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Determinants and Implications of Online Class Adoption among University Students during COVID-19: Insights from the UTAUT Model

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Abstract

This study investigates the driving factors behind positive perceptions, attitudes, and behavioral intentions related to online class adoption among university students during COVID-19, utilizing a refined UTAUT model. It elucidates students' reflections on their recent virtual learning experiences through responses to an online questionnaire. A cross-sectional, quantitative survey was employed, gathering data from 414 voluntary participants and analyzed using the Exploratory Structural Equation Model (ESEM). The thematic representation of qualitative responses revealed insights into the multifaceted experiences of learners. Findings suggest performance expectancy, social influence, and facilitating conditions as influential determinants shaping attitudes, with performance and effort expectancy, along with social influence, impacting behavioral intentions to embrace online learning. Participants acknowledged the imperative and beneficial nature of governmental mandates on virtual learning but called for increased practicality. Challenges were mainly due to resource scarcity and lack of proficiency in adapting to new learning modalities. Concerns were raised regarding the effectiveness of online classes in enhancing academic performance. The derived insights are pivotal for stakeholders, policymakers, and administrators, emphasizing the necessity for strategic interventions to optimize online learning experiences in the prevailing pandemic scenario.

Keywords: *UTAUT Model, Online Learning, University Students, COVID-19, Behavioral Intentions, Virtual Learning Adoption, Quality Education during a pandemic*.

INTRODUCTION

The abrupt emergence of the COVID-19 pandemic has precipitated a profound reliance on online classes, sparking extensive debate and research in the realms of education and technology acceptance. The question of which factors promote positive perceptions, intentions, or adoption of online learning has piqued the interest of social scientists particularly within this unprecedented context.

Various technology acceptance models, whether long-established or recently developed, aim to identify pivotal factors leading to user acceptance, each sharing the fundamental premise that external elements trigger individual

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reactions, shaping intentions and subsequently actual technology usage (Venkatesh, Morris, Davis, & Davis, 2003).

It has been empirically validated that there are significant factors (Wang, & Liu, 2019) leading university students to take online courses (Tseng, Lin; Okuboyejo, & Adeniji, 2018; Mei, et al., 2018) prior to the pandemic. Within the pandemic framework, current research confirms that theorized factors influencing attitude (Lazim et al., 2021), intentions (Tiwari, 2020), and actual technology use (Samat et al., 2020) are positively correlated. Nevertheless, some have contested these implications (Chayomchai, 2020), suggesting inconclusive or contradictory correlations (Sangeeta & Tandon, 2020; Sukendro et al., 2020).

One widely used method in these research studies is the implementation of the Unified Theory of Acceptance and Use of Technology model (UTAUT) (Venkatesh et al., 2003). This model combines elements from different acceptance theories to create cohesive constructs, resulting in the creation of customized models for specific situations, such as the extended and revised UTAUT models (Venkatesh et al., 2012; Dwivedi et al., 2019).

The current study amends the UTAUT model (Fishbein & Ajzen, 1975; Tandon & Kiran, 2019; Tandon & Kiran, 2019; Dwivedi et al., 2019; Sangeeta & Tandon, 2020) and presents a new theoretical framework that incorporates attitude, disregards non-practical moderators, and explores alternative pathways to understand their significance in shaping behavioral intention, especially in light of the ongoing pandemic where the actual use behavior has been observed to be incongruous with the intention.

This research aims to analyze the impact of revised UTAUT factors on the behavioral intention of students at Rajamangala University of Technology, Tawan-ok, regarding the adoption of online classes. The study is conducted in the context of the COVID-19 pandemic and the government's promotion of online learning (Mala, 2020; Mala, 2021). The objective is to gain insights into students' perspectives and experiences with current online courses. The proposed research emphasized providing valuable recommendations for university stakeholders, policymakers, and administrators to enhance the transition to and implementation of online learning during pandemic.

LITERATURE REVIEW

2.1 Theoretical Models

Research focusing on technology acceptance has perennially emphasized understanding user behavior and establishing the critical factors influencing individuals' interaction and adaptation to information technology (IT) and information systems (IS). This focus gained prominence in the 1980s, marked by a surge in IT & IS investments (Westland & Clark, 2000), reflecting the realization that the efficacy of technology is inherently linked to the user's acceptance.

Classical Models

The Theory of Reasoned Action (Fishbein & Ajzen, 1975) posits that user behavior is determined by behavioral intentions, attitudes, and subjective norms. Following this, Technology Acceptance Model (Davis, 1989) was conceptualized, focusing on an individual's perception of the technology’s usefulness and ease of use as determinants of acceptance or adoption.

Advancements and Integrations

The Theory of Planned Behavior, as proposed by Taylor and Todd in 1995, brought about significant advancements in the realm of behavioral models by introducing the element of perceived control as a key determinant of behavioral intention. In addition to this foundational theory, various other models have contributed to the enriched comprehension of technology acceptance dynamics. These include the Motivational Model introduced by Davis and colleagues in 1992, the Combined TAM & TPB model devised by Davis in 1989, the Model of PC Utilization formulated by Thompson and colleagues in 1991, the Innovation Diffusion Theory put forth by Moore and Benbasat in 1991, and the Social Cognitive Theory by Compeau and Higgins in 1995. Each of these models has played a distinctive role in enhancing our insights into the complex landscape of technology adoption and utilization.

Contemporary Adaptations

The pandemic-induced surge in online learning prompted a plethora of studies, exploring and validating theoretical models in the context of the sudden shift to virtual environments. For instance, studies by Imsa-ard (2020) and Tiwari (2020) explored perceptions and impacts on students regarding the abrupt transition to and adoption of online learning, reflecting the evolving dynamics in technology acceptance in education.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model (Venkatesh et al., 2003) is a framework that integrates various factors from earlier models into clear constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions. This model has been useful in understanding both behavioral intentions and actual usage, taking into account factors such as age, gender, experience, and the voluntariness of usage. The model has been refined into UTAUT2 (Venkatesh et al., 2012) and the Revised UTAUT (Dwivedi et al., 2019) to cater to specific requirements across different settings.

The labyrinth of theoretical models, from classical theories to contemporary adaptations, continues to illuminate the multifaceted nature of technology acceptance, reflecting the evolving interplay between user perceptions, behavioral intentions, and external influences, especially in the paradigm of unprecedented global events like pandemics. The ongoing advancements in these theoretical frameworks are pivotal for aligning technology design and implementation with user expectations and preferences, ensuring a harmonious integration of technology in our daily lives.

2.2 Hypotheses Development

The research hypotheses were developed in accordance with recent investigations into students' adoption of online learning, particularly in light of the COVID-19 pandemic. The study utilized the revised Unified Theory of Acceptance and Use of Technology (UTAUT) framework, as outlined by Dwivedi and colleagues in 2019. This framework builds upon the foundational work of the original UTAUT introduced by Venkatesh and colleagues in 2003. By incorporating the framework, the study was able to provide a thorough and current examination of technology adoption in the context of online learning. Additionally, the inclusion of the 'attitude' construct in this model helps to enhance the understanding of behavioral intention (Davis, 1989; Taylor & Todd, 1995), a concept supported by previous studies (Fishbein & Ajzen, 1975; Dwivedi et al., 2017).

The deliberate exclusion of the final dependent variable, 'use behavior', is premised on recent insights indicating its potential insignificance in mandatory settings, where students have no alternative but to pursue their studies online.

Specific Hypotheses Development

- Hypotheses 1-9: These are dedicated to examining the influence of the revised UTAUT factors on students' attitude and their behavioral intention.

- Hypotheses 10-13: Students' behavior towards adopting online classes is investigated in relation to exogenous UTAUT factors, and attitudes play a mediating role in this relationship.

Each hypothesis is meticulously structured to provide nuanced insights into the intricate dynamics of students' approach and interaction with online learning platforms during unprecedented circumstances like a pandemic. By delving into the associations between varied UTAUT constructs and behavioral intentions, this segment aims to render a comprehensive understanding of the factors propelling or impeding the adoption of online learning modalities.

The carefully calibrated inclusion and exclusion of variables in this study are designed to offer a focused lens on the most pivotal elements influencing online learning adoption, thereby shedding light on the crucial areas that warrant consideration in designing and implementing online learning frameworks, especially in compulsory learning environments. The exploration of these hypotheses will enrich the discourse around technology acceptance in education, providing actionable insights for optimizing the alignment between user preferences and technological solutions.

2.2.1 Performance Expectancy → Attitude & Behavioral Intention

It is a fundamental in understanding user acceptance and use of technology, denoting the extent to which an individual believes utilizing a system will augment their job or task performance (Venkatesh et al., 2003). In the foundational UTAUT model, attitude was presumed to be inherently integrated within performance and effort expectancy. However, the revision by Dwivedi et al. (2019) argued for the distinct retention of 'attitude,' emphasizing its critical role in shaping an individual's interaction with technology, influenced by perceptions of performance improvement or deterioration and ease or difficulty of use. Both voluntary and mandatory settings of technology use retain performance expectancy as a key determinant of behavioral intention (Venkatesh et al., 2003).

Hypotheses

- Ha1: As a result of the COVID-19 pandemic, students' performance expectations will significantly influence their attitude toward online classes.

- Ha2: When the COVID-19 pandemic hits, students' performance expectations will significantly impact their decision to take online classes.

The centrality of performance expectancy in this model recognizes the weight individuals place on the anticipated outcomes and benefits of utilizing a system or technology. If students perceive that the adoption of online classes will yield substantial enhancements in their learning experience and outcomes, it is likely to foster a favorable attitude and effective behavioral intention to adopt such technology.

In this context, exploring the relationship between performance expectancy, attitude, and behavioral intention provides profound insights into the motivational drivers behind students' inclination or reluctance to embrace online classes amidst the pandemic. Understanding this dynamic is crucial for educators and policymakers as they navigate the integration of technology in educational environments, ensuring that the technology not only meets but exceeds the performance expectations of the students, subsequently fostering positive attitudes and intentions to use.

2.2.2 Effort Expectancy → Attitude & Behavioral Intention

Effort expectancy, as defined by Venkatesh and his colleagues in 2003, represents the level of ease that users associate with the utilization of a system. This concept holds a pivotal role within technology acceptance models, encapsulating the user's subjective perception of how user-friendly a particular technology is. Much like performance expectancy, effort expectancy carries substantial weight in both voluntary and obligatory technology usage scenarios, making it crucial to comprehend its impact on users' attitudes and their subsequent intentions to use a given technology. Understanding the influence of effort expectancy is paramount for a comprehensive exploration of technology adoption behavior.

Hypotheses

- Ha3: The positive influence of effort expectancy on students' attitudes toward adopting online classes during the COVID-19 pandemic is significant.

- Ha4: The positive impact of effort expectancy on students' intention to adopt online classes during the COVID-19 pandemic is significant.

Effort expectancy emphasizes the importance of the user-friendly experience in technology adoption. In the context of online learning, if students perceive the technology to be straightforward and easy to use, it is likely to cultivate a positive attitude and an enhanced behavioral intention to adopt online classes.

Understanding the relationship between effort expectancy and both attitude and behavioral intention is pivotal in implementing online learning systems. A system perceived as user-friendly and intuitive is more likely to be embraced by students, reducing resistance and fostering a conducive learning environment. It underscores the necessity for educational institutions and system developers to prioritize user experience and simplicity in designing and implementing online learning platforms, as these are crucial factors determining the adoption success amidst the abrupt transitions and adaptations necessitated by the COVID-19 pandemic.

Given the mandatory nature of online classes during the pandemic, the ease of use becomes even more critical, as students have no alternative but to adapt to the new learning modality. The incorporation of user-friendly features, clear instructions, and support can significantly alleviate the perceived effort, enhancing students’ attitude and intention to use the online learning systems effectively. This comprehensive understanding of effort expectancy’s influence on attitude and behavioral intention is essential to facilitate smoother transitions to online learning environments and ensure the attainment of learning objectives.

2.2.3 Social Influence → Attitude & Behavioral Intention

Social influence, as described by Venkatesh and colleagues in 2003, refers to how much individuals believe that influential people in their lives support the use of a new system. This idea encompasses the significant influence that societal and peer pressures have on shaping individuals' attitudes and behaviors towards adopting technology. Recognizing the role of social influence is essential for understanding how people embrace and engage with technology, highlighting the impact of the collective on individual decisions and actions. The revised UTAUT model by Dwivedi et al. (2019) also emphasizes the interplay between external social pressures and individual internal attitudes in influencing behavioral intentions, reflecting that an individual's actions, while being influenced by referents, may also align with their intrinsic beliefs and feelings (Davis, 1985; Warshaw, 1980).

Hypotheses

- Ha5: Social influence will significantly and positively influence students' attitude toward adopting online classes during the COVID-19 pandemic.

- Ha6: The influence of social factors will have a significant and positive impact on students' intention to use online classes during the COVID-19 pandemic.

Social influence emphasizes the role of external factors like peer opinions and societal norms in shaping individual attitudes and behaviors. In the context of online learning during the COVID-19 pandemic, students might experience both external and internal pressures influencing their adoption of online classes.

Understanding the relationship between social influence and students' attitudes and intentions is crucial, as it highlights the impact of the external environment on individual decisions. For example, a supportive and encouraging environment created by peers, family, and educators can positively influence students' attitudes and, in turn, their behavioral intentions toward adopting online classes, even when faced with challenges.

The external pressures, combined with internal alignments, create a complex environment where students navigate their choices, balancing what is expected of them with what they believe and feel. Educational institutions can leverage this understanding by fostering a supportive and inclusive learning environment and encouraging positive social norms around online learning. This would not only align external social influence with individual internal attitudes but also enhance the overall acceptance and effectiveness of online learning during such unprecedented times.

The exploration of the intersection between social influence and individual attitudes in the revised UTAUT provides a richer, more nuanced understanding of the dynamics involved in technology acceptance, especially in mandatory and emergency settings like the COVID-19 pandemic, allowing for more effective interventions and strategies to enhance online learning adoption.

2.2.4 Facilitating Conditions → Attitude & Behavioral Intention

The extent to which individuals perceive that there exists an organizational and technical infrastructure to support the use of the system is referred to as facilitating conditions (Venkatesh et al., 2003). This component is crucial as it deals with the perceived ease and support available to individuals when interacting with a new system, influencing technology acceptance in both voluntary and mandatory settings.

In the refined UTAUT model by Dwivedi et al. (2019), the role of facilitating conditions was expanded to include its impact on attitudes, acknowledging the supportive contexts and resources, such as training and help desks, that can help shape positive attitudes and behaviors toward technology use. This emphasizes the importance of providing the necessary support and resources to help individuals adapt to new technologies and systems, particularly in the adoption of online classes during the COVID-19 pandemic.

Hypotheses

- Ha7: The favorable conditions will have a considerable and positive impact on the students' inclination to use online classes during the COVID-19 pandemic.

- Ha8: The favorable conditions will significantly and positively impact the students' willingness to use online classes during the COVID-19 pandemic.

Facilitating conditions, including the availability of support, resources, and infrastructure, play a pivotal role in shaping individual attitudes and behaviors towards technology adoption. In the context of online learning, when students perceive that there are adequate support and resources available to help them navigate the online learning environment, they are more likely to develop positive attitudes and intentions towards online classes.

This underscores the importance for educational institutions to ensure that students have access to the necessary support and resources, including technical assistance and training programs, to facilitate their adaptation to online learning platforms. Such supportive environments can help in mitigating the challenges and anxieties associated with online learning and can significantly impact students' acceptance and usage of online learning systems.

The enhanced understanding of the role of facilitating conditions in the revised UTAUT model provides insights into the multifaceted relationship between external support, individual attitudes, and behavioral intentions. It emphasizes the need for a holistic approach in designing and implementing online learning systems, considering both the external environment and individual perceptions, to ensure successful technology adoption in unprecedented situations like the COVID-19 pandemic.

2.2.5 Attitude → Behavioral Intention

Attitude is a crucial construct when exploring behavioral intentions. Despite being overlooked in the original UTAUT model, the UTAUT model proposed by Dwivedi et al. (2019) re-emphasizes the importance of attitude in determining behavioral intention, aligning with the prevailing literature in behavioral sciences and technology acceptance.

Hypothesis

- Ha9: The students' behavioral intention to adopt online classes is significantly influenced by their attitude during the COVID-19 pandemic.

Dwivedi et al. (2019) argue that attitude is a significant predictor of behavioral intention, serving as a key mechanism through which individuals form intentions to perform behaviors towards which they have positive feelings. This notion supports the widely accepted belief in the literature that an individual's positive attitude toward a technology or system will significantly contribute to their willingness to use it.

The significance of the study lies in the comprehension of the attitude's role, which provides a deeper understanding of how students perceive and respond to online classes during the pandemic. A positive attitude toward online learning platforms can create a favorable learning environment, encouraging active participation and engagement, and ultimately affecting their willingness to adopt online classes.

The revised UTAUT model proposed by Dwivedi et al. (2019) provides a more nuanced perspective on how personal evaluations and predispositions impact technology acceptance and usage. By examining how attitudes influence behavioral intentions, this study can offer valuable insights for educators and policymakers looking to enhance the adoption of online learning platforms, especially during times of unprecedented change, such as the COVID-19 pandemic. By fostering positive attitudes towards online learning, stakeholders can develop more effective strategies to promote digital learning and facilitate the adoption of innovative educational technologies.

The integration of attitude in the revised UTAUT model underscores its pivotal role in shaping behavioral intentions towards technology adoption. In the context of students facing the challenges brought about by the COVID-19 pandemic, it is important to understand the connection between one's attitude and their intention to act. This understanding is crucial in promoting the effective and widespread implementation of online classes, which in turn enhances the resilience and adaptability of educational systems when faced with unexpected disruptions.

2.3 Conceptual Framework

The enhanced conceptual framework employed in this research draws its primary inspiration from the revised UTAUT Model, as put forth by Dwivedi and colleagues in 2019. This model has been chosen as it accommodates the complexity and diverse variables affecting technology acceptance and use, particularly in an educational context amid the COVID-19 pandemic. Within this model, the interplay between four core constructs—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—is explored, each mediated by attitude, to elucidate their impact on behavioral intention. It is crucial to note that the final factor, ‘use behavior,’ has been deliberately excluded from this framework due to its insignificance in the mandatory settings of the current study.

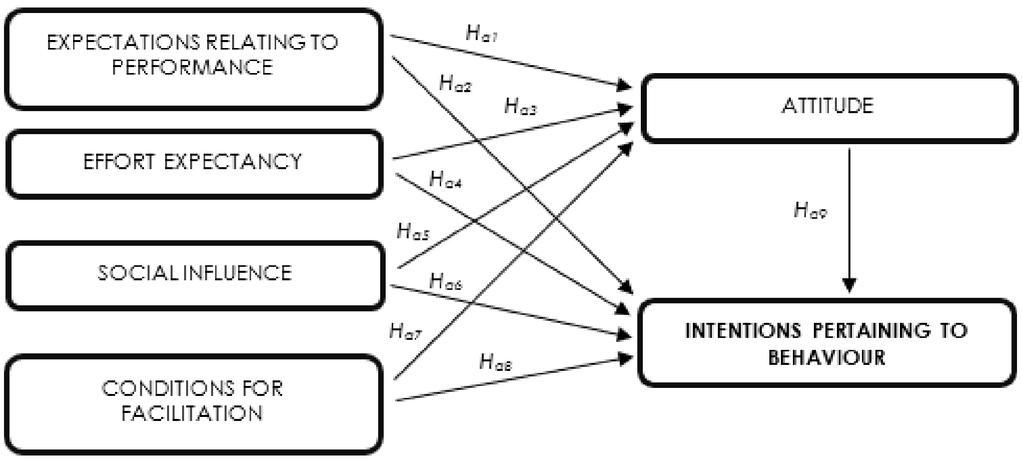

Figure 1. This Study’ Proposed Model

In this proposed model, each construct, aligned with revised UTAUT Model theories, acts as a potential predictor of students' attitudes and behavioral intentions towards the adoption of online learning during the pandemic. A clear and concise depiction of relationships among these constructs is pivotal for guiding the subsequent research processes and understanding the nuances of technology adoption in the educational sphere.

Key Components of the Model:

1. Performance Expectancy: Anticipated gains in job or academic performance due to system use.

2. Effort Expectancy: Users' perception of the system's ease of use.

3. Social Influence: Individuals' perception of the extent to which others believe that they should use the new system.

4. Facilitating Conditions: Individuals' beliefs about the organizational and technical infrastructure supporting system use.

5. Attitude: Perception of the behavior by the individual as positive or negative.

6. Behavioral Intention: An individual's conscious intention to commit to or abstain from a specific future action.

The model hypothesizes that the four constructs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions) significantly influence attitude, which in turn significantly influences behavioral intention to adopt online classes during the COVID-19 pandemic.

Implications of the Model:

This model provides a structured approach to analyze and understand the myriad factors influencing students' acceptance and use of online learning technologies. By evaluating the interrelations between these key constructs, educators and policymakers can garner insights to formulate effective strategies and interventions to foster a positive attitude and enhance the adoption of online learning platforms, ensuring continuity and adaptability in education during challenging times.

The conceptual framework, grounded in the revised UTAUT model, serves as a robust theoretical base to investigate the underlying dynamics affecting students' attitudes and behavioral intentions towards online learning. By exploring the relationships between these core constructs, this study aims to contribute valuable knowledge and practical recommendations to optimize the implementation and reception of online education systems amidst the ongoing global pandemic.

RESEARCH METHODOLOGY

This study utilized a non-experimental quantitative research design to gather voluntary responses from university students. A total of 414 students from Rajamangala University of Technology, Tawan-ok (RMUTTO), who were enrolled in Semester 1, 2021, participated in the research. The student sample was diverse, including variations in gender, age, faculty, and campus affiliations. Data collection was conducted through a Google Forms questionnaire, consisting of an introduction, demographic information, a 23-item Likert scale survey, and three open-ended questions to ensure a thorough assessment.

The validity and reliability of the questionnaire were assured by adopting items from established studies, expert reviews, and a pilot test, yielding acceptable Cronbach's Alpha scores for each construct as follows:

Table 1. Instrument's Reliability

Constructs	α
Expectations Relating to Performance	.894
Effort Expectancy	.903
Social Influence	.843
Conditions for Facilitation	.907
Attitude	.937
Intentions pertaining to behavior	.953

The questionnaire was provided in Thai to accommodate the participants' language preference. Upon receiving approval from the university's president, the questionnaire was disseminated through email links by the university's ICT department, focusing on students' experience with and attitudes toward online learning. The responses were collected over two weeks.

In order to describe characteristics, explain central tendencies, and validate constructs and their relationships, descriptive statistics and an exploratory structural equation model (ESEM) were utilized to analyze the gathered data.

1. Descriptive Statistics: These statistical techniques are utilized to provide a comprehensive overview of the data's central tendencies and variability, which may include measures such as the mean, range, and standard deviation.

2. Exploratory Factor Analysis (EFA): EFA is employed as a tool for assessing and validating the construct items within the data.

3. Confirmatory Factor Analysis (CFA): CFA serves as a valuable method for confirming the validity of the constructs defined in the study.

4. Structural Equation Model (SEM): SEM is strategically employed to scrutinize and validate the relationships between constructs in the research framework.

In the case of open-ended questions regarding students' embrace of online classes, responses were systematically grouped into common themes and then quantified, allowing for the presentation of results in tabular statistics. This meticulously designed research methodology aimed to explore the university students' attitudes and behavioral intentions towards online learning, using a validated and reliable instrument. The insights derived from this study are expected to significantly contribute to understanding the dynamics of online learning adoption among university students.

ANALYSIS OF DATA

4.1 Descriptive Statistics

Demographic information is shown in Table 2

N = 414	**Learners**	
	f	**%**
Gender		
male	112	27
female	302	73
Age		
18-30	388	94
31-40	14	3
41-50	9	2
51 and above	3	1
Campus		
Bang Phra	90	22
Chantaburi	102	25
Chakrabongse Bhuvanat	207	50
Uthen Thawai	15	3

The majority of the respondents were female, making up 73% of the total, with males constituting 27%. The vast majority of participants were aged 30 and below, representing 94% of the total. Only 6% were above the age of 30. Half of the respondents belonged to the Chakrabongse Bhuvanat Campus. The other three campuses had significantly lower representation, with Bang Phra and

Chantaburi campuses at 22% and 25%, respectively, and Uthen Thawai Campus at just 3%.

Table 3. Mean & Standard Deviation

Construct Items		**Learners**	
		x̄	**σ**
Performance Expectancy			
1. *In an outbreak such as the COVID-19, adopting classes online would be useful.*	PE01	3.72	1.189
2. *It is easier for me to achieve tasks when I take classes online.*	PE02	3.36	1.358
3. *By taking classes online, I am able to accomplish tasks more easily.*	PE03	3.22	1.296
4. *By taking classes online, I can improve my educational performance.*	PE04	3.13	1.430
Effort Expectancy			
5. *It would be clearer and easier to understand classes if they were offered online.*	EE01	3.02	1.344
6. *It would be easy for me to become skillful at adopting classes online.*	EE02	3.06	1.309
7. *The process of adopting classes online would be easy for me.*	EE03	3.62	1.273
8. *The process of adopting classes online is easy for me.*	EE04	3.61	1.304
Social Influence			
9. *A person who influences my behavior recommends I take online courses during outbreaks like COVID-19.*	SI01	3.75	1.197
10. *I am being encouraged to take online courses by people I respect.*	SI02	3.64	1.234
11. *The support of those in my social circle has positively influenced my transition to online classes.*	SI03	3.70	1.234
12. *I have been supported in my adoption of online courses by the university.*	SI04	3.50	1.239
Facilitating Conditions			
13. *It is feasible for me to teach online during an outbreak like COVID-19 since I have the resources to do so.*	FC01	3.30	1.328
14. *I possess the requisite knowledge for embracing online classes*	FC02	3.51	1.189
15. *It is compatible with other technology I use to take online classes.*	FC03	3.77	1.134
16. *If I have difficulty adopting classes online, assistance is available.*	FC04	3.46	1.236
Attitude Towards Use of Technology			
17. *My instructor is available to assist me if I am having difficulty adopting classes online.*	ATT01	3.81	1.275
18. *Adopting online classes is more interesting.*	ATT02	3.17	1.395
19. *Adopting online makes classes fun.*	ATT03	3.22	1.394
20. *I can contact my instructor if I need help adjusting to online courses.*	ATT04	3.40	1.431
Behavioral Intention			
21. *I intend to adopt online classes when an outbreak like COVID-19 happens.*	BI01	3.95	1.203
22. *In the event of an outbreak like COVID-19, I am confident I will use online classes.*	BI02	3.97	1.171
23. *In the event of an outbreak such as COVID-19, I intend to adopt online classes.*	BI03	4.00	1.147

Table 3 provides an insight into the participants' perceptions and attitudes towards adopting online classes, represented using a Likert scale.

• Performance Expectancy: The majority of the students recognized the utility of adopting online classes during outbreaks like COVID-19. The average score for this construct ranged from a neutral stance on better educational results (3.13) to a favorable view of online class adoption during the pandemic (3.72).

• Effort Expectancy: Students showed a mixed response. While they found online classes generally clear and understandable (3.02), they strongly felt that learning and using online classes were easy, with scores of 3.62 and 3.61, respectively.

• Social Influence: Participants indicated a mild agreement on feeling encouraged by influential people in their lives to adopt online classes during the pandemic, with scores ranging from 3.50 to 3.75.

• Facilitating Conditions: The respondents showed a neutral to mild agreement on having the necessary resources and knowledge for online class adoption. They showed stronger agreement (3.77) on the compatibility of online classes with other technologies they use.

• Attitude Towards Use of Technology: The learners displayed a range of attitudes towards the adoption of online classes. While they were neutral about online classes being more interesting (3.17), they seemed to agree more that online classes were a good idea during an outbreak (3.81).

• Behavioral Intention: This construct revealed strong agreement among the learners about their intention, prediction, and plan to adopt online classes during outbreaks like COVID-19. The scores were closely clustered, ranging from 3.95 to 4.00.

In conclusion, the data illustrates that while learners see the utility and benefits of online class adoption during outbreaks, their perceptions towards the actual implementation and experience of online classes are mixed. The descriptive statistics provide a foundation for deeper analysis of the factors affecting learners' behavioral intentions.

4.2 Data Analysis

4.2.1 Construct Items Analysis

When using the ESEM method introduced by Asparouhov and Muthén in 2009, the first step involves conducting an Exploratory Factor Analysis (EFA) according to the guidelines provided by Child in 1990. This initial procedure aims to evaluate the construct items and determine their appropriateness, validity, and reliability. These assessments are crucial for ensuring the reliability of subsequent analyses, such as the Confirmatory Factor Analysis (CFA) discussed by Marsh and colleagues in 2010.

Table 4. Demonstrates the results of SPSS: KMO and Bartlett’s Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.940
Bartlett's Test of Sphericity	Approx. Chi-Square	8054.223
	df	105
	Sig.	.000

For data adequacy, initial results yielded a .964 KMO value and a .000 significance in Bartlett’s Test. After eliminating instances of cross-loading, the KMO value was adjusted to .940, with Bartlett’s Test maintaining a .000 significance. This adjustment indicates that the construct items remained appropriate for establishing construct relationships, supporting the concept of data adequacy in ESEM (Arsham & Lovric, 2011).

Table 5. Demonstrates the results of SPSS: Component Correlation Matrix

Component Correlation Matrix

Component	1	2	3	4	5	6
1	1.000	.548	.606	.452	.650	.629
2	.548	1.000	.715	.634	.627	.660
3	.606	.715	1.000	.588	.651	.671
4	.452	.634	.588	1.000	.507	.584
5	.650	.627	.651	.507	1.000	.646
6	.629	.660	.671	.584	.646	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

When considering data validity, the focus was to identify strong convergent validity and minimize discriminant validity among the construct items. This was accomplished by using the Pattern Matrix technique, which was described by Campbell and Fiske in 1959. To maintain high convergent validity, it was necessary to resolve and eliminate eight major cross-loaders, ensuring no factor loadings fell below 0.7 (Lyytinen & Gaskin, 2016). A minimal correlation at .715 between two constructs was found but considered negligible, maintaining discriminant validity (Gaskin & Lim, 2016).

Table 6. Demonstrates the Construct Reliability Before & After Item Deletion

Cronbach's a	***Deleted Items***	***Learners***	
		a	***a after deletion***
Expectations Relating to Performance	PE04	.905	.868
Effort Expectancy	EE01 EE02	.897	.860
Social Influence	SI03 SI04	.864	.917
Conditions for facilitation	FC02 FC03	.894	.837
Attitude Towards Use of Technology	ATT01	.925	.936
Intentions pertaining to behavior	-	.959	no items deleted

The reliability of the construct items was further established, accounting for the deletion of cross-loading items. An assessment of the internal consistency of the constructs, depicted through Cronbach's Alpha values, revealed high reliability, consistently surpassing the 0.6 threshold even after deletions (Nunnally, 1978). This ensured that the constructs appropriately represented the latent variables for both groups.

In conclusion, the construct items, after undergoing meticulous EFA, were corroborated to be adequate, valid, and reliable. This substantiated their alignment and representational accuracy of latent variables in subsequent analyses. The methodical elimination of items not meeting these standards was paramount in preserving the integrity and internal consistency of the constructs, setting a reliable premise for the succeeding Confirmatory Factor Analysis. This meticulous approach ensures that the constructs are accurate representations and are well-suited for more advanced analyses and interpretations in the study.

4.2.2 Analysis of the measurement model

After formulating the items, we examined the measurement model fit of the specified constructs using Confirmatory Factor Analysis (CFA). This thorough procedure involved determining factor loadings, evaluating model fit, making potential model refinements, and verifying construct reliability and validity.

Table 7. Shows the Summary of the Standardized Factor Loadings

Construct Items	Standard Estimates	Standard Error	Critical Ratio	p-value
PE01	.733			
PE02	.814	.064	19.771	***
PE03	.876	.061	21.389	***
PE04	.880	.066	21.471	***
EE01	.880			
EE02	.836	.036	27.075	***
EE03	.776	.035	23.698	***
EE04	.765	.036	23.138	***
SI01	.827			
SI02	.853	.044	24.431	***
SI03	.692	.047	18.252	***
SI04	.716	.048	19.102	***
FC01	.750			
FC02	.859	.046	21.331	***
FC03	.827	.044	20.451	***
FC04	.787	.048	21.332	***
ATT01	.690			
ATT02	.924	.073	20.639	***
ATT03	.907	.074	20.318	***
ATT04	.872	.074	19.599	***
BI01	.914			
BI02	.957	.024	42.548	***
BI03	.942	.024	40.662	***

The table presented the standardized estimates, which showed that all constructs had items with factor loadings greater than 0.5, indicating a high level of significance. According to Gao, Mokhtarian, and Johnston (2008), this conclusion was supported by the standard error, critical ratio (t-value), and p-value.

The initial model fit was not satisfactory, but after re-specifying the model, the goodness of fit indices improved significantly, indicating an excellent model fit: CMIN/DF = 2.281, CFI = 0.985, SRMR = 0.025, RMSEA = 0.056, and PClose = 0.191, as stated by Hu and Bentler (1999).

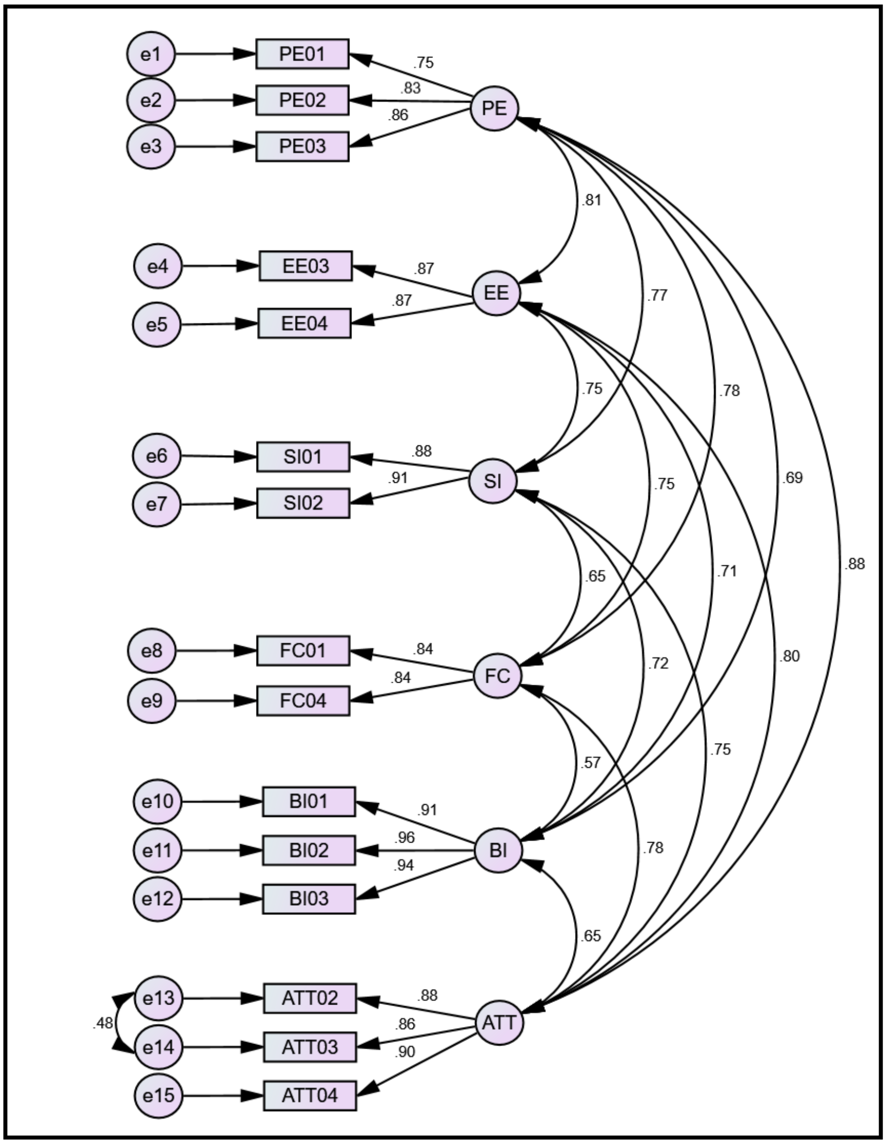

Figure 2: Shows Finalized construct measurement model

Table 8. Demonstrates the Composite Reliability, Average Variance Extracted, and Maximal Reliability

Constructs		Learners		
		CR	AVE	MaxR(H)
Expectations Relating to Performance	PE	*0.899*	*0.749*	*0.903*
Effort Expectancy	EE	*0.860*	*0.754*	*0.860*
Social Influence	SI	*0.918*	*0.847*	*0.921*
Conditions for facilitation	FC	*0.842*	*0.731*	*0.843*
Attitude	ATT	*0.943*	*0.838*	*0.948*
Intentions pertaining to behaviour	BI	*0.963*	*0.891*	*0.970*

The reliability and convergent validity of the constructs were effectively established. Composite Reliability (CR) and Maximal Reliability (MaxR(H)) exceeded the recommended threshold of 0.70, and the Average Variance Extracted (AVE) reported no values lower than 0.50 (Awang, 2015; Hair, Black, Babin, & Anderson, 2010). The CR values for all the constructs were higher than their respective AVE, confirming the reliability and convergent validity of the constructs.

Table 9. Heterotrait-Monotrait Ratio of Correlations

	PE	**SI**	**FC**	**ATT**	**EE**	**BI**
PE						
SI	0.791					
FC	0.838	0.730				
ATT	0.889	0.821	0.827			
EE	0.789	0.811	0.788	0.811		
BI	0.691	0.743	0.629	0.720	0.748	

Discriminant validity was rigorously confirmed using the Heterotrait-Monotrait Ratio of Correlations (HTMT) approach, with none of the computed values exceeding the 0.90 threshold for inter-construct correlations. This meticulous validation procedure aligns with the guidelines established by Gold, Malhotra, and Segars in 2001.

The comprehensive analysis involving Confirmatory Factor Analysis (CFA) has thus concluded that the constructs are reliable and valid, showing excellent model fit after re-specification. The factors loaded effectively, and both convergent and discriminant validity were substantiated. This meticulous and iterative process of measurement model analysis ensures the credibility and reliability of the constructs, laying a solid foundation for the subsequent phases of the research.

4.2.3 Structural Model Analysis

After conducting the Exploratory Factor Analysis (EFA) for the construct items and the Confirmatory Factor Analysis (CFA) for the constructs, the next step was to examine the pre-theorized relationships using Structural Equation Modeling (SEM). This involved assessing the fit of the structural model, drawing conclusions about the hypotheses, and conducting path analyses.

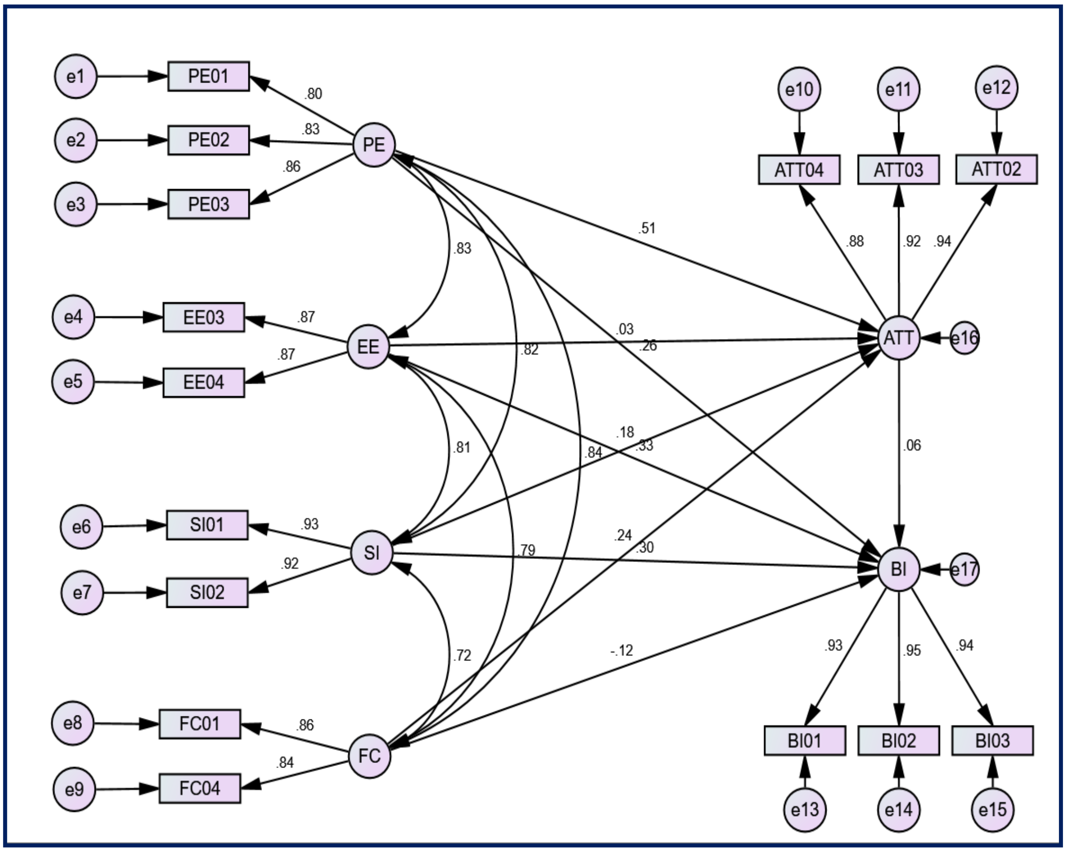

Figure 3. Represents the Framework of Structural Model

The structural model exhibited a satisfying fit for learners with CMIN/DF = 2.439, CFI = 0.983, SRMR = 0.028, RMSEA = 0.059, and PClose = 0.083, corroborating the established fit criteria (Hu & Bentler, 1999).

Table 10. Hypotheses Against Regression Weights

No.	Hypothesis	Standard Estimates	Standard Error	Critical Ratio	p-value	Decision
H1	PE → ATT	.514	.129	5.490	***	Supported
H2	PE → BI	.263	.155	1.991	.047	Supported
H3	EE → ATT	.030	.086	.410	.682	Not supported
H4	EE → BI	.332	.094	3.577	***	Supported
H5	SI → ATT	.185	.075	2.918	.004	Supported
H6	SI → BI	.298	.082	3.679	***	Supported
H7	FC → ATT	.240	.084	3.314	***	Supported
H8	FC → BI	-.122	.092	-1.300	.194	Not supported
H9	ATT → BI	.061	.089	.588	.556	Not supported

*** significant at p-value < 0.001”

The table presents the results of the analysis of hypotheses in relation to the SEM-reported regression weights. It indicates strong theoretical relationships, such as the correlation between Performance Expectancy and Attitude (H1) and Behavioral Intention (H2), Effort Expectancy and Behavioral Intention (H4), Social Influence and Attitude (H5) and Behavioral Intention (H6) and Facilitating Conditions and Attitude (H7). However, several other expected connections, including Effort Expectancy and Attitude (H3), Facilitating Conditions and Behavioral Intention (H8), and Attitude and Behavioral Intention (H9), were not supported by the data.

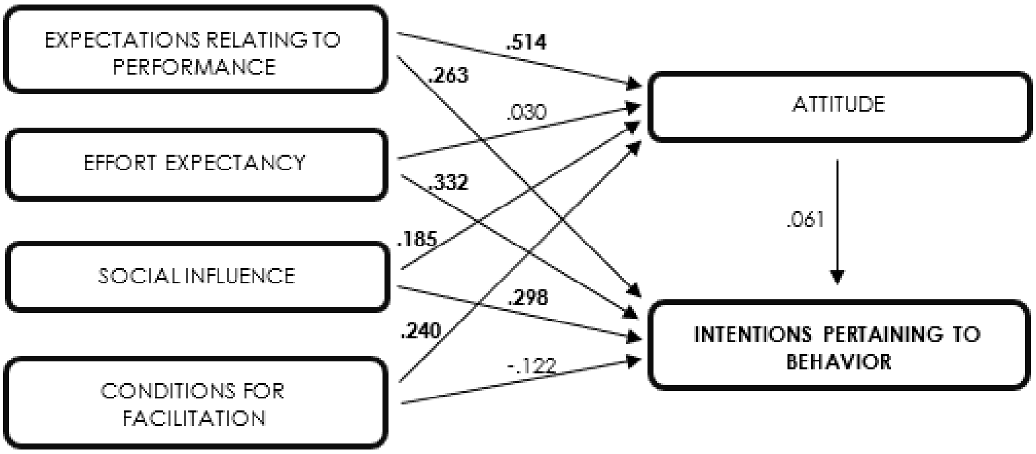

Figure 4. Demonstrates the Learners’ Path Coefficients and Squared Multiple Correlations

The delineated theoretical framework revealed significant linear relationships between various constructs, including positive and negative coefficients. The descending order of coefficients from highest to lowest demonstrated the relationships of Performance Expectancy with Attitude (.514), Effort Expectancy with Behavioral Intention (.332), Social Influence with Behavioral Intention (.298), Performance Expectancy with Behavioral Intention (.263), Facilitating Conditions with Attitude (.240), Social Influence with Attitude (.185), Effort Expectancy with Attitude (.030), Attitude with Behavioral Intention (.061), and Facilitating Conditions with Behavioral Intention (-.122).

The structural model analysis through SEM showcased the interconnectedness of various constructs and their significance, corroborating some of the pre-theorized relationships while refuting others. The validation of these relationships was pivotal for interpreting the influences and interactions among the constructs, thereby providing insights and implications that are valuable for both theory and practice. The illustration of path coefficients enriched the understanding of the nature and extent of these relations, unfolding nuanced perspectives on the constructs' interactions in the learners' context.

4.3 Report on the Open-Ended Questions

A series of open-ended follow-up questions was asked to examine learners' perceptions of switching from classroom to online classes during the COVID-19 pandemic. A total of 414 responses from Thai participants were translated into English by a professional translator, and the answers were categorized into distinct themes.

4.3.1 The research aimed to gather views on the introduction of online classes by the government during the COVID-19 pandemic. The responses were classified into themes based on criteria identified in Policy Debates (Bellon, 2008), to determine the policy's perceived necessity, benefit, practicality, and overall reception by different stakeholders.

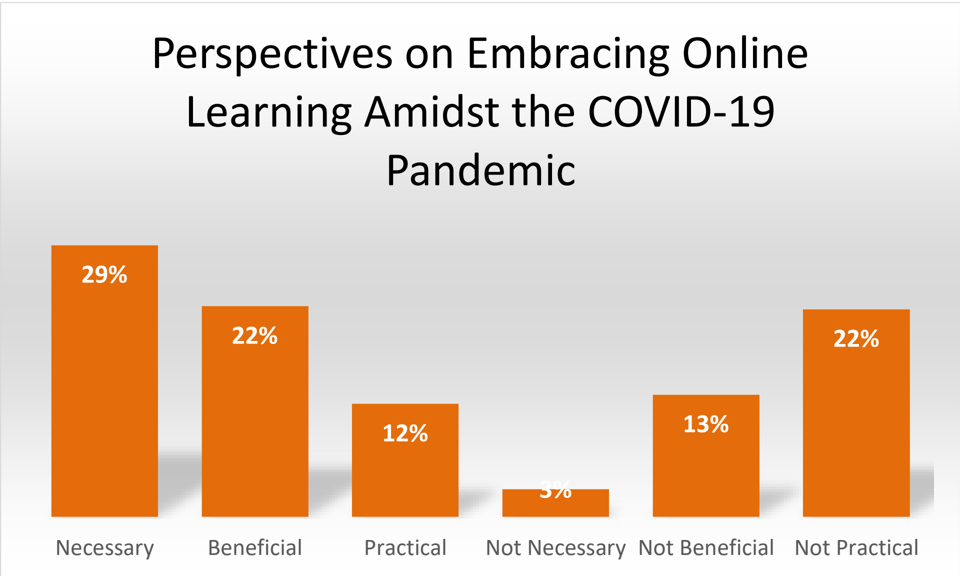

Figure 5: Demonstrates the Reply Summary for Question 1

A prominent portion of the learners viewed the adoption of online classes during the pandemic as primarily necessary (29%). The majority believed that this policy was imperative to 1) Maintain public safety by minimizing the virus spread through reduced physical interactions, and 2) Provide an appropriate solution to prevent further disruptions in education.

Another substantial portion found online classes beneficial (22%), noting that online learning 1) Aided them in achieving their educational goals amidst the pandemic, 2) Presented merits, although not equivalent to traditional learning experiences, and 3) Opened up modern, digital avenues, expanding their learning platform options.

However, an equal proportion of learners (22%) considered the approach impractical, with comments suggesting the transition was 1) Too abrupt, lacking proper preparation, and 2) Inconvenient due to insufficient support and anticipation, exemplified by weak Wi-Fi signals and frequent platform issues.

A minority of participants found the mandated online classes policy not beneficial (13%) but practical (12%), and a very small percentage deemed it unnecessary (3%).

This section provided valuable insights into the perceived necessity, benefits, and practicality of the sudden shift to online learning. The varied responses highlighted the complexities surrounding the abrupt transition to digital platforms, revealing a spectrum of experiences and perceptions. While some learners acknowledged the essential and advantageous nature of online learning during such times, others expressed concerns over its practicality and execution, emphasizing the need for a more thoughtful and supportive implementation process.

4.3.2 Challenges Encountered in Adopting Online Classes

To ascertain the difficulties faced by learners in transitioning to online classes, the second question focused on challenges, categorized based on the themes outlined by Tinio (2002) regarding the use of ICT in higher education. The identified challenges were associated with infrastructure, capacity, cost, and paucity.

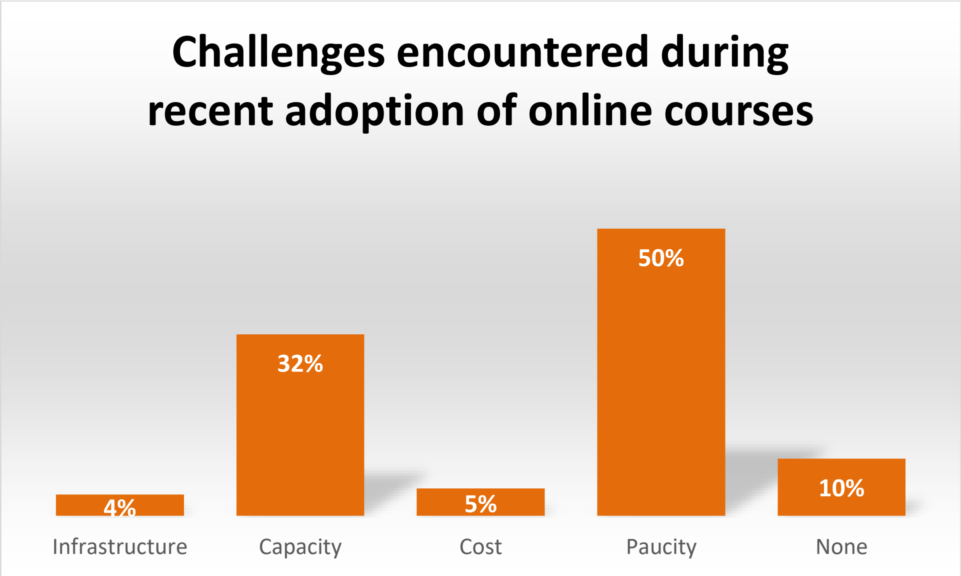

Figure 6. Demonstrates the Responses to Question 2

The presented data reveals that the predominant challenge learners faced was related to paucity (50%). Learners attributed the hesitation in adopting online classes to the unavoidable hitches stemming from a lack of stability, such as inconsistent internet connectivity, login errors, and system lags on digital platforms.

A significant number of learners (32%) also pointed to capacity-related challenges, referencing the unavoidable learning curve and adjustments required for navigating the digital learning environment for the first time. On the other hand, a minority of participants cited challenges related to cost (5%), such as the expenses incurred for internet data to facilitate continuous learning, and infrastructure (4%), where some learners lacked personal devices like computers, tablets, or phones to access the classes. Interestingly, a higher minority (10%) reported experiencing no difficulties in transitioning to online classes.

This section elucidates the spectrum of challenges experienced by learners while adopting online classes. A substantial number of learners struggled with issues related to the stability and reliability of online platforms and connectivity, highlighting the paucity and capacity issues. Although less prevalent, infrastructural limitations and cost implications also emerged as significant barriers for some learners, underscoring the multifaceted nature of challenges in online education. Yet, a noteworthy minority of learners encountered no difficulties, emphasizing the variability in individual experiences and adaptability in navigating digital learning landscapes.

4.3.3 Suggestions on Future Adoption of Online Classes

In seeking suggestions regarding the potential resumption of online classes, the third question aimed to understand the learners' concerns about continuing online education. The derived themes, informed by Tinio's (2002) framework on ICT in higher education, touched upon aspects like effectiveness, cost, equity, and sustainability.

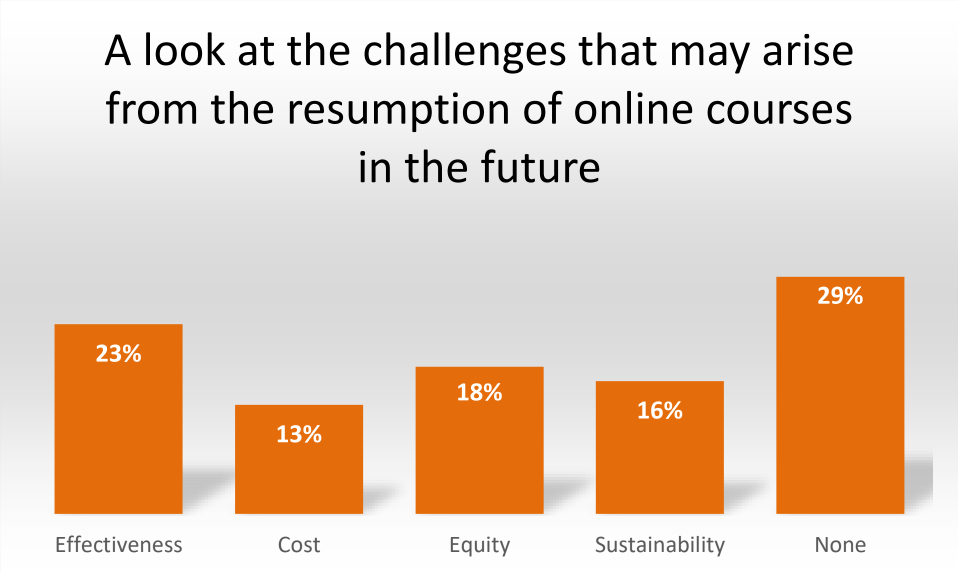

Figure 7. A demonstration of the responses to Question 3

The majority of the learners did not foresee any significant issues (29%) if online classes were to continue. However, a significant portion of participants emphasized the need for effectiveness (23%), advocating for online classes to not just serve as a substitute for face-to-face sessions but to enhance learning experiences and build competence.

Equity emerged as another crucial consideration (18%), with suggestions emphasizing the necessity for modifications to accommodate the distinct nature of online learning environments. Learners voiced concerns over adapting class durations, modifying assignment and test frequencies, and ensuring all participants are adequately prepared for a shift to online learning.

Sustainability (16%) was also highlighted, with suggestions focusing on reinforcing the stability of learning systems through enhanced internet connectivity, resolving login issues, and providing necessary technical support. Finally, a smaller portion of learners (13%) flagged cost as a potential issue, emphasizing the need for financial strategies to support prolonged online learning endeavors, if necessary.

This section illustrates the diversified opinions and suggestions of learners on the future adoption of online classes. While some did not anticipate any significant challenges, many underlined the imperative of ensuring effectiveness, equity, and sustainability in the online learning ecosystem. From bolstering learning experiences and competencies to fostering an equitable and stable learning environment, the suggestions reflect a nuanced understanding of the varied dimensions of online education. Moreover, considerations around cost and resource allocation underscore the pragmatic concerns of sustaining online learning as a long-term educational model.

DISCUSSIONS

5.1 Discussion on Performance Expectancy's Influence

Performance Expectancy and Attitude:

In the adapted UTAUT model, Performance Expectancy (PE) elucidates its crucial role in shaping attitude and behavioral intention towards technology adoption. It is evident that the perception of the utility and benefits of technology significantly molds users' attitudes, as indicated by Dwivedi et al. (2019). In consistent concurrence, the data reflected that regardless of the setting being voluntary or obligatory, Performance Expectancy proved to be the paramount determinant of behavioral intention to use technology, corroborating the findings of Venkatesh et al. (2003).

The significance of the relationship between PE and Attitude (ATT) was notably prominent, with a path coefficient of $\mu = .514$ (H1), signifying that the learners' attitudes towards adopting online classes were significantly shaped by their perceived utility of technology in achieving educational objectives. This aligns with contemporary research (Tiwari, 2020; Sukendro et al., 2020; Maphosa, Dube, & Jita, 2020), conducted in the backdrop of the ongoing pandemic, reinforcing that a positive attitude towards online learning is intricately linked to the perceived helpfulness of the technology implemented.

Performance Expectancy and Behavioral Intention:

The relationship between PE and Behavioral Intention (BI) was also substantiated (H2: $\mu = .263$), indicating a direct influence of perceived usefulness on learners' intentions to adopt the technology. This relationship is supported by a slew of recent studies (Tiwari, 2020; Samat et al., 2020; Raza et al., 2020), particularly emphasizing the pandemic context, which highlighted PE as a predominant predictor of BI. These studies convey a universal consensus: there is a heightened inclination among learners to embrace online classes when the deployed technology is perceived as conducive to positive learning experiences.

This discussion delineates the pivotal role of Performance Expectancy in cultivating favorable attitudes and fostering behavioral intentions towards the adoption of online classes. The discernible influence of perceived utility of technology in education settings, especially amid unprecedented situations like a pandemic, underscores the imperative of aligning technological solutions with learners' expectations and educational aspirations to facilitate widespread acceptance and successful implementation.

5.2 Discussion on Effort Expectancy's Influence

Effort Expectancy and Attitude:

Effort Expectancy (EE) investigates how the perceived ease or complexity of technology influences individuals' attitudes toward its use (Dwivedi et al., 2019). Within the UTAUT framework, EE is deemed significant in both voluntary and mandatory contexts but tends to wane over prolonged usage (Venkatesh et al., 2003). Understanding the influence of EE on attitude and behavioral intention is critical in the context of this study.

Interestingly, the hypothesized relationship between EE and Attitude (ATT) was not significant for learners (H3: μ = .030), suggesting that the ease or difficulty in adopting online classes didn’t significantly influence their attitude towards it. One plausible explanation is the inherent familiarity and comfort of the younger generation, who are “digital natives,” with technology, minimizing perceived difficulties and efforts in using new technologies. Consequently, age, acting as a moderator, could be influencing EE’s significance on attitude across different age groups (Venkatesh et al., 2012).

Effort Expectancy and Behavioral Intention:

Conversely, the relationship between EE and Behavioral Intention (BI) was found to be highly significant (H4: μ = .332), indicating a strong influence of perceived ease of use on learners' intentions to adopt online classes. This finding aligns with recent research (Chayomchai, 2020; Chayomchai et al., 2020; Raza et al., 2021; Tiwari, 2020) which underscored the significant impact of perceived ease of use, a component of EE, on the behavioral intention to use technology.

This discussion highlights the nuanced role of Effort Expectancy in influencing attitude and behavioral intention in the adoption of online classes. While the ease or complexity of technology does not significantly influence the attitude of digital natives, it has a marked impact on their intention to use technology, emphasizing the importance of user-friendly and intuitive technological solutions in fostering higher adoption rates, especially in educational contexts. The dichotomy in the influence of EE on attitude and behavioral intention underscores the importance of understanding the diverse factors influencing technology adoption among different demographics.

5.3 Discussion on Social Influence’s Impact

Social Influence and Attitude:

Social Influence (SI) reflects how the opinions and behaviors of important others shape individual attitudes and decisions regarding technology use (Dwivedi et al., 2019). In professional environments, decisions related to technology adoption often stem from compliance mechanisms rather than pure identification or internalization with influential figures (Venkatesh et al., 2012).

In this study, there was a significant correlation between SI and Attitude (ATT) for learners (H5: μ = .185). This indicates that the perceptions and opinions of significant others, such as friends and family, have a notable influence on students' attitudes towards the sudden shift to online learning during the pandemic. This finding is supported by previous research (Dwivedi et al., 2017; Mosunmola et al., 2018; Tseng et al., 2019), which shows that factors like peer identification and parental concerns do affect learners' willingness to embrace technology.

Social Influence and Behavioral Intention:

Similarly, the relationship between SI and Behavioral Intention (BI) was significant for learners (H6: μ = .298), indicating that the opinions of important individuals significantly molded learners' intentions to adopt online classes. This significance is supported by recent studies (Samat et al., 2020; Raza et al., 2021; Asvial et al., 2021), which suggest that students' willingness to comply with online learning mandates was positively reinforced by the concerns and opinions of their loved ones, especially regarding safety during the pandemic.

Social Influence thus plays a pivotal role in shaping both attitudes and behavioral intentions towards online learning adoption among learners. The perceptions and concerns of influential figures, such as peers and family, significantly influence students' attitudes and compliance with online learning policies, reinforcing the crucial role of social contexts and relationships in technology acceptance and adoption processes, especially during unprecedented times such as a pandemic. Balancing compliance with personal identification and internalization is critical for ensuring smoother transitions and adaptability in such scenarios.

5.4 Discussion on the Impact of Facilitating Conditions

Facilitating Conditions and Attitude:

The presence of Facilitating Conditions (FC), including essential support mechanisms like help desks and customer support, plays a pivotal role in molding users' perceptions and attitudes towards the utilization of technology. In this study, the hypothesis associating FC and Attitude (ATT) was validated for learners (H7: μ = .240). This means that the presence or absence of technological support significantly influenced learners' sentiments towards technology usage. Research from Sangeeta and Tandon (2020) aligns with this finding, highlighting how the availability of training programs during the pandemic positively influenced both teachers’ and learners’ willingness to utilize the proposed programs in Rajpura, India.

Facilitating Conditions and Behavioral Intention:

However, the correlation between FC and Behavioral Intention (BI) was not substantiated (H8: μ = -.122). Thus, the accessibility of supportive facilities and organizational backing did not significantly bolster the intent to employ technology. Recent studies conducted during the pandemic (Chayomchai et al., 2020; Asvial et al., 2021) further emphasize this finding, indicating that facilitating conditions have a stronger influence on actual technology usage rather than on the intention to use technology. This distinction aligns with the fundamental concept within the original UTAUT model (Venkatesh et al., 2003), suggesting that facilitating conditions can impact behavioral intention independently of the initial two constructs (Foon & Fah, 2011): Performance Expectancy and Effort Expectancy. This perspective is supported by previous empirical research findings (Eckhardt, Laumer, & Weitzel, 2009; Yeow & Loo, 2009).

Facilitating conditions are crucial in shaping attitudes towards technology use, with their presence or absence significantly affecting how users feel about employing technology. However, their influence does not seemingly extend to shaping behavioral intentions to use technology, with more impact on actual use behavior. The nuanced understanding of how facilitating conditions interact with other constructs to influence attitude and behavior provides a richer perspective on technology adoption processes, especially in learning environments disrupted by external factors like a pandemic. Balancing these facilitating conditions with user expectations and needs is paramount for fostering positive attitudes and effective technology utilization in educational contexts.

5.5 Attitude on Behavioral Intention

The final two constructs in the revised UTAUT framework are attitude and behavioral intention, and they are expected to have a significant relationship. While attitude has been a recurring element in the original UTAUT model, Dwivedi et al. (2019) argue that it continues to be an important factor in shaping behavioral intention. Research shows that individuals tend to form intentions to engage in behaviors that they have a favorable attitude towards. The hypothesis linking attitude to behavioral intention was found to be insignificant among learners (H9: μ = .061), indicating a noticeable difference between their technological sentiments and their intentions to use it. This finding aligns with a recent study by Asvial et al. (2021) among Indonesian middle school students, who also faced challenges in embracing online classes during the COVID-19 pandemic. It was concluded that, due to their lack of preparedness for technology use, the link between attitude and behavioral intention could not be established. The same may apply to this study, as the constraints imposed by the COVID-19 context may limit the learners' choices. In this context, their current attitudes have minimal impact on their intentions to use technology. Another possible explanation may be found in the original UTAUT research by Venkatesh et al. (2003), which noted that attitude shared common indicators with performance expectancy and effort expectancy, resulting in redundancy and limited contribution to the establishment of the unified model of technology acceptance.

CONCLUSIONS

6.1 Synopsis of Principal Discoveries:

This study utilized the revised UTAUT model to examine learners' perceptions and intentions towards online classes during the COVID-19 pandemic. The findings revealed diverse perspectives among learners regarding their current adoption of online learning. Three main factors, namely performance expectancy, social influence, and facilitating conditions, were identified as key drivers of learners' attitudes. Furthermore, the study established that performance expectancy, effort expectancy, and social influence have a significant impact on learners' behavioral intentions in this context.

Learners viewed the adoption of online classes as necessary and beneficial but believed improvements in practicality were required. They identified challenges related to lack of preparedness, including unstable internet and lack of proficiency with online tools, and raised concerns regarding the effectiveness of online classes in the long term. A Delphi study by Tee et al. (20220 would confirm how technology optimization was a critical consequence for the this educational landscape in the new normal.

6.2 Practical Implications:

The findings reveal strategies for universities to foster learners’ adoption of online classes. Performance expectancy emerged as a pivotal element, implying that improving the online learning experience and addressing practical issues related to unpreparedness is crucial. Effort expectancy and a more user-friendly and accessible approach also significantly impact adoption intention, suggesting that a unified, easy-to-navigate platform with tutorials would be beneficial.

Social influence was found to play a vital role, emphasizing the need to involve learners' close circles in fostering supportive environments for online learning. The significant impact of facilitating conditions underscores the necessity to provision sufficient resources, knowledge, compatibility, and assistance, with administrators providing timely updates, trainings, and support.

6.3 Suggestions for Subsequent Research

While the research has successfully yielded substantial insights, it provides a foundation for broader and deeper explorations in the future. One potential avenue is the incorporation of additional moderators and constructs, specifically "use behavior," as posited in the original UTAUT model. Despite the mandatory nature of this study, integrating these elements could unearth different theoretical implications, enhancing the understanding of user acceptance of technology.

Furthermore, subsequent studies should seek to integrate more specific parameters, such as the impact of COVID-19 anxiety and perceptions about lecturers on technology acceptance. By doing so, the results obtained would be more context-specific and meaningful, allowing for a more nuanced understanding of the various factors influencing learners' acceptance and use of online learning platforms during pandemics.

Additionally, there is a pronounced need for future research to employ a more demographically representative sample, ensuring diverse representation across age, gender, and other subgroups. Such an approach would facilitate a more comprehensive understanding of technology acceptance phenomena and address potential bias considerations effectively, thus contributing to the robustness and generalizability of the findings.

Lastly, the exploration of mediating effects, in addition to the identification of direct effects, is warranted for a richer and more intricate understanding of the internal relationships among the constructs under study. This nuanced approach to hypothesis testing can illuminate the intricate interplay of factors influencing technology acceptance, providing deeper insights into the multifaceted nature of learners' attitudes and behavioral intentions towards online learning platforms.

This study illuminates the multifaceted influences on learners' acceptance of technology, providing a scaffold for enhancing online learning experiences. The significant findings and insights garnered pave the way for improved practical applications and guide further research endeavors in the realm of online education, particularly during such exigent times as a pandemic. Balancing efficacy, accessibility, and support is key to optimizing learning experiences and fostering a conducive learning environment in the ever-evolving educational landscape.

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