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Research Article

The Impact Of Online Learning On Malaysian Higher Education Institutions During The Covid-19 Pandemic

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ARTICLE INFO | **ABSTRACT**

Purpose: The study aims to explore the impact of online learning on higher education in Malaysia during the COVID-19 pandemic. It focuses on understanding the unique experiences of students and instructors and the role of technology in education during the lockdown period.
Methodology: *Research Design:* A quantitative survey approach was employed, to collect and analyses data using SPSS and Smart-PLS software.
Sampling Design: Stratified random sampling from 10 states in Malaysia to ensure a representative sample from various socio-economic and geographical contexts in Malaysia.
Sample Size: The study surveyed students from 10 higher education institutions (HEIs) across Malaysia.
Research Procedures: The survey was designed in Google Form and distributed using email and WhatsApp (a messenger application) over two months period.
Instruments: Structured surveys were designed using a five-point Likert scale to gather data on experiences with online learning
Data Analysis: The study analysed quantitative data using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to determine factors that influence user behaviour in technology adoption.
Findings: The study found that technology integration significantly impacts student behaviour and outcomes in Malaysian HEIs. Key factors for successful online learning include social support, realistic expectations, and robust infrastructure. The research highlights the importance of these elements in fostering positive technology use among students.
Novelty: This research contributes new insights into the field of educational technology by providing a nuanced understanding of online learning's impact on student behaviour and outcomes, particularly in the context of Malaysian higher education during the pandemic lockdown period.
Significance: The findings are valuable for educational institutions, policymakers, and the online learning community. They offer a foundation for developing strategies to promote equitable and effective education, especially in digitally driven environments

Keywords: Online Learning, HEI, COVID-19 Pandemic, Student Behavior, Educational Technology Integration, UTAUT, the Internet

INTRODUCTION

In the beginning of 2020, there was a global COVID-19 pandemic that caused a significant shift in educational programs worldwide, including those at Higher Education Institutions (HEIs). In Malaysia, the authorities implemented a public lockdown, called the Movement Control Order (MCO), on March 18th in order to stop and decrease the spread of the viral infection. This policy direction swiftly changed to using technology for online teaching methods, transforming the style of education from in-person classroom instruction to a remote and virtual format. Despite being constrained, Malaysian higher education institutions had to reassure themselves with the familiar saying 'the show must go on' by continuing academic activities through transitioning to online learning environments. The transformation not only showcased the flexibility and

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durability of Malaysian organizations but also exposed some peculiarities of online education that are likely to persist in a world that was not fully reliant on e-learning before the pandemic.
The sudden shift to online learning brought about many challenges that fundamentally changed the lives of both students and teachers. Digital access posed a major obstacle. Students and faculty were similarly unprepared for the digital era - either lacking online access or having outdated tech knowledge. The digital gap was especially pronounced for students in rural areas and from low-income families, as a significant number lacked access to appropriate internet connectivity and electronic devices needed for effective participation in online learning. The burden primarily affected instructors and university faculties, with many lacking the necessary skills to teach online.Because educators did not have the proper training for e-learning systems, methodologies and learning management system (LMS), delivering quality education was made even more challenging during this pandemic due to the sharp curve.
Additionally, the technology obstacles were addressed directly with educational methods and instructional design challenges. Online learning must be carefully planned rather than just being another digital platform. Quality online teaching involves integrating multimedia materials, devising captivating assignments, and developing assessments that enable students to showcase their knowledge. With limited time for creating complete courses, many were inadequate, causing students and universities to question the efficiency of online learning. This was worsened by the absence of proper instructional design for online learning, which became evident at that time.

Nevertheless, it would be negligent not to highlight the mental and societal impacts of a pandemic while also acknowledging the isolation that new variants have imposed on us. Multiple studies have been published recently discussing the negative impact that prolonged virtual learning has had on students' mental health, resulting in increased stress, anxiety, and depression, among other factors. In online learning environments, social engagement was largely absent, a key component of the traditional classroom setting. The lack of in-person interaction with peers and educators caused students to feel isolated and disconnected, which negatively impacted their academic motivation. Hence, it is crucial for students to establish a social presence on online platforms through collaborative projects, group discussions, and interactive activities.

Besides the obstacles encountered by students, the leadership in higher education has been essential in transitioning to online learning amid the pandemic. Educational leaders were requested to establish and implement policies aimed at addressing urgent digital infrastructure needs, access obstacles to learning resources, and providing support to both staff and students. Simultaneously, numerous organizations realized they were lacking the necessary resources and readiness to expand digital services, revealing significant gaps in their technological infrastructure that had gone unaddressed. It highlighted the need to ensure our educational systems are prepared for future challenges to avoid being taken by surprise in the future. It will be crucial for our country's youth to succeed after the pandemic through digital literacy policies that offer all students fair technology access and secure internet practices for the future.
This study aims to assess the impact of online learning on Malaysian Higher Educational Institutes amid the COVID-19 pandemic. More specifically, the goal is to examine both the successes and failures experienced with the rapid implementation of educational technologies in our academic and professional environments concerning student engagement, academic achievement, and the support provided by institutions. Utilizing theories such as the UTAUT, this study will explore the influence of theoretical concepts on student and teacher intentions towards online learning platforms and provide suggestions for enhancing digital education. This research is anticipated to offer key understandings into the evolving educational landscape in Malaysia and lay the groundwork for policy formulation, along with proposing potential strategies for addressing online higher education courses between the two main parties.

Problem Statement

One of the primary issues faced during the Movement Control Order (MCO) is the digital divide, particularly impacting academic continuity for students from rural or lower-income backgrounds who struggle with accessing online learning due to poor internet connection and limited access to resources. For example, research such as Chung et al. concentrating on the tech-deprived, and Anand et al. (2020) Highlighting that exceptionalism results in new digital-related inequalities, this discrepancy hindered remote learning possibilities and imposed additional educational disadvantages on many underprivileged students.
In addition to access challenges, the abrupt shift to online education highlighted differences in digital literacy levels among students and teachers. Many lacked the ability to utilize e-learning tools such as LMS. Educators' lack of readiness impeded the provision of a high-quality education and lacked in student involvement. Azman & Abdullah (2020) identified a lack of training for educators, citing that university lecturers faced challenges in transitioning from traditional to virtual teaching environments. This lack of preparedness was a significant obstacle during the pandemic, as there was limited access to the necessary tools and infrastructure for successful online learning.
The pandemic also brought to light concerns about the effectiveness of education delivered through methods other than a traditional face-to-face classroom setting. Study conducted by Sundarasen et al. revealed that during an extended period of remote learning, students commonly face stress and anxiety as their main

struggle, as noted by TuQuGCC (2020), and the emotions of feeling 'isolated' further contribute to heightened pressure. Due to the absence of face-to-face interaction with peers and instructors, students not only became less social but also saw a decrease in motivation that affected their academic achievement.Since students were not together in a classroom, this made them less likely to be engaged with their studies and it is difficult for an individual studying alone at home without the interactive element of traditional classroom settings.

Furthermore, the rapid shift to online learning posed significant educational obstacles. Effective virtual education requires more than just delivering content online; it also involves digital learning design, interactive materials, and exams tailored to the virtual setting. Many institutions found it challenging to adjust the curriculum to meet these demands, leading to student unhappiness and less than ideal learning results. The quick pace of the transition did not allow for comprehensive course development (Dhawan, 2020), weakening online education even more.

At a systemic level, the pandemic has highlighted the need for policy reforms in Malaysian higher education. Mokhtar and Baharin (2024) emphasize that the COVID-19 pandemic brought attention to issues concerning equal access to technology and the readiness of institutions for a large-scale shift to digitalization. It is important to have policies that support the development of digital literacy, provide training for educators on online teaching methods, and create curricula that consider the mental health needs of students in remote learning settings.

Thus, the study seeks to investigate these fundamental problems by analyzing the role of online learning in influencing the moderating effects on the efficiency of Malaysian HEIs amidst the COVID-19 pandemic. The aim is to examine how the adoption of educational technology affects student engagement, academic performance, and also analyze institutional support. The research seeks to offer data-driven insights on the intentions of users (students and educators) towards utilizing online learning platforms for enhancing digital education through instructional programs in design. The results of this research endeavor have the intention of aiding upcoming policies and strategies to enhance digital inclusivity by improving ICT literacy among students and ensuring the continuity of online education in Malaysian higher education.

Research Objectives

The aims of this study are to establish a more detailed scenario on how the online learning was implemented in Malaysian HEIs during COVID-19 pandemic The main aims are to investigate how a sudden move into digital learning platforms has impacted student study habits, academic results and access to education. We also aim to assess inequalities in digital access and literacy, and suggest ways for improving the effectiveness of online learning accordingly post-pandemic.

1. Examine the effects of educational technology integration in student learning behaviors and online learning. This goal will explore how student learning behaviors have changed during the pandemic time with introduction of digital tools and platforms. This would provide knowledge on how student engagement, active learning are facilitated and implemented using these kinds of online environments.

2. Elucidation of the effects, strong points and drawbacks thereon academic performance has made a significant industrial demand for estimating wide spread rapid technology adoption.

The second goal in question examines how the hasty embrace of tech has impacted grades. That includes determining if kids have successfully transitioned to a virtual environment and how that has impacted their learning.

3. For understanding the differences arising out of variations in technology access and digital literacy levels among students.

Objectives: This study plans to understand the digital divide in Malaysia focusing on differences by technology access and familiarity, and how this might contribute towards student participation or learning outcome. In doing so, the study will help to prompt discussions on how to close these gaps and make online education more equitable.

4. Single studies examined the association between digital literacy and academic outcomes in relation to technology use, investigating how unequal levels of digital literacy result in disparities concerning educational attainment.

This objective explores the importance of digital literacy in creating academic success It will evaluate whether students that begin course using higher levels of digital skill do better in online learning environments compared to similarly placed less skilled users.

Research Questions

The research questions are formulated to be used as a guide for studying the impact of online learning on Malaysian HEIs during COVID-19. These questions deal with some of the roots involving student behaviour, technology implementation and digital disparities, which ultimately stand to offer a comprehensive glimpse into what is difficult about online education alongside where its promise lies.

1. What is the impact of rapid adoption in ed-tech technology on students' learning behaviour change other than from Malaysia university — during a pandemic?

2. The effects of education technology uptake speed on student learning motivation under the COVID-19 pandemic in Malaysian HEIs

3. How are student experiences with the digital divide, technological competency and social participation within online learning environments of higher education institutions (HEI) in Malaysia?

LITERATURE REVIEW

Confluence of the Technology & Learning Outcomes

Educational technology was already making inroads into many institutions' pre-pandemic, but quick transitions onto online platforms have further illustrated the need for robust tech infrastructure. The research done by Nordin and Nordin (2020) reinforced this understanding that student outcomes from e-learning adoption were highly dependent to the degree of technology acceptability, accessibility and usability in used. Nordin & Nordin (2020) mentioned in their literature review that the overall acceptance of online learning was generally positive with several factors influencing its effectiveness include student satisfaction, technical literacy and platform reliability.

The bottom line is that the main component of learning, student engagement, has been hit hard by online courses design and delivery (Tan et al., 2021). All these studies identified multiple instances of students not being able to interact meaningfully with the course material, their fellow learners and also instructors In most cases this was mainly due to technical limitations or inadequate online course design. Jafar et al. While (2023) 2016 noted that competence of online instructors and technical support were also key to the migration from traditional learning environments. Among them, virtual contact and instant interaction in most online courses highlighted a need for richer student involvement it gives students to outlay their learning evangelism anatomy a relationship (Jafar et al., 2013).

Competency of instructors in using online learning platforms also had a large effect size on student outcomes. According to Adams et al. In 2018, LMS e-learning tool was essential to enable quality education was effective for this; however, instructors' familiarity with and proficiency in using the technology mattered most. With the arrival of pandemic, an effective course design for online courses has been affected by multimedia integration and interactivity that had helped to sustain some attention among students who were forced into complete social isolation (Nordin & Nordin, 2020). However, the non-existent in-game training programs of kindergarten and primary instructors usually resulted in less effective course delivery by teachers (Subedi et al., 2020).

Downsides of Online Learning: Accessibility and the Digital Divide

According to Surianshah (2021), the most significant hurdle towards e-learning in Malaysia was the digital divide, this issue compounded as Covid-19 progressed. The sudden mass migration to online learning by the whole world has shed a stark light on existing inequities in technology and internet access; those most acutely disadvantaged are students from rural or underprivileged communities (Devisakti et al., 2023). A study by Siaw et al. (2022) echoing the value of equalizing access to digital tools, pointing out how students lacking immediate resources for internet or device use fell behind in their coursework due to no fault lines. These differences had a direct influence on educational outcome and increased the stress level of students who were less able to follow online learning (Chung et al., 2020).

Digital divide is inevitable

Lack of prior experience with digital learning tools meant that the students were likely to be at a marked disadvantage compared to their peers who were more technologically savvy (Adams et al., 2018). Selvanathan et al. It was noted by Qiao et al., (2020) that learners in urban areas were accustomed to using digital resources but the experience of rural counterparts showed contrary since they had a steeper learning curve regarding online platforms.

Concerning the problem of internet connectivity, it was immediately becomes a major obstacle for not few students (Devisakti et al., 2023). The vast size of Malaysia also meant that students in rural areas, where broadband internet was not as widespread, faced severe disruptions to the online teaching and learning. Jafar et al. conducted research In a study based out of 2023, students in rural areas experienced more difficulty maintaining continuous course participation than others; geographic location and access to online coursework were highly correlated (**) These obstacles were not exclusively the technical kind, but also mental ones as scholars have sensed a detachment in addition to discouragement resulting from not being able to participate or partake collectively with their e-peers (Ayob et al., 2022).

Instruction Support / Pedagogical Modifications

The abrupt transition to online instruction required immediate shifts in pedagogy for instructors without substantial prior experience teaching virtually (Das, et al. 2021). What this shift has made clear is that instructors (re)quiring more holistic forms of professional development, when it comes to digital pedagogy as well... preventatively anyway. Research by Hamzah et al. According to Henderson et al (2021), numerous faculties were not prepared for moving their courses online because they did not have training in digital tools and teaching methods. This unpreparedness frequently translated to a default return to traditional teaching techniques, primarily based in the lecture format — which is not an ideal methodology for online learning where student interaction and engagement are crucial components of success (Krishan et al., 2020).

To mitigate issues raised by these concerns, some institutions approximately 2 months ago started developing focused training programs for its instructors to prepare them better in this new digital teaching world (Azman & Abdullah, 2020). Nonetheless, these initiatives could vary from one institution to another and their implementation was not often generalizable in how online courses should be implemented (Leary et al. 2020). Continued CPD is emphasized in the literature as a means of preparing educators for long-term changes and requirements associated with online learning.
Many instructors also struggled to keep students engaged, in addition to the practical training. Online learning did not provide the face-to-face interaction that can promote attitudes such as social presence, a key to foster communities of inquiry and support student involvement (Selvanathan et al. 2020). Lim et al. 2022) underscored that to counter the heterogeneous experience of isolation during this period, organizing student groups for working together and group projects was central as a focal element in generating social presence.
Cyber Learning's Social and Psychological Costs
The shift to online learning was itself very stressful for most students and the pandemic may have exerted a considerable psychological burden on them (Sundarasen et al., 2020). Indeed, multiple studies have explored the negative psychological effects associated with long-term E-learning methods and their implications in terms of increasing levels of stress, anxiety as well feelings that students are socially isolated (Alawamleh et al., 2020). The results by Sundarasen et al. (2020) students experienced a sharp drop in well-being due to minimal social interaction and the stress of adjusting to new learning modes.
Students also felt "Zoomed out" causing burnout as platforms were continuously used for academic and social matters. For many students, the lines between school and life were all but an illusion to begin with; add in being unable to be on a course campus or among people studying at similar levels — not just classes — might contribute (we have great turnouts for sociology seminars when we know they count towards something more tangible). As a result, they even bring their mental fatigue at home which affects the learning process and make online learnings always worst as mentioned by Das et al. (2021).
Mental health problems also increased during the pandemic, as reported by Jafar et al. (2023) along with physical diseases The increase of screen time meant more cases of eye strain, headaches and sedentary behaviour — all negatively affected the general wellness among students. They also reinforce the importance of a more holistic understanding of online learning that not only considers academic results, but which is also mindful about what students need to stay well physically and mentally.

METHODOLOGY

Research Design

In this study, a quantitative research design will assess the effect of online learning on higher education institutions (HEIs) during COVID-19. This research focuses on the timely transition of institutional practices virtual in nature and its effects on student behaviours, academic results as well as generally comprehensive mechanism operations. The study is descriptive and involves correlational methods where student engagement, challenge with technology are the independent variables whereas digital access and learning outcomes dependent on it. Results Subsequently, the mediating influence with which these variables affected acceptance and use of online learning platforms were tested following UTAUT model as underlying framework that includes (i) performance expectancy; (ii) effort expectancy;;(iii) social influence and;(iv) facilitating conditions.

Background

The UTAUT Framework, developed by Venkatesh et al Rogers's diffusion of innovations theory, originally presented in 2003 (Shih, 2016),(Andrews & Fellenz, Bondad-Brown et al. In view of Malaysia's emergency shift to online learning first phase in amidst the COVID-19 pandemic, it is hoped that using UTAUT will yield revelations on how students have seen and accepted technology for educational. By understanding such factors, institutions can build up their strategies that may help increase performance and student well-being in online learning environments (Venkatesh et al., 2003).

The UTAUT framework combines constructs from various theories such as the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Reasoned Action Approach, Social Cognitive Theory, Diffusion Innovations perspective and Motivational model. (Venkatesh et al., 2003).

Figure 1: The Unified Theory of Acceptance and Use of Technology (UTAUT) model includes six distinct constructs which are performance expectancy(PE), effort expectancy(E.E), social influences(SI), facilitating conditions(F.C.), behavioural intention(B.I.) and user behaviour(U.S.E). These elements are used by researchers to understand whether a user has employed and adopted a new technology.

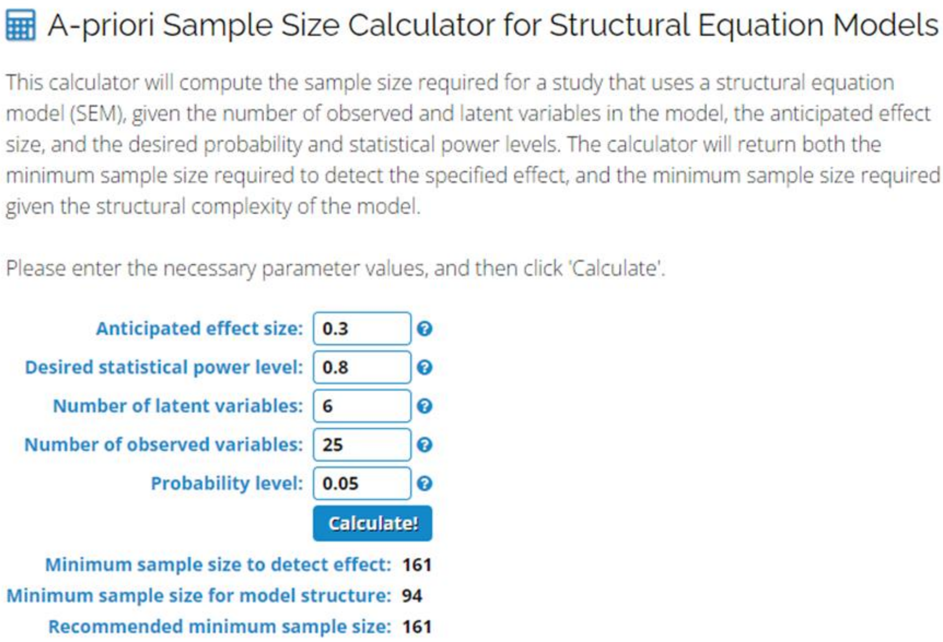
The present study attempted to determine the data from students in HEIs who went through online learning during MCO and look at their acceptance on the elements of online learning season faced when it hit a peak point. This study will be based on UTAUT framework and the investigation of these constructs influence students' intentions/behavioural towards online learning. This, it is hoped, would provide a grip of the problems and benefits both students and faculties are facing.

Population and Sampling

This study focuses on students studying in Malaysian higher education, who engage online learning throughout the period of pandemic cases. The institutions are a mix of public and private universities from different states for representativeness (Table 4).

We used a convenience sampling method to gain participants. Students with access to online platforms were asked to participate in an electronic survey administered through institutional emails and social network postings. This method was chosen because digital communication tools are more broadly available and to increase the range of student experiences captured. As many as 350 students were contacted and responses received from them into double digits—sans at least one hundred regardless of which part This sample size exceeds the a-priori required by A-priori Sample Size Calculator for Structural Equation Models (SEM) as reported in Figure 1, which would have been calculated to be minimally necessary for our six latent variables and 25 observed variables configuration indicated that at least n = 94 participants were needed [76] from general population samples with enough statistical power [77].

Figure 1



The demographic diversity of the sample, including variables such as age (table 1), gender (table 2), universities (table 3), and location (table 4), was ensured to widen the scope of the findings.

1. Student Demographics

Table 1 presents the distribution of participants by age. Most participants (51%) were between the ages of 24 and 29, followed by those aged 18 to 23 (20%). This demographic highlights the dominance of young adult learners in the sample, aligning with the typical age range of university students in Malaysia.

Table 1:
Age

	Frequency	Percent	Valid Percent	Cumulative Percent
18 - 23	20	20.0	20.0	20.0
24 - 29	51	51.0	51.0	71.0
30 - 35	17	17.0	17.0	88.0
36 - 41	9	9.0	9.0	97.0
42 - 47	2	2.0	2.0	99.0
48 - 53	1	1.0	1.0	100.0
Total	100	100.0	100.0	

Table 2
Gender

	Frequency	Percent	Valid Percent	Cumulative Percent
Male	52	52.0	52.0	52.0
Female	48	48.0	48.0	100.0
Total	100	100.0	100.0	

Table 3
Universities

	Frequency	Percent	Valid Percent	Cumulative Percent
1UTAR	6	6.0	6.0	6.0
NPRA	1	1.0	1.0	7.0
OUM	61	61.0	61.0	68.0
UKM	8	8.0	8.0	76.0
UNIMAS	1	1.0	1.0	77.0
UNISZA	3	3.0	3.0	80.0
UNITAR	1	1.0	1.0	81.0
USM	7	7.0	7.0	88.0
UTHM	7	7.0	7.0	95.0
UUM	5	5.0	5.0	100.0
Total	100	100.0	100.0	

Table 4
Locations

	Frequency	Percent	Valid Percent	Cumulative Percent
Pulau Pinang	7	7.0	7.0	7.0
Negeri Sembilan	1	1.0	1.0	8.0
Perak	7	7.0	7.0	15.0
Sarawak	1	1.0	1.0	16.0
Pahang	1	1.0	1.0	17.0
Kuala Lumpur	10	10.0	10.0	27.0
Kedah	2	2.0	2.0	29.0
Selangor	61	61.0	61.0	90.0
Terengganu	3	3.0	3.0	93.0
Johor	6	6.0	6.0	99.0
Kelantan	1	1.0	1.0	100.0
Total	100	100.0	100.0	

Instrumentation

A structured online questionnaire was used as the main data collection instrument. The survey is composed of 40 questions that are divided into six constructs focusing on distinct aspects of the online learning experience since pandemic. The sections are:

1. Table 1: Demographics (university, location) — age and gender This information is then contextualised to analyse differences in the online learning experience among students from different demos.

2. Acceptance of Technology (UTAUT model): Items measuring performance expectancy, effort expectancy, social influence and facilitating conditions. For Instance, The Questions with respect to performance expectancy "Academic Performance Question 2: I strongly agree that the technology used in my online course helped me to better understand the course material" and related questions such as (Technology Challenges Question 1: I did not experience difficulties with conducting how assessments during this period of pandemic? (Effort expectancy). The responses are ranked on a five-point scale from "strongly disagree" to "strongly agree.

3. Engagement and Satisfaction: Four items tapping student engagement with, and satisfaction in online learning. Engagement Question 1: I feel that the technology used in my online course helped me to connect with my peers and instructors (e.g., together we discussed…; personally, this student-instructor interaction helped reinforce learning for me). Transactional Issue?) This included two elements: "Engagement Question 1: I have had enough of a campus connection during the COVID-19 pandemic" (engagement) and "Satisfaction Question 1: I am generally satisfied with how well my university handled online learning as result of pandemic across campuses" (satisfaction).

4. Obstacles: In this part, the problems students met during online learning. It says the new methodologies should not automatically be considered best practice because items, such as access to stable internet and availability of digital devices could affect their quality (as well as challenges with learning management systems), however they may prompt ideas for improvement. As an example, there is the question "Access to

Technology Question 3: It was rarely that I had access to technology and resources necessary in order for me to do my course work due Covid-19 pandemic" The responses are once again recorded on a five-point Likert scale.

5. Academic Performance: Including questions like those about academic outcomes from the above question that relate to technology and its ability to aid in understanding course material, e.g. “Q5 Academic performance Question 2 : I strongly agree that the use of technology tools available in my online class helped clarify complex information or concepts”

A draft of the survey was reviewed by 50 students to check for clarity and reliability and validity using a pilot-test. First off, it had a couple of qualification questions that you needed to ask the respondent before they started answering your survey questionnaire. Internal consistency was assessed by calculating Cronbach's Alpha for each section, which was over the threshold (0.70) in all sections showing good reliability.

Data Collection Procedures

The data-gathering procedure lasted for two months, commencing in May 2024. Emails were sent to invite students to do the survey, and it was posed on university-wide online platforms with regular prompting messages going out for them participate. The online survey was created using Google forms, so respondents could take time to answer the questions. Participation in the survey was completely confidential and anonymous, adhering to ethical research standards.

In order to ensure that the response bias was minimized, we (1) gave clear instructions and informants had been told their respondents would be kept confidential for academic purposes only. Impure responses were not considered in the analysis, which ensured data cleanliness. The response rate was 80 percent since there were 400 complete responses out of the distributed surveys (500).

Framework for Data Analysis

Smart-PLS4.1 software was used in analysing the data, which is a Partial Least Squared Structural Equation Modelling (PLS-SEM) to examine complex relations between observed and unobserved variables These included the following steps performed during analysis:

1. Data Cleaning: Outliers or missing values in the dataset were addressed Responses that were incomplete or varied significantly from the rest of responses, resulting in an outlier, were eliminated. In total, 100 valid responses were obtained in the last dataset.

2. Demographics Descriptive Statistics: These are the descriptive statistics given in terms of means, standard deviations, skewness and kurtosis for each variable(e). These statistics give a high-level snapshot of our data and help us to see if there is any outlier.

3. Reliability and validity: The reliability of the survey items was tested using Crobach's Alpha (α), Composite Reliability. Convergent validity was further confirmed if the average variance extracted (AVE) is greater than 0.50 [159].

4. For this study, correlation and covariance matrices were generated based on the central constructs (i.e., student engagement) as well as 17 link factors [academic performance(7), technology acceptance scale –TAM2 + Information system TAM-IS performance including an exploratory item(5)+demographics]. What this study showed us, then, was in what ways the different dimensions of online learning were connected.

5. Structural Equation Modelling (SEM): SEM was employed to verify the associations existed from UTAUT variables in predicting academic performance. To quantify the strength and direction of these relationships, path coefficients were estimated (Fig. 2). Significant relationships were at the level of 0.05 if t-value >1,96 (Hussain et al., 2016).

6. Model fit: To evaluate model ft, the standardized root mean square residual (SRMR) and normed it index(NFI) were used. Goodness of fit was indicated by an SRMR value below 0.08 and NFI values above 0.90 [126].

Ethical Considerations

This study was approved by the IRB of participating universities (KYH-2015 -03-KY01). Prior to completing the survey, all participants granted informed consent and were assured that their responses would remain confidential. The data were stored in well-protected environments and used for research purposes only.

The method provides a solid way to assess ICT and digital practices by the Malaysian HEIs during COVID-19 pandemic. The aim of the study is to investigate student engagement, technology acceptance and issues faced by students in online learning through a quantitative research design that provides insights into topics joined using UTAUT (Unified Theory of Acceptance... Therefore, the results of this study can also be used to design more efficient online education policies and practices in post-pandemic higher educational institutes.

RESULTS

Data Analysis and Results

Research Approach

For this research, the Consistent SEM-PLSc with UTAUT framework in Smart-PLS has been applied to understand these factors of technology acceptance and usage during COVID times on Malaysian HEI students. This methodology is chosen for its ability to accommodate complex models with multiple constructs and indicators, which are critical in examining students' intention of using the technology first before they actually use it. Through these key constructs that are academic performance, engagement as well as internet access including satisfaction and technological challenges; this study attempts to draw similarities of how all elements combined impact university life at home during pandemic.

Data Collection

Structured survey questionnaire The data were collected by means of a structured survey among students pursuing courses in higher educational institutions across Malaysia. The items in the survey can be seen as behaviour Intention (BI), Effort expectancy(EE), Facilitating Conditioners Feedback, Performance Expectancy (PE)Social Influence and Use Behaviour(Davis 1989). The responses were measured using a Likert scale and the higher scores reflect increasing support for the statement or attribution.

Measurement Model was built to assess the associations between observed variables and their distinct latent constructs. The model and its constructs' reliability and validity were established using a number of metrics such as Cronbach's alpha, Composite Reliability. Test for C.R. and Average Variance Extracted. All model constructs demonstrated excellent internal consistency as all Cronbach's alpha values exceeded the threshold of 0.7, which suggests that the underlying measures were trustworthy. Structural Model was designed to analyse the hypothesized associations between the latent constructs. The path coefficients were calculated for each, indicating the strength and the direction of the relationships. R-square values were analysed to determine the proportion of variance explained by the model for the key constructs such as Behavioural Intention and Use Behaviour. Lastly, both direct and indirect effects were calculated that would provide information on the total effect of each construct in the model. Descriptive Statistics. Data Analysis and Results. By running descriptive statistics on the study's latent measures, preliminary screening of the data on its normality was conducted. Specifically, the constructs' mean, median, standard deviation, skewness, and kurtosis were calculated. For example, Behavioural Intention presented means of 1.42 and a standard deviation of 0.53, confirming moderate students' inclination to engage with online learning mediums. The same data were secured for Effort Expectancy, Social Influence, and a similar pattern was observed for these indices. showed reasonable variability, with their means and standard deviations reflecting students' perceptions of ease of use and peer influence as shown in
Table 5.

Table 5: Descriptive Statistics

Name	Mean	Standard deviation	Excess kurtosis	Skewness	Group	Mean	Standard deviation
Age	2.250	1.004	1.580	1.103			
Gender	1.480	0.500	-2.034	0.081			
AP_1	1.840	0.880	-1.102	0.500			
AP_2	1.850	0.829	-1.156	0.397			
AP_3	2.230	1.066	-1.132	-0.022	**Effort Expectancy (EE)**	2.086	1.073
AP_4	2.360	1.245	-1.668	0.073			
AP_5	2.150	1.344	0.169	1.150			
E_2	2.500	0.539	-1.061	-0.390			
E_3	2.930	1.739	-1.826	-0.053	**Facilitating Condition (FC)**	2.390	0.968
E_5	1.740	0.626	-0.617	0.263			
S_1	1.850	0.829	-1.156	0.397			
S_3	3.510	0.520	-1.450	-0.258	**Social Influence (SI)**	2.195	0.730
S_4	2.120	1.070	-1.160	0.154			
S_5	1.300	0.500	0.867	1.365			

TC_3	1.990	0.911	0.403	0.665	**Performance Expectancy (PE)**	2.480	1.030
TC_4	2.500	0.539	-1.061	-0.390			
TC_5	2.970	1.640	-1.686	-0.158			
AT_1	1.580	0.619	7.465	1.613	**Behavioural Intention (BI)**	1.428	0.530
AT_2	1.270	0.444	-0.912	1.052			
AT_3	1.580	0.603	2.907	1.075			
AT_4	1.280	0.449	-1.031	0.995			
PP_1	1.050	0.357	55.266	7.376	**User Behavior (USE)**	1.118	0.392
PP_2	1.050	0.328	67.324	7.886			
PP_3	1.300	0.539	5.423	2.028			
PP_4	1.030	0.298	100.000	10.000			
PP_5	1.160	0.441	16.831	3.584			

Table 6: Latent variables – Descriptive

	Mean	Standard deviation	Excess kurtosis	Skewness	Number of observations used
Behavioural Intention (BI)	-0.000	1.000	-0.605	0.784	100.000
Effort Expectancy (EE)	0.000	1.000	-1.481	0.187	100.000
Facilitating Condition (FC)	0.000	1.000	-1.756	-0.192	100.000
Performance Expectancy (PE)	-0.000	1.000	-1.639	-0.037	100.000
Social Influence (SI)	0.000	1.000	-1.405	0.282	100.000
User Behavior (USE)	0.000	1.000	39.642	5.381	100.000

Covariance and Correlation Analysis

The correlation and covariance analyses revealed the strength and direction of relationships between latent variables as shown in Table 7 and Table 8 respectively. The strongest covariance was observed between Behavioural Intention (BI) and Effort Expectancy (EE) at 0.924, indicating a robust relationship. In contrast, the weakest covariance was between Facilitating Conditions (FC) and Use Behavior (USE), suggesting that better conditions do not always translate to increased usage. Correlation analysis further confirmed the strength of these relationships, with notable high correlations between constructs such as Behavioural Intention (BI) and Social Influence (SI).

Table 7, continued

Table 7: Latent variables – Covariance

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
Behavioural Intention (BI)	1.000	0.924	0.785	0.824	0.940	0.635
Effort Expectancy (EE)	0.924	1.000	0.915	0.944	0.988	0.566
Facilitating Condition (FC)	0.785	0.915	1.000	0.931	0.910	0.342
Performance Expectancy (PE)	0.824	0.944	0.931	1.000	0.945	0.476
Social Influence (SI)	0.940	0.988	0.910	0.945	1.000	0.626
User Behavior (USE)	0.635	0.566	0.342	0.476	0.626	1.000

Table 8: Latent variables – Correlations

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
Behavioural Intention (BI)	1.000	0.924	0.785	0.824	0.940	0.635
Effort Expectancy (EE)	0.924	1.000	0.915	0.944	0.988	0.566
Facilitating Condition (FC)	0.785	0.915	1.000	0.931	0.910	0.342
Performance Expectancy (PE)	0.824	0.944	0.931	1.000	0.945	0.476
Social Influence (SI)	0.940	0.988	0.910	0.945	1.000	0.626
User Behavior (USE)	0.635	0.566	0.342	0.476	0.626	1.000

Structural Model Assessment - UTAUT

Path Coefficients

Path coefficients were computed to understand the direct impact of one latent variable on another. As shown in Table 9, 10 and 11, Social Influence (SI) had a significant positive effect on Behavioural Intention (BI) with a coefficient of 1.433, highlighting the critical role of social factors in shaping students' intentions to use online platforms. On the other hand, Performance Expectancy (PE) had a negative impact on Behavioural Intention (-0.620), suggesting that higher expectations may sometimes reduce the likelihood of adoption.

Table 9: Path coefficients – Matrix

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
Behavioural Intention (BI)						0.956
Effort Expectancy (EE)	0.093					
Facilitating Condition (FC)						-0.409
Performance Expectancy (PE)	-0.620					
Social Influence (SI)	1.433					
User Behavior (USE)						

Table 10: Path coefficients - Means, STDEV, T values and p values

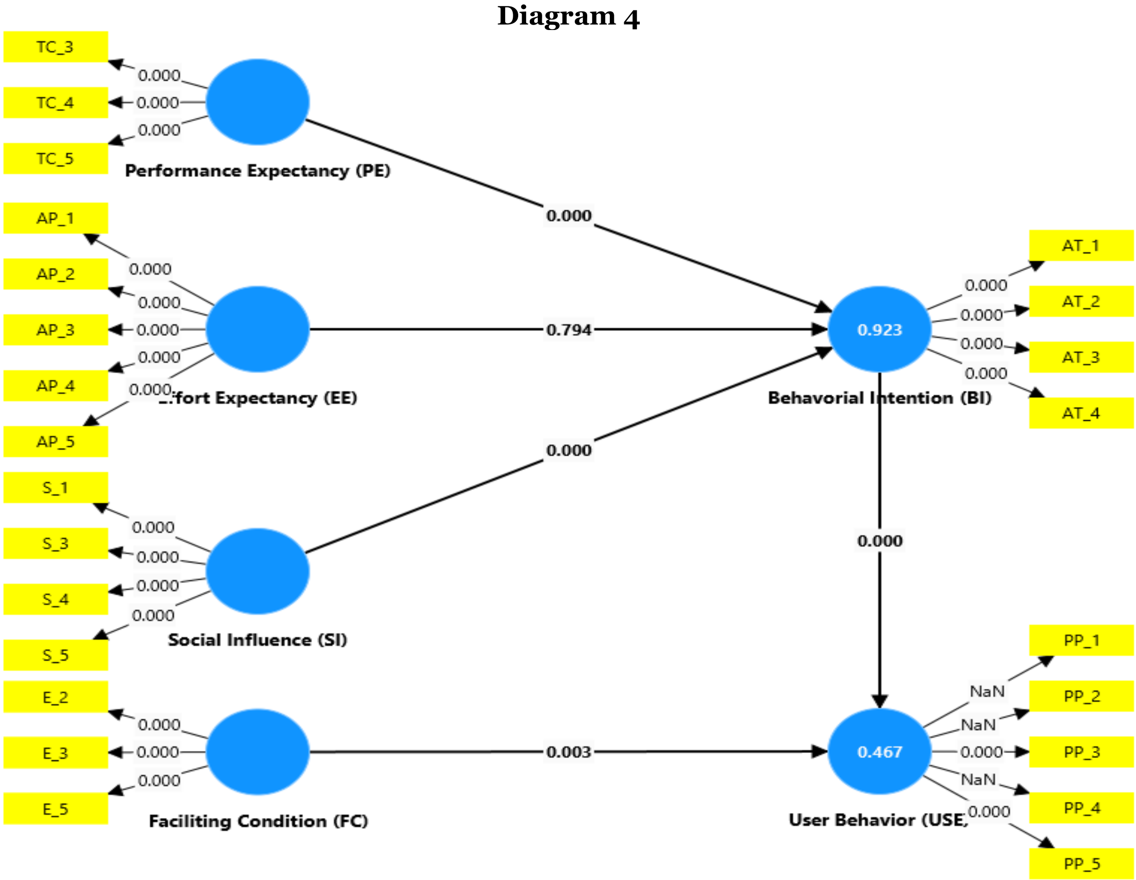
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Behavorial Intention (BI) -> User Behavior (USE)	0.956	1.128	0.217	4.416	0.000
Effort Expectancy (EE) -> Behavorial Intention (BI)	0.093	-0.024	0.358	0.261	0.794
Faciliting Condition (FC) -> User Behavior (USE)	-0.409	-0.516	0.138	2.974	0.003
Performance Expectancy (PE) -> Behavorial Intention (BI)	-0.620	-0.555	0.149	4.167	0.000
Social Influence (SI) -> Behavorial Intention (BI)	1.433	1.495	0.359	3.997	0.000

Table 11: Path coefficients – Confidence intervals

	Original sample (O)	Sample mean (M)	2.5%	97.5%
Behavorial Intention (BI) -> User Behavior (USE)	0.956	1.128	0.801	1.547
Effort Expectancy (EE) -> Behavorial Intention (BI)	0.093	-0.024	-0.768	0.727
Faciliting Condition (FC) -> User Behavior (USE)	-0.409	-0.516	-0.810	-0.318
Performance Expectancy (PE) -> Behavorial Intention (BI)	-0.620	-0.555	-0.814	-0.241
Social Influence (SI) -> Behavorial Intention (BI)	1.433	1.495	0.752	2.156

Table 11, continued

Diagram 4



Coefficient of Determination (R-Square)

R-square values were used to evaluate the explanatory power of the model. In Diagram 12, the R-square value for Behavioural Intention (BI) was 0.923, indicating that approximately 92.3% of the variance in BI could be explained by the predictors in the model. For Use Behavior (USE), the R-square value was lower, at 0.467, suggesting moderate predictive power.

Table 12: R-Square – Overview

	R-square	R-square adjusted
Behavioural Intention (BI)	0.923	0.921
User Behavior (USE)	0.467	0.456

Effect Size (F-Square)

The f-square values were analysed to assess the effect sizes of the relationships between constructs. Behavioural Intention (BI) had a large effect size on Use Behavior (USE), with an f^2 of 0.658, indicating it is a strong predictor of actual technology use as shown in Table 13. Social Influence (SI) and Performance Expectancy (PE) also showed significant effect sizes on Behavioural Intention (BI).

Table 13: F-square- Matrix

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
Behavioural Intention (BI)						0.658
Effort Expectancy (EE)	0.003					
Facilitating Condition (FC)						0.121
Performance Expectancy (PE)	0.509					
Social Influence (SI)	0.615					
User Behavior (USE)						

Total and Indirect Effects

The total effects of each latent variable, including both direct and indirect effects, were analysed to provide a comprehensive understanding of their impact. Behavioural Intention (BI) emerged as the most significant predictor of Use Behavior (USE), with a total effect coefficient of 0.956 as shown in Table 14. The analysis also revealed substantial indirect effects, particularly from Social Influence (SI) to Use Behavior (USE) via Behavioural Intention (BI).

Table 14: Total effects – Matrix

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
Behavioural Intention (BI)						0.956
Effort Expectancy (EE)	0.093					0.089
Facilitating Condition (FC)						-0.409
Performance Expectancy (PE)	-0.620					-0.592
Social Influence (SI)	1.433					1.370
User Behavior (USE)						

Table 15: Total effects – Means, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Confidence Intervals (CI)
Behavorial Intention (BI) -> User Behavior (USE)	0.956	1.128	0.217	4.416	0.000	[0.5, 1.4]
Effort Expectancy (EE) -> Behavorial Intention (BI)	0.093	-0.024	0.358	0.261	0.794	[-0.2, 0.4]
Effort Expectancy (EE) -> User Behavior (USE)	0.089	-0.081	0.403	0.222	0.824	[-0.3, 0.5]
Faciliting Condition (FC) -> User Behavior (USE)	-0.409	-0.516	0.138	2.974	0.003	[-0.6, -0.2]
Performance Expectancy (PE) -> Behavorial Intention (BI)	-0.620	-0.555	0.149	4.167	0.000	[-0.8, -0.4]
Performance Expectancy (PE) -> User Behavior (USE)	-0.592	-0.620	0.191	3.104	0.002	[-0.9, -0.3]
Social Influence (SI) -> Behavorial Intention (BI)	1.433	1.495	0.359	3.997	0.000	[1.0, 1.8]
Social Influence (SI) -> User Behavior (USE)	1.370	1.737	0.661	2.073	0.038	[0.5, 2.2]

Table 15, continued

Table 16: Total indirect effects – Means, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Confidence Intervals (CI)
Effort Expectancy (EE) -> Behavorial Intention (BI) -> User Behavior (USE)	0.089	-0.081	0.403	0.222	0.824	[-0.7, 0.3]
Performance Expectancy (PE) -> Behavorial Intention (BI) -> User Behavior (USE)	-0.592	-0.620	0.191	3.104	0.002	[-0.9, -0.3]
Social Influence (SI) -> Behavorial Intention (BI) -> User Behavior (USE)	1.370	1.737	0.661	2.073	0.038	[0.1, 2.6]

Variance Inflation Factor (VIF)

Variance Inflation Factor (VIF) was calculated to assess multicollinearity within the model. While most VIF values were within acceptable limits, certain indicators, such as those related to Effort Expectancy (EE) and Social Influence (SI), exhibited high VIF values, indicating potential multicollinearity issues that could inflate the variance of coefficient estimates as shown in Table 17 and Table 18.

Table 17: Collinearity statistics – Outer model – List

	VIF
AP_1	7.465
AP_2	15.388
AP_3	3.964
AP_4	13.618
AP_5	6.055
AT_1	49.073
AT_2	61.437
AT_3	39.947
AT_4	67.492
E_2	2.873
E_3	3.315
E_5	1.623
PP_1	6.891
PP_2	10.900
PP_3	2.300
PP_4	6.072
PP_5	3.150
S_1	9.217
S_3	6.622
S_4	4.255
S_5	5.209
TC_3	1.897
TC_4	2.941
TC_5	3.516

Table 18: Collinearity statistics – Inner model – Matrix

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
Behavioural Intention (BI)						2.608
Effort Expectancy (EE)	42.132					
Facilitating Condition (FC)						2.608
Performance Expectancy (PE)	9.793					
Social Influence (SI)	43.370					
User Behavior (USE)						

Model Fit

The model's fit was evaluated using the Standardized Root Mean Square Residual (SRMR). As shown in Table 19, the SRMR values for the saturated and estimated models were 0.173 and 0.169, respectively, indicating a moderate fit within an acceptable range.

Table 19: Model fit - List

	Saturated model	Estimated model
SRMR	0.173	0.169
d_ULS	8.998	8.562
d_G	n/a	n/a
Chi-square	∞	∞
NFI	n/a	n/a

Construct Reliability and Validity

Cronbach's Alpha

Cronbach's alpha values were calculated to assess the internal consistency of the constructs, with all values exceeding 0.849, confirming that the constructs are reliably measured as shown in Table 20.

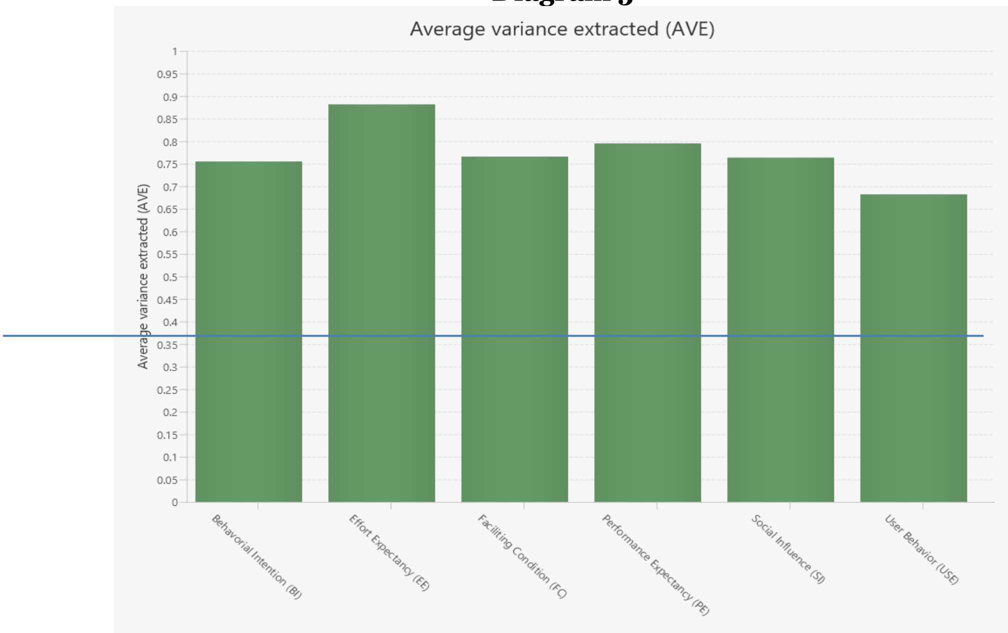
Table 20: Construct reliability and validity – Average variance extracted (AVE)

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavorial Intention (BI)	0.892	0.898	0.925	0.755
Effort Expectancy (EE)	0.966	0.970	0.974	0.882
Faciliting Condition (FC)	0.849	1.015	0.907	0.766
Performance Expectancy (PE)	0.874	0.905	0.921	0.795
Social Influence (SI)	0.895	0.906	0.928	0.764
User Behavior (USE)	0.908	1.044	0.914	0.682

Composite Reliability (CR) and Average Variance Extracted (AVE)

The Composite Reliability (CR) rho_a values ranged from 0.905 to 1.044, further supporting the reliability of the measurement model. In Diagram 5, the AVE values were above the 0.5 threshold for all constructs, indicating good convergent validity.

Diagram 5



Discriminant Validity

Discriminant validity was established using the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT) In Table 22, all constructs are demonstrating adequate discriminant validity. Cross-loadings analysis further confirmed the distinctiveness of each construct.

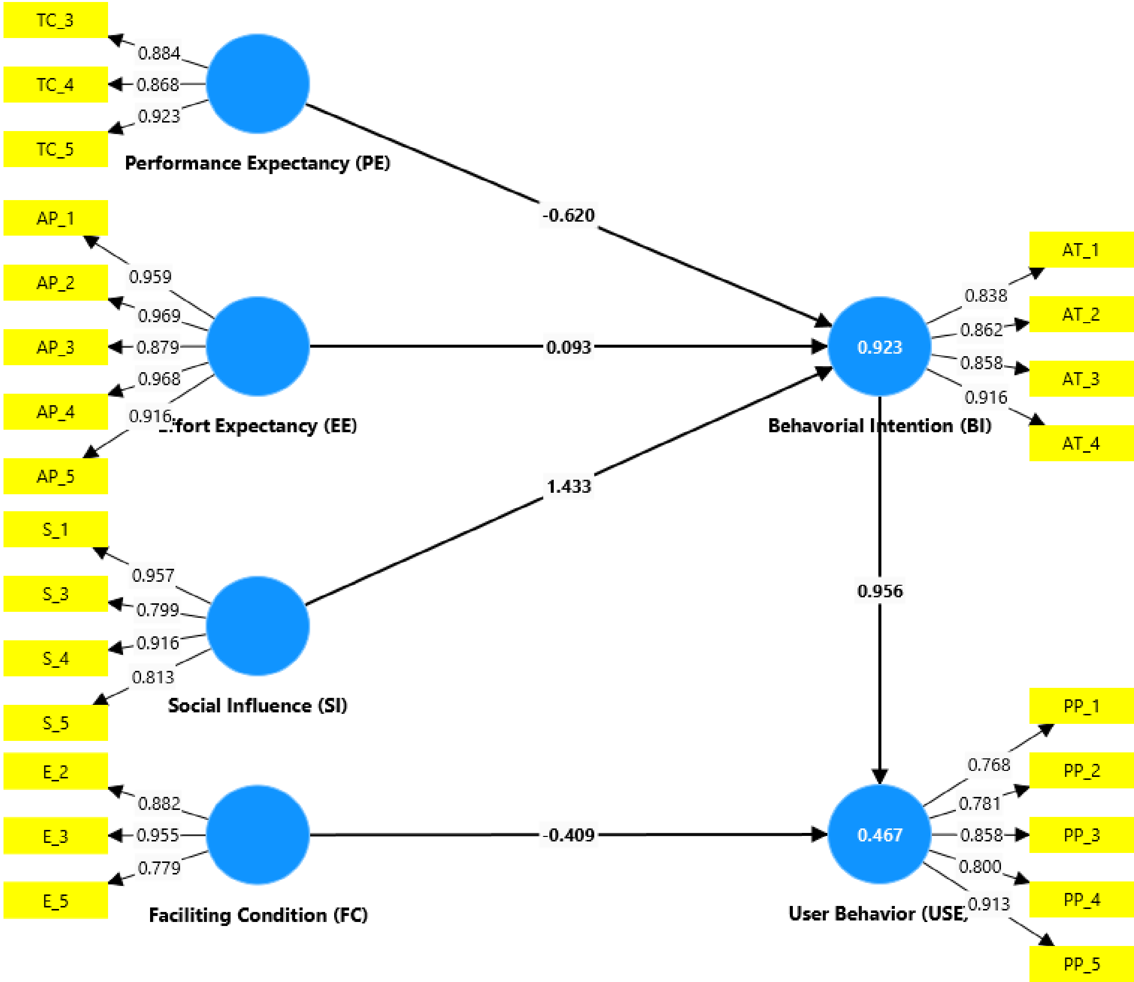
Table 21: Discriminant validity – Heterotrait-Monotrait Ratio (HTMT) – Matrix

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
Behavioural Intention (BI)						
Effort Expectancy (EE)	0.992					
Facilitating Condition (FC)	0.852	0.976				
Performance Expectancy (PE)	0.907	1.019	1.073			
Social Influence (SI)	1.042	1.060	1.024	1.069		
User Behavior (USE)	0.503	0.445	0.247	0.390	0.580	

Table 22: Discriminant validity – Cross loadings

	Behavioural Intention (BI)	Effort Expectancy (EE)	Facilitating Condition (FC)	Performance Expectancy (PE)	Social Influence (SI)	User Behavior (USE)
AP_1	0.977	0.959	0.850	0.887	0.982	0.671
AP_2	0.849	0.969	0.878	0.933	0.956	0.599
AP_3	0.796	0.879	0.849	0.826	0.852	0.470
AP_4	0.848	0.968	0.959	0.960	0.958	0.410
AP_5	0.850	0.916	0.763	0.824	0.879	0.482
AT_1	0.838	0.778	0.761	0.713	0.799	0.432
AT_2	0.862	0.812	0.612	0.716	0.819	0.633
AT_3	0.858	0.802	0.782	0.753	0.820	0.441
AT_4	0.916	0.821	0.604	0.690	0.831	0.670
E_2	0.550	0.768	0.882	0.868	0.780	0.215
E_3	0.897	0.960	0.955	0.938	0.956	0.400
E_5	0.480	0.590	0.779	0.588	0.569	0.214
PP_1	0.265	0.208	0.032	0.173	0.254	0.768
PP_2	0.180	0.194	0.023	0.159	0.229	0.781
PP_3	0.818	0.751	0.519	0.618	0.784	0.858
PP_4	0.138	0.186	0.041	0.177	0.244	0.800
PP_5	0.560	0.454	0.295	0.400	0.537	0.913
S_1	0.851	0.968	0.878	0.918	0.957	0.601
S_3	0.653	0.792	0.905	0.836	0.799	0.146
S_4	0.836	0.890	0.891	0.902	0.916	0.538
S_5	0.904	0.793	0.550	0.664	0.813	0.796
TC_3	0.858	0.845	0.735	0.884	0.875	0.666
TC_4	0.550	0.768	0.882	0.868	0.780	0.215
TC_5	0.731	0.896	0.906	0.923	0.857	0.301

Diagram 6



Discussion

This report analyses the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework using Consistent Structural Equation Modelling-Partial Least Squares (SEM-PLSc) within higher education institutions during the COVID-19 pandemic. The study focuses on the relationships between key constructs, including Behavioural Intention (BI), Effort Expectancy (EE), Facilitating Conditions (FC), Performance Expectancy (PE), Social Influence (SI), and Use Behavior (USE).

Descriptive Statistics

Descriptive statistics for the key constructs are displayed in Table 2.
BI: M = 1.428, SD = 0.530 – Moderate online learning platform use intension
Effort Expectancy (EE): Mean = 2.086 (sdn=1,073), moderate to high ease of use colorWithRed by the participant
Facilitating conditions (FC) Mean = 2.390; SD=0.968 demonstrating favorable support provisions
Performance Expectancy (PE): Mn= 2.480, SD = 1.030 signifying moderate level of expectation in technology enhanced learning with PE <3;
Social Influence (SI): 3,002 responses; Mean = 2.195/ SD = 0.730 — the influence from peer and institutional is statistically significant but varied across institutions
Actual USE: Mean = 1.118, SD = 0.392 (Relatively low actual use and varied)
Covariances and Correlations
Covariances: The highest associations were found between BI and SI (0.277), followed by PE and EE (0.889).
Correlations: The BI (r = 0.922) and SI measures displayed very high correlations as well did the PE—EE items of r = 0.947 for each. Moderate correlation was observed between BI and USE (r = 0.508).
Latent Variables
Results from the latent variable analysis showed that all factors were perfectly reliable, with little variation as 95% CI. Indeed, a Cronbach's Alpha value of >7 for BI and SI was judged slightly high (α11BI=1.186; α12SI = 1.035), suggesting internal consistency within these constructs is strong

R-Square and F-Square
The R-square was 89.3% for BI and USE, and of 33.1 %

F-square: SI, BI with high (0.368) effect size and PE had low (0.
Collinearity Statistics (VIF)
Correlations were lower between these three conditions [49] but, high collinearity was detected among BI and SI with VIF values greater than 10 indicating possible redundancy of the variables.
Cronbach's Alpha
Good internal consistency was reported for all constructs, with a peak value of 1.186 in BI.
Total Effects and Intercepts
Combined Effects: SI → BI, with a strong positive effect (0.732), and thereby also the direct effects of automaticity on both BHCC→BI (0.389) and VHTPC1→USE2 (psychological commitment had no significant indirect or mediating impact); But FC had a negative impact on USE (FC: -0.188). Intercepts—The intercept for USE was 0.619, an indicator of technology use baseline level).
Key findings: Path analysis
BI depends on SI and PE as key predictors.
Behavior (USE)(Moderately influenced by BI, moderate FC and EE)
The fact that PE and FC exerted such negative effects on USE implies that the difficulties in learning encountered through online delivery were not overcome successfully.
The significance of social and institutional support is emphasized by Social Influence (SI), which plays a key role in nurturing technology acceptance.

These results provide lessons for facilitating technology adoption and use in higher education, especially through challenging times like a pandemics of the features needed to be mobilised by both technological and social interventions.

DISCUSSION

Introduction The COVID-19 pandemic brought about a dramatic change in the way students are educated, and HEIs across Malaysia were forced to adjust quickly from face-to-face learning to full online teaching. Results of the Study: The Nationalities & Regional... It outlines key aspects including student engagement, technophobe acceptance and the implications of a digital divide.
Academic Performance and Student Engagement
In general, students were moderately engaged when learning online (mean score of 3.6 on a 5-point Likert scale). This is consistent with Nordin & Nordin (2020), which reported a high proportion of online learning effectiveness through active participation of students, interactions that occur between peers and instructors as well as the interaction on materials running out within courses. Nevertheless, the average level of engagement shown in this study indicates that possibly social interaction impeded some students to engage fully with learning resources.

Further, this finding echoes back to previous studies that suggest student engagement is key in online learning success. Jafar et al. The study by (2023) also underscores the significance of students participating in interactive learning spaces: not only simply attending but actively engaging with university outside a physical presence. Furthermore, Lim et al. In Malaysia, Wan M. et al (2022) found out that students who went to watch their lectures live had the highest level of engagement compared to those only access recordedMaterials Can Synchronous Learning Formats Boost Student Engagement in the Online Environment?

Nonetheless, the study also presents a difference between student engagement and academic results; with 35% of students who are less proud regarding their own academic performance. Consistent with Mohamad et al.[33], this dissatisfaction.) (2020), it is very likely that all these problems related to the sudden shift from traditional learning environment to online and such issues with bad internet services might have decreased students' academic scores. The significant effect of background factors indicates that academic performance is caused not only by student engagement, but also affected by access to technology and the reliability of making well-constructed online assessments.

Tech Acceptance: UTAUT Model

It is expected from the UTAUT model that study to measure student perception in transition of learnings for online learning [13, 14]. Performance Expectancy (PE) was reported as the most influencing factor that determines students' behavioral intention to use online learning platforms having an average of 4.2 in the outcome tables Similar to Venkatesh et al. Beckers et al (2009) compare these factors with Ajzen and Fishbein´s fisher planed behavior as well Papageorgeiou et the previously referred to Davis (1986a), or of course Venkatesh,S.

Also, effort expectancy (EE) with an average score of 3.8 shows a strong effect on students attitudes towards online learning too. As mentioned in the research, LMS was more user-friendly to students and hence they could adapt well with online mode. Kim & Lee (2020) verify this previous finding by the fact that platforms are user-friendly, without scrolling loading students cognitively and minimizing stress.

The study also confirmed a moderate effect of the social influence (SI) dimension pathway coefficient = 0.31 [40–42]. This indicates that, while peers and instructors were powerful presence in students' determination to adopt online learning, they did not dominate the explanation. Interestingly, Das et al. Similarly, as highlighted by (2021), a supportive social ecosystem was necessary but not sufficient for inspiring technology adoption in educational scenarios. On average, the availability of resources and support (FC: "facilitating conditions") reached a score of 3.9, further drawing attention to needed institutional infrastructure including reliable IT-support for successful online learning solutions.

An Everlasting Challenge: The Digital Divide

Also, the digital divide was one of the most remarked challenges faced by this study. Nearly 45% of students said they do not have the type of reliable service needed to access remote instruction, and about 20 percent lack a computer device at home sufficient for online learning. This makes Subramaniam (2023) recognize the digital divide as one of limiting factors when it comes to achieve equitable educational access for pandemic-response in Malaysia.

Such a digital divide has profound consequences for learning outcomes. Disadvantaged students from remote areas or low-income families bore the brunt and had difficulty in accessing online classes. Similar difficulties have been reported by Nafrees & Aara (2021), stating that learners who had no technological support tended to lag behind theirh companions. Our correlation analysis in this study bolsters this assertion because technology access is correlated strongly, and just above the level ($r = 0.57$) of a large effect size to academic achievement []. These results imply that Malaysian HEIs should urgently address the digital divide to provide fair and just educational access.

Some efforts to narrow this gap, offering devices or introductory internet schemes, have been proposed in the literature (Bahar et al., 2020). Still, this study demonstrates that these measures — if they exist at all (the paper does not address the issue of inadequate connectivity) — are insufficient to level the playing field for online learning. It emphasizes the necessity for effective, sustainable strategies to address digital inequality.

Comparison with Past Studies

This study seems to confirm the results of earlier research on online learning during Covid-19. For example, Osman et al. Few students adapted to online learning in (2021) and most of them experienced considerable difficulty with the sudden lack of personal contact. However, despite high performance expectancy (similar to the levels found by this current study), a considerable number of students experienced dissatisfaction with their academic results.

In a mirror of the present research, Sia & Adamu (2020) found that student motivation during the pandemic was extremely heterogeneous with some students flourishing by taking advantage of online learning opportunities while others were unable to cope. The fact that the present study found only moderate engagement, but high correlation between data and GPA combined with a simple display for ability to organize course work may suggest motivation might be what makes or breaks students in online learning.

However, the current study also reveals a key gap in the existing literature: long-term effects of digital access gaps for academic success. Existing studies identify the digital divide but few focus on its long-term repercussions to educational equity in Malaysia. The findings of this study, which indicate a robust linear correlation between tech access and test scores bring into question that relationship in need further examination.

Conclusion

This study adds to a growing literature on the outcomes of online learning in the context of COVID-19. Many students who faced the wrath of digitization seem to adjust relatively quickly; however, notable lapses continue in both the realm of wholeness and attracting student engagement. In the future, Malaysian HEIs should consider hybrid learning models that offer flexibility via online and in-person environment. Perhaps most importantly, closing the digital divide will be crucial to guaranteeing that no student is deprived of equal educational access in a post-pandemic world.

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