongly disagree) to 5 (strongly agree).	Alshare et al., (2011).
	3. The online learning system has a positive impact on my learning.	(strongly agree).	Alshare et al., (2011).
	4. The performance of the online learning system is good.	Alshare et al., (2011).	Alshare et al., (2011).
	5. Overall, the online learning system is successful.	Alshare et al., (2011).	Alshare et al., (2011).

Data Analysis

The SPSS version 21.0 was used to compute the distribution of the respondents' profile. In addition, PLS-SEM was performed to validate the measurement model, structural model, and mediation model for hypothesis testing. PLS-SEM is claimed to be useful in behavioral and social sciences research to assess the multidimensionality, reliability, and validity of each construct along with the degree of measurement error (Sarstedt & Cheah, 2019; Tee et al., 2021, 2022).

RESULTS

Assessment of Measurement Model

To assess the reliability and validity of the reflective constructs (TSQ, QC, PEU, PU, attitude, and satisfaction), internal consistency reliability, convergent validity and discriminant validity were tested. Table 1 summarizes the results of the measurement model assessment, which shows that all model evaluation criteria were met, providing support for the reliability and validity of the model. All indicators had a loading of 0.70 or above and the average variance extracted (AVE) values for all constructs ranged from 0.794 to 0.923, exceeding the threshold value of 0.50. Hence, the internal consistency reliability and convergent validity of all measurement items were affirmed without the need for deletion (Hair et al., 2017).

Next, the Heterotrait-Monotrait ratio of correlations (HTMT) was utilized to evaluate the discriminant validity among the constructs (Ramayah et al., 2018). However, the HTMT scores for several constructs, particularly for PU, were above 0.90, which Henseler et al. (2015) described as inadequate discriminant validity. The researchers attempted to address this issue by deleting several items with lower loadings, but further attempts yielded no positive results. Therefore, the researchers concluded that the issue may be related to the PU construct not being meaningful to the respondents. Consequently, the PU construct was removed, along with the items TSQ5, PEU1, and PEU2. As a result, the HTMT values returned to acceptable levels, which justified the researchers' decision (Table 2). Table 2 presents the final results of the measurement model.

Table 2

Results of Measurement Model

Construct	Item	Outer Loading	AVE	DV
Technical System Quality	TSQ1	0.736	0.63	0.794
	TSQ2	0.812		
	TSQ3	0.839		
	TSQ4	0.785		
Quality of Content	QC1	0.817	0.647	0.804
	QC2	0.798		
	QC3	0.804		
	QC4	0.828		
	QC5	0.774		
Attitude	ATT1	0.922	0.725	0.851
	ATT2	0.931		
	ATT3	0.931		
	ATT4	0.917		
	ATT5	0.913		
Perceived Ease of Use	PEU3	0.775	0.668	0.818
	PEU4	0.802		
	PEU5	0.872		
Student Satisfaction	SAT1	0.922	0.852	0.923
	SAT2	0.931		
	SAT3	0.931		
	SAT4	0.917		
	SAT5	0.913		

AVE indicates average variance extracted; DV indicates discriminant validity; TSQ indicates technical system quality; QC indicates quality of content; ATT indicates attitude; PEU indicates perceived ease of use; SAT indicates student satisfaction.

Table 3

Heterotrait-Monotrait ratio of correlations (HTMT)

Construct	1	2	3	4	5
Attitude					
Perceived Ease of Use	0.760				
Quality of Content	0.899	0.867			
Student Satisfaction	0.852	0.624	0.532		
Technical System Quality	0.868	0.856	0.847	0.864	

Assessment of Structural Model

Table 3 presents the results for the structural model assessment and hypothesis testing for all direct relationships. The bootstrapping technique was used to calculate one-tailed t-values and p-values for the single-direction hypotheses. The findings indicated that most of the path correlations had significant positive relationships (TSQ → Attitude, $\beta = 0.356$; TSQ → Satisfaction, $\beta = 0.831$; TSQ → PEU, $\beta = 0.348$; CQ → Attitude, $\beta = 0.534$; CQ → PEU, $\beta = 0.424$) with t-values greater than 1.645 and p-values less than 0.05. However, some of the path correlations (i.e., CQ → Satisfaction, Attitude → PEU, and PEU → Satisfaction) were not significant ($t < 1.645$, $p > 0.05$). In summary, hypotheses H1, H2, H3, H5, and H7 were supported, while hypotheses H6, H9, and H11 were rejected. Hypotheses H4, H8, H10, and H12 were excluded due to the deletion of invalid constructs.

Next, the researchers quantified effect size (f^2) to examine the impact of the exogenous constructs on the endogenous constructs. Based on Cohen’s (1988) guidelines (i.e., no effect, $f^2=0$; small effect, $f^2<0.02$; moderate effect, $f^2<0.15$; large effect, $f^2<0.35$), the findings in Table 3 show that the effect size of the exogenous variables ranged from large to small. Thus, changes in the exogenous variables have diverse effects on the endogenous variables.

Table 4

Results of Hypothesis Testing

Hypothesis	Path	Std. Beta	Std. Error	t-value	p-value	Effect Size, f^2	Decision
H1	TSQ → ATT	0.356	0.109	3.281	0.001	0.200	Supported
H2	TSQ → SAT	0.831	0.113	6.969	>0.001	0.662	Supported
H3	TSQ → PEU	0.348	0.144	2.520	0.012	0.125	Supported
H4							
H5	CQ → ATT	0.534	0.105	5.027	>0.001	0.448	Supported
H6	CQ → SAT	-0.095	0.15	0.968	0.333	0.022	Rejected
H7	CQ → PEU	0.424	0.147	2.786	0.005	0.132	Supported
H8							

(continued)

Hypothesis	Path	Std. Beta	Std. Error	t-value	p-value	Effect Size, f ²	Decision
H9	ATT → PEU	0.038	0.167	0.248	0.804	0.001	Rejected
H10							
H11	PEU → SAT	0.116	0.152	0.764	0.445	0.105	Rejected
H12							

TSQ indicates technical system quality; QC indicates quality of content; ATT indicates attitude; PEU indicates perceived ease of use; SAT indicates student satisfaction.

Furthermore, the results of the coefficient of determination (R^2) and predictive relevance (Q^2) in Table 4 indicate that the structural model satisfactorily explained the variance in attitude (68%) and substantially explained the variance in PEU and student satisfaction (PEU = 55.9%; SAT = 59.4%). Overall, the model had acceptable fit and predictive relevance, since all the Q^2 values were larger than zero (Chin, 1998).

Table 5

Results of the Coefficient of Determination and Predictive Relevance

Construct	R^2	Q^2
Attitude	0.680	0.470
Perceived Ease of Use	0.559	0.350
Student Satisfaction	0.594	0.497

Discussion and Implications of the Study

Due to the unsatisfactory validity and reliability test results for PU, the researchers decided to delete the PU construct, assuming that online learning is now mandatory rather than optional. In this “forced” situation, where there is no choice provided, online learning is the only effective way of learning, whether it is perceived as useful now or in the future. The results justify this assumption, as the usefulness of the online learning system is no longer a perception or cognition but a fact. Looking at the theoretical framework in a broader sense, the conative outcomes (both TSQ and QC) were found to be significantly related to students’ attitude towards online learning. Conative outcomes, as

described by Mohsin and Ahmad (2012) and Tee et al. (2022), relate to students' likelihood and belief of participating in online learning, as well as their learning outcomes. In the post-Covid era, when students have no choice about study mode, they are highly motivated to develop a positive attitude towards online learning. It is important to note that conation is required to explain how knowledge and emotion translate into behavior (Baggozi, 1992), which is supported by the current findings on the relationship between conative outcomes and attitude.

Additionally, the analysis results indicate a significant influence of conative outcomes on students' cognition, implying that what was done (or forced to be done) has a significant impact on how students think. As the abrupt transition to online learning was mandatorily imposed at the time, students were adopting it for the first time, cognition (thinking) was not an initial primary concern. The reason is that whether students agreed or not, online learning was the only option. Once students became acquainted with online learning, they began to believe in its benefits as class could continue as usual even though while other physical activities were still restricted. Due to the forced condition, the results of the current study contradict mainstream findings that attitude has a positive influence on consumer self-cognition, leading to conation (Zeng et al., 2023). This explains why the current study supports the hypothesis on the influence of conation on cognition, while rejecting the hypothesis on the influence of attitude on cognition.

However, findings regarding the relationship between conative outcomes and affective outcomes, specifically student satisfaction, were inconsistent. This suggests that different conative outcomes (i.e., what the students did) have varying effects on affective outcomes (i.e., how the students feel). In the context of the current study, for example, the students had no choice over the technical system used; thus, if the system provided the benefit of allowing learning to continue, most of the students would be satisfied. Nonetheless, since the content is delivered by a teacher in the usual manner, the students' expectations have been set based on prior knowledge and experience; thus, their satisfaction cannot be guaranteed. Similarly, regarding cognitive and affective outcomes, what the students think is useful may not necessarily affect how they feel. That is, they may believe the system to be extremely useful, but they may be dissatisfied with

current offerings because the online learning environment is being “forced”.

A clearer justification and recommendation could be provided by focusing on the dimensions of the constructs. The cognitive outcomes of TSQ have a positive effect on attitude, PEU, and student satisfaction. This indicates that TSQ can influence both the affective and cognitive aspects of student satisfaction with online learning, regardless of whether it is being “forced” or is the norm. The relationship between TSQ and attitude has also been proven, which is consistent with the findings of Lin and Lu (2000) and Muthuprasad et al. (2021). This shows that the online learning system’s features, such as clear organization of information on the screen, quick log-in time, friendly layout and user interface design, ease of searching for courses, rare disconnections, and safety of using the system, can influence students’ positive attitude. This positive attitude towards the system leads to a favorable correlation between TSQ and student satisfaction. In general, students are satisfied with the quality of the e-learning system and believe that it has been well-implemented.

In terms of the QC of online learning materials, it was discovered that students’ perception of high-quality content influences their PEU of the online learning system. QC, on the other hand, appears to have no beneficial influence on student satisfaction with online learning. This clearly expounds those students who are dissatisfied with the information uploaded to the online learning system, which has failed to meet their expectations. This might be due to learning content that is too complicated and inapplicable to the activities or assignments being developed. Furthermore, pedagogical challenges arise mostly due to both instructors’ and students’ lack of digital capabilities. Indeed, teachers’ lack of social and cognitive presence, as well as students’ lack of engagement, motivation, and rapport, have been observed in the online learning classroom (Ferri et al., 2020). Eventually, this leads students to become dissatisfied with their online learning.

According to the current study’s findings, there is no relationship between attitude and PEU. Although students believe online learning is generally a good idea, they find it challenging to use after a certain period, even when the online system is no longer new to them. This may mean that the online learning system is challenging to understand

and takes considerable mental effort. Consequently, PEU is irrelevant in terms of student satisfaction with online learning. This again indicates that students are unsatisfied with the benefits of the online learning system in their learning. As such, instructors must be familiar with technology and capable of developing adaptable programs to assist students in learning more efficiently (Dhawan, 2020).

It is evident that students are not satisfied with the quality of online learning materials, which calls for higher education institutions to train their instructors on how to upload quality content or improve their delivery of online class content. Furthermore, these institutions must maintain the TAM's quality dimensions for online learning on a regular basis. While students can return to face-to-face classes, the institutions ought to examine the efficacy of the online learning system in deciding whether to continue using it. The current study also recommends that future research incorporates the perspectives of instructors and education service providers in adapting the existing framework. As for the study's limitations, it only studied undergraduate students; therefore, the findings cannot be generalized to students at higher or lower levels. Meanwhile, the research sample was collected in Malaysia, meaning that the results may not be applicable to other countries. Future researchers are recommended to collect data from various countries if they wish to examine university students' response from "forced" to "normal" online learning systems in a larger context.

CONCLUSION

In conclusion, it is unlikely that online learning will be able to satisfy all students, regardless of whether it is before, during, or after the Covid-19 pandemic, or in any other circumstance. However, the current study has revealed an interesting finding that PU is not important in the context of online learning during and after the Covid-19 pandemic. As there are no other options, the online learning platform is currently the most advantageous platform. This study provides insight into how higher education service providers should run their online learning systems during a pandemic by focusing on the quality of the technical system, content, attitude, and ease of use in relation to student satisfaction. Even though perceived usefulness was shown to be insignificant in this study, service providers must ensure that the learning platform is always beneficial to educators and students.

ACKNOWLEDGMENT

The authors received no funding for the research, authorship, and/or publication of this article.

REFERENCES

- Afzal, M.T., Safdar, A., & Ambreen, M. (2015). Teachers' perceptions and needs towards the use of e-learning in teaching of physics at secondary level. *American Journal of Educational Research*, 3(8). <http://pubs.sciepub.com/education/3/8/16/index.html>
- Alqurashi, E. (2019). Predicting student satisfaction and perceived learning within online learning environments. *Distance Education*, 40(1), 133-148. <https://doi.org/10.1080/01587919.2018.1553562>
- Alshare, K. A., Freeze, R. D., Lane, P. L., & Wen, H. J. (2011). The impacts of system and human factors on online learning systems use and learner satisfaction. *Decision Sciences Journal of Innovative Education*, 9(3), 437-461. <https://doi.org/10.1111/j.1540-4609.2011.00321.x>
- Bagozzi, R. P. (1992). The self-regulation of attitudes, intentions, and behavior. *Social Psychology Quarterly*, 55(2)178-204. <https://doi.org/10.2307/2786945>
- Boca, G. D. (2021). Factors influencing students' behavior and attitude towards online education during COVID-19. *Sustainability*, 13(13), 7469. <https://doi.org/10.3390/su13137469>
- Brown, H., Friston, K. J., & Bestmann, S. (2011). Active inference, attention, and motor preparation. *Frontiers in Psychology*, 2, 218-229. <https://doi.org/10.3389/fpsyg.2011.00218>
- Cabrera, A., Collins, W. C., & Salgado, J. F. (2006). Determinants of individual engagement in knowledge sharing. *The International Journal of Human Resource Management*, 17(2), 245-264. <https://doi.org/10.1080/09585190500404614>
- Cahen, A., & Tacca, M. C. (2013). Linking perception and cognition. *Frontiers in Psychology*, 4, 144-156. <https://doi.org/10.3389/fpsyg.2013.00144>
- Calisir, F., Altin Gumussoy, C., Bayraktaroglu, A. E., & Karaali, D. (2014). Predicting the intention to use a web-based learning system: Perceived content quality, anxiety, perceived system quality, image, and the technology acceptance model. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 24(5), 515-531. <https://doi.org/10.1002/hfm.20548>

- Chang, S. C., & Tung, F. C. (2008). An empirical investigation of students' behavioural intentions to use the online learning course websites. *British Journal of Educational Technology*, 39(1), 71–83. <https://doi.org/10.1111/j.1467-8535.2007.00742.x>
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, 295(2), 295-336. <https://psycnet.apa.org/record/1998-07269-010>
- Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2nd ed.). Lawrence Erlbaum Associates, Publishers.
- Cheong, J. H., & Park, M. C. (2005). Mobile internet acceptance in Korea. *Internet Research*, 15(2), 125-140. <https://doi.org/10.1108/10662240510590324>
- Coussement, K., Phan, M., De Caigny, A., Benoit, D. F., & Raes, A. (2020). Predicting student dropout in subscription-based online learning environments: The beneficial impact of the Logit Leaf Model. *Decision Support Systems*, 135, 113325. <https://doi.org/10.1016/j.dss.2020.113325>
- Cranny, C. J., Smith, P. C., & Stone, E. (1992). *Job satisfaction: How people feel about their jobs and how it affects their performance*. Lexington Books.
- Brown, H., Friston, K. J., & Bestmann, S. (2011). Active inference, attention, and motor preparation. *Frontiers in Psychology*, 2, 218–229. <https://doi.org/10.3389/fpsyg.2011.00218>
- Cabrera, A., Collins, W. C., & Salgado, J. F. (2006). Determinants of individual engagement in knowledge sharing. *The International Journal of Human Resource Management*, 17(2), 245–264. <https://doi.org/10.1080/09585190500404614>
- Cahen, A., & Tacca, M. C. (2013). Linking perception and cognition. *Frontiers in Psychology*, 4, 144–156. <https://doi.org/10.3389/fpsyg.2013.00144>
- Chang, S. C., & Tung, F. C. (2008). An empirical investigation of students' behavioural intentions to use the online learning course websites. *British Journal of Educational Technology*, 39(1), 71–83. <https://doi.org/10.1111/j.1467-8535.2007.00742.x>
- Calisir, F., Altin Gumussoy, C., Bayraktaroglu, A. E., & Karaali, D. (2014). Predicting the intention to use a web-based learning system: Perceived content quality, anxiety, perceived system quality, image, and the technology acceptance model. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 24(5), 515–531. <https://doi.org/10.1002/hfm.20548>

- Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2nd ed.). Lawrence Erlbaum Associates, Publishers.
- Coussement, K., Phan, M., De Caigny, A., Benoit, D. F., & Raes, A. (2020). Predicting student dropout in subscription-based online learning environments: The beneficial impact of the Logit Leaf Model. *Decision Support Systems*, 135, 113325. <https://doi.org/10.1016/j.dss.2020.113325>
- Cranny, C. J., Smith, P. C., & Stone, E. (1992). *Job satisfaction: How people feel about their jobs and how it affects their performance*. Lexington Books.
- Daghan, G., & Akkoyunlu, B. (2016). Modeling the continuance usage intention of online learning environments. *Computers in Human Behavior*, 60, 198–211. <https://doi.org/10.1016/j.chb.2016.02.066>
- Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems. *Massachusetts Institute of Technology*. <http://hdl.handle.net/1721.1/15192>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <http://dx.doi.org/10.2307/249008>
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of Applied Social Psychology*, 22(14), 1111–1132. <https://psycnet.apa.org/doi/10.1111/j.1559-1816.1992.tb00945.x>
- Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, 49(1), 5–22. <https://doi.org/10.1177/0047239520934018>
- Digital transformation for higher education post COVID-19. (2021). *Research Outreach* (124). <https://doi.org/10.32907/RO-124-1532036805>
- Efron, R. (1969). What is perception? In *Proceedings of the Boston Colloquium for the Philosophy of Science 1966/1968* (pp. 137–173). Springer, Dordrecht. https://doi.org/10.1007/978-94-010-3378-7_4
- Ferrer, J., Ringer, A., Saville, K., Parris, M. A., & Kashi, K. (2020). Students' motivation and engagement in higher education: The importance of attitude to online learning. *Higher Education*, 1–22. <https://doi.org/10.1007/s10734-020-00657-5>
- Ferri, F., Grifoni, P., & Guzzo, T. (2020). Online learning and emergency remote teaching: Opportunities and challenges in emergency situations. *Societies*, 10(4), 86–104. <http://dx.doi.org/10.3390/soc10040086>

- Finneran, C. M., & Zhang, P. (2003). A person–artefact–task (PAT) model of flow antecedents in computer-mediated environments. *International Journal of Human-Computer Studies*, 59(4), 475–496. [https://psycnet.apa.org/doi/10.1016/S1071-5819\(03\)00112-5](https://psycnet.apa.org/doi/10.1016/S1071-5819(03)00112-5)
- Firestone, C., & Scholl, B. J. (2016). Cognition does not affect perception: Evaluating the evidence for “top-down” effects. *Behavioral and Brain Sciences*, 39. <https://doi.org/10.1017/s0140525x15000965>
- Fricker, R. D. (2008). Sampling methods for web and e-mail surveys. *The SAGE handbook of online research methods*. London: SAGE Publications Ltd.
- Goh, E., & Wen, J. (2021). Applying the technology acceptance model to understand hospitality management students’ intentions to use electronic discussion boards as a learning tool. *Journal of Teaching in Travel & Tourism*, 21(2), 142–154. <http://dx.doi.org/10.1080/15313220.2020.1768621>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A premier on partial least squares structural equation modelling (PLS-SEM)* (2nd ed.). Sage Publications.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <http://dx.doi.org/10.1007/s11747-014-0403-8>
- Homburg, C., Koschate, N., & Hoyer, W. D. (2006). The role of cognition and affect in the formation of customer satisfaction: A dynamic perspective. *Journal of Marketing*, 70(3), 21–31. <https://doi.org/10.1509%2Fjmk.70.3.021>
- Hussein, E., Daoud, S., Alrabaiah, H., & Badawi, R. (2020). Exploring undergraduate students’ attitudes towards emergency online learning during COVID-19: A case from the UAE. *Children and Youth Services Review*, 119, 105699. <http://dx.doi.org/10.1016/j.childyouth.2020.105699>
- Jaffar, M. N., Mahmud, N. H., Amran, M. F., Rahman, M. H. A., Abd Aziz, N. H., & Noh, M. A. C. (2022). Online learning and teaching technology services USIM’s experience during COVID-19 pandemic. In *Frontiers in Education*. Frontiers Media SA. <https://doi.org/10.3389/feduc.2022.813679>
- Jamaludin, S., Azmir, N. A., Ayob, A. F. M., & Zainal, N. (2020). COVID-19 exit strategy: Transitioning towards a new

- normal. *Annals of Medicine and Surgery*, 59, 165–170. <https://doi.org/10.1016/j.amsu.2020.09.046>
- Joo, Y. J., Lim, K. Y., & Kim, E. K. (2011). Online university students' satisfaction and persistence: Examining perceived level of presence, usefulness and ease of use as predictors in a structural model. *Computers & Education*, 57(2), 1654–1664. <http://dx.doi.org/10.1016/j.compedu.2011.02.008>
- Kim, J. S., Yang, H. D., Rowley, C., & Kim, J. K. (2013). The facilitation of stakeholder consensus for the success of corporate e-learning systems. *International Journal of Management in Education*, 7(1–2), 103–130. <http://dx.doi.org/10.1504/IJMIE.2013.050816>
- Kraft, P., Drozd, F., & Olsen, E. (2008, June). Digital therapy: Addressing willpower as part of the cognitive-affective processing system in the service of habit change. In *International Conference on Persuasive Technology* (pp. 177–188). Springer. http://dx.doi.org/10.1007/978-3-540-68504-3_16
- Lee, J. W. (2010). Online support service quality, online learning acceptance, and student satisfaction. *The Internet and Higher Education*, 13(4), 277–283. <https://doi.org/10.1016/j.iheduc.2010.08.002>
- Lee, K., Fanguy, M., Lu, X. S., & Bligh, B. (2021). Student learning during COVID-19: It was not as bad as we feared. *Distance Education*, 42(1), 164–172. <https://doi.org/10.1080/01587919.2020.1869529>
- Lin, J. C.-C., & Lu, H. (2000). Towards an understanding of the behavioural intention to use a web site. *International Journal of Information Management*, 20(3), 197–208. [https://doi.org/10.1016/S0268-4012\(00\)00005-0](https://doi.org/10.1016/S0268-4012(00)00005-0)
- Lin, K.-M. (2011). E-learning continuance intention: Moderating effects of user e-learning experience. *Computers and Education*, 56, 515–526. <https://doi.org/10.1016/j.compedu.2010.09.017>
- Locke, E. A. (1969). What is job satisfaction? *Organizational behavior and human performance*, 4(4), 309–336. [https://doi.org/10.1016/0030-5073\(69\)90013-0](https://doi.org/10.1016/0030-5073(69)90013-0)
- Maqableh, M., & Alia, M. (2021). Evaluation online learning of undergraduate students under lockdown amidst COVID-19 pandemic: The online learning experience and students' satisfaction. *Children and Youth Services Review*, 128. <https://doi.org/10.1016/j.childyouth.2021.106160>

- Masrom, M. (2007). Technology acceptance model and e-learning. *12th International Conference on Education*, 21–24 May 2007, Brunei Darussalam: Universiti Brunei Darussalam, 1–10. <https://tinyurl.com/9a3xy8te>
- Mobarra, M., Rezkallah, M., & Ilinca, A. (2022). Variable speed diesel generators: Performance and characteristic comparison. *Energies*, *15*(2), 592. <https://doi.org/10.3390/en15020592>
- Mo, C. Y., Hsieh, T. H., Lin, C. L., Jin, Y. Q., & Su, Y. S. (2021). Exploring the critical factors, the online learning continuance usage during COVID-19 pandemic. *Sustainability*, *13*(10), 5471. <https://www.mdpi.com/2071-1050/13/10/5471#>
- Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, *45*, 359–374. <https://doi.org/10.1016/j.chb.2014.07.044>
- Mohsin, A., & Ahmad, S. (2012, May). Towards the selection of future 4G mobile service provider from customers' perspective. In *2012 Ninth International Conference on Computer Science and Software Engineering (JCSSE)* (pp. 120–125). IEEE. <http://dx.doi.org/10.1109/JCSSE.2012.6261937>
- Muthuprasad, T., Aiswarya, S., Aditya, K. S., & Jha, G. K. (2021). Students' perception and preference for online education in India during COVID-19 pandemic. *Social Sciences & Humanities Open*, *3*(1), 100101. <https://doi.org/10.1016/j.ssaho.2020.100101>
- Nam, C. W., & Zellner, R. D. (2011). The relative effects of positive interdependence and group processing on student achievement and attitude in online cooperative learning. *Computers & Education*, *56*(3), 680–688. <http://dx.doi.org/10.1016/j.compedu.2010.10.010>
- Nejati, V. (2021). Effect of stimulus dimension on perception and cognition. *Acta Psychologica*, *212*, 103208. <https://doi.org/10.1016/j.actpsy.2020.103208>
- Ngah, A. H., Abdul Rashid, R., Ariffin, N. A., Ibrahim, F., Abu Osman, N. A., Kamalrulzaman, N. I., & Harun, N. O. (2021, June). Fostering students' attitude towards online learning: The mediation effect of satisfaction and perceived performance. In *International Conference on Emerging Technologies and Intelligent Systems* (pp. 290–302). Springer, Cham. https://doi.org/10.1007/978-3-030-82616-1_26

- Peng, H., Tsai, C. C., & Wu, Y. T. (2006). University students' self-efficacy and their attitudes toward the Internet: The role of students' perceptions of the Internet. *Educational Studies*, 32(1), 73–86. <https://doi.org/10.1080/03055690500416025>
- Potter, M. C. (2012). Conceptual short term memory in perception and thought. *Frontiers in Psychology*, 3, 113. <https://doi.org/10.3389/fpsyg.2012.00113>
- Rafique, G. M., Mahmood, K., Warraich, N. F., & Rehman, S. U. (2021). Readiness for online learning during COVID-19 pandemic: A survey of Pakistani LIS students. *The Journal of Academic Librarianship*, 47(3), 102346. <https://doi.org/10.1016/j.acalib.2021.102346>
- Ramayah, T., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). *Partial least squares structural equation modelling (PLS-SEM) using SmartPLS 3.0: An updated and practical guide to statistical analysis* (2nd ed.). Pearson.
- Roffe, I. (2002). E-learning: Engagement, enhancement and execution. *Quality Assurance in Education*, 10(1), 40–50. <http://dx.doi.org/10.1108/09684880210416102>
- Rosenberg, M. J., & Hanland, J. C. (1960). Low-commitment consumer behavior. *Journal of Abnormal and Social Psychology*, 2(11), 367–372.
- Sarstedt, M., & Cheah, J. H. (2019). Partial least squares structural equation modeling using SmartPLS: A software review. *Journal of Marketing Analytics*, 7(3), 196–202. <http://dx.doi.org/10.1057/s41270-019-00058-3>
- Selvanathan, M., Hussin, N. A. M., & Azazi, N. A. N. (2020). Students learning experiences during COVID-19: Work from home period in Malaysian Higher Learning Institutions. *Teaching Public Administration*, 41(1), 13-22. <https://doi.org/10.1177%2F0144739420977900>
- Simamora, R. M. (2020). The challenges of online learning during the COVID-19 pandemic: An essay analysis of performing arts education students. *Studies in Learning and Teaching*, 1(2), 86–103. <https://doi.org/10.46627/silet.v1i2.38>
- Stawowy, M., Olchowik, W., Rosiński, A., & Dąbrowski, T. (2021). The analysis and modelling of the quality of information acquired from weather station sensors. *Remote Sensing*, 13(4), 693–711. <https://doi.org/10.3390/rs13040693>
- Sugihartono, T., Putra, R. R. C., Romadiana, P., Pradana, H. A., & Wahyuningsih, D. (2020). The impact of ease of use and attitude toward using document submission system application

- on behavior intention. In *2020 8th International Conference on Cyber and IT Service Management (CITSM)* (pp. 1–4). IEEE. <https://doi.org/10.1109/CITSM50537.2020.9268813>
- Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research*, 6(2), 144–176. <https://www.jstor.org/stable/23011007>
- Tee, P. K., Cham, T. H., Low, M. P., & Lau, T. C. (2021). The role of organizational career management: Comparing the academic staff' perception of internal and external employability in determining success in academia. *Malaysian Online Journal of Educational Management*, 9(3), 41–58. <https://ejournal.um.edu.my/index.php/MOJEM/article/view/30570/13109>
- Tee, P. K., Cham, T. H., Low, M. P., & Lau, T. C. (2022). The role of perceived employability in the relationship between protean career attitude and career success, *Australian Journal of Career Development*, 31(1), 66–76. <http://dx.doi.org/10.1177/1038416221102194>
- Tee, P. K., Gharleghi, B., & Chan, Y. F. (2014). E-Ticketing in airline industries among Malaysian: The determinants. *International Journal of Business & Social Science*, 5(9), 168–174. <https://tinyurl.com/5h6sha9e>
- Tee, P. K., Eaw, H. C, Oh, S. P., & Han, K. S. (2019). The employability of Chinese graduate in Malaysia upon returning to China employment market. *International Journal of Recent Technology & Engineering*, 8(2S), 358–365. shorturl.at/dAEX8
- Tharanya., A. (2020, April 20). *Covid19, MCO force education sector to grapple with technology, virtual classrooms*. *New Straits Times*. <https://www.nst.com.my/news/nation/2020/04/586033/covid19-mco-force-education-sector-grapple-technology-virtual-classrooms>
- Teräs, M., Suoranta, J., Teräs, H., & Curcher, M. (2020). Post-Covid-19 education and education technology 'solutionism': A seller's market. *Postdigital Science and Education*, 2(3), 863–878. <https://doi.org/10.1007/s42438-020-00164-x>
- Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences*, 27(3), 451–481. <https://doi.org/10.1111/j.1540-5915.1996.tb00860.x>
- Wang, G., Zhang, Y., Zhao, J., Zhang, J., & Jiang, F. (2020). Mitigate the effects of home confinement on children during

- the COVID-19 outbreak. *The Lancet*, 395(10228), 945–947. [https://psycnet.apa.org/doi/10.1016/S0140-6736\(20\)30547-X](https://psycnet.apa.org/doi/10.1016/S0140-6736(20)30547-X)
- Wong, L. C., Tee, P. K., Cham, T. H., & Lim, M. F. (2023a). Online learning during Covid-19 pandemic: A view of undergraduate student perspective in Malaysia. In M., Al-Emran, M. A., Al-Sharafi, K., Shaalan. (Eds.), *International Conference on Information Systems and Intelligent Applications (ICISIA 2022)*. Lecture Notes in Networks and Systems, vol 550. Springer, Cham. https://doi.org/10.1007/978-3-031-16865-9_32
- Wong, L. C., Tee, P. K., Yap, C. K., & Cham, T. H. (2023b). Examining intentions to use mobile check-in for airlines services: A view from East Malaysia consumers. In M., Al-Emran, M. A., Al-Sharafi, K., Shaalan. (Eds.), *International Conference on Information Systems and Intelligent Applications (ICISIA 2022)*. Lecture Notes in Networks and Systems, vol 550. Springer, Cham. https://doi.org/10.1007/978-3-031-16865-9_13
- Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221–232. <https://doi.org/10.1016/j.chb.2016.10.028>
- Xin, X., Shu-Jiang, Y., Nan, P., ChenXu, D., & Dan, L. (2022). Review on A big data-based innovative knowledge teaching evaluation system in universities. *Journal of Innovation & Knowledge*, 7(3), 100197. <https://doi.org/10.1016/j.jik.2022.100197>
- Yiswaree, P. (2020, May 27). Higher Education Ministry: All university lectures to be online-only until end 2020, with a few exceptions. *Malay Mail*, <https://www.malaymail.com/news/malaysia/2020/05/27/higher-education-ministry-all-university-lectures-to-be-online-only-until-e/1869975>
- Yu, J. S., & Kim, P. (2019). Analysis of factors affecting digital textbook pricing in Korea. *International Journal of Higher Education*, 8(3), 171–184. <https://doi.org/10.5430/IJHE.V8N3P171>
- Zalat, M. M., Hamed, M. S., & Bolbol, S. A. (2021). The experiences, challenges, and acceptance of e-learning as a tool for teaching during the COVID-19 pandemic among university medical staff. *PloS One*, 16(3), e0248758. <https://doi.org/10.1371/journal.pone.0248758>

- Zeng, S., Lin, X., & Zhou, L. (2023). Factors affecting consumer attitudes towards using digital media platforms on health knowledge communication: Findings of cognition–affect–conation pattern. *Frontiers in Psychology*, 14. <https://doi.org/10.3389/fpsyg.2023.1008427>
- Zhao, S., & Zhang, J. (2020). Can perception be altered by change of reference? A test of the Social Reference Theory utilizing college students' judgments of attractiveness. *The Journal of General Psychology*, 147(4), 398–413. <https://doi.org/10.1080/00221309.2019.1690973>
- Zhou, R., Wang, X., Shi, Y., Zhang, R., Zhang, L., & Guo, H. (2019). Measuring e-service quality and its importance to customer satisfaction and loyalty: An empirical study in a telecom setting. *Electronic Commerce Research*, 19(3), 477–499. https://libkey.io/10.1007/s10660-018-9301-3?utm_source=ideas