

THE INTENTIONS TO ADOPT E-LEARNING USING UTAUT-3 MODEL: A POST COVID-19 PERSPECTIVE

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ABSTRACT

The COVID-19 pandemic has led to significant changes to e-learning systems, highlighting the importance of understanding the factors affecting their adoption. This study highlights the importance of e-learning by blending UTAUT (Unified Theory of Acceptance and Use of Technology) and UTAUT-3 theories to examine post-COVID adoption in e-learning programs. The purpose of this study is to investigate the influence of effort expectancy, performance expectancy, social influence, and facilitating conditions on the use of behavioral intentions in e-learning and the relationship between behavioral intentions and e-learning adoption behavior. The study sample consisted of 303 university students who continued to use e-learning systems after the COVID-19 pandemic, collected using a convenience sampling technique. Partial least squares structural equation modeling (PLS-SEM) through SmartPLS was used to analyze the collected data. The results revealed that effort expectancy, performance expectancy, and social influence significantly influence the behavioral intention to use e-learning. In contrast, the relationship between behavioral intention to use e-learning and acceptance of e-learning use is not significant. This study proved that significant changes in e-learning systems caused by the COVID-19 pandemic, and these changes are likely to continue after the pandemic. The study's findings can help learners, learning providers, and policymakers plan and execute their online strategies.

Keywords: UTAUT, UTAUT-3, Technology Adoption, Performance Expectancy, Social Influence, Effort Expectancy, Behavioral Intention.

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1. INTRODUCTION

Wuhan is the center of high-tech industry in China. Even though thousands of Chinese perished in this city's pandemic at the end of 2019 and many residents suffered significantly, it remains an appealing commercial hub in the twenty-first century. The lethal virus that caused this devastation was named "COVID-19" by Chinese scientists (Shereen et al., 2020). The coronavirus sickness caused by this virus is highly contagious (WHO, 2020). At the beginning of the year 2020, the virus spread to 210 countries, each of which launched its own public awareness campaign to stop and curtail the illness's spread. However, a large number of people were affected by this virus, and most nations chose to restrict human interactions in an effort to halt the rapid rate of infection spread. Schools and all other public meeting places that might serve as a vehicle for the spread of viruses were temporarily shutdown.

Educational institutions had to switch to online education systems to prevent pupils from losing out on educational opportunities (Adeoye et al., 2020). According to UNESCO (2020), 91% of students globally suffered as a result of educational establishments being closed. Everyone was impacted by the permanent or brief closure of schools, colleges, and institutions, including students and even teachers. As a result of the COVID-19 public health emergency, academic sessions at educational institutions were also disrupted. Apart from that, it harmed the educational system, and disrupted businesses all over the world. The majority of higher education institutions had to adopt e-learning or online learning and online teaching methods (Mohammed, 2020) as a result of this epidemic's impact on all educational institutions worldwide, particularly universities. To maintain both the learning process for students and the viability of educational institutions, it is preferable for nations to employ readily accessible learning options, such as mobile learning applications and e-learning systems. The COVID-19 era raised awareness of the importance of introducing online education and embracing e-learning options. Even if online and distance learning are not new to students, they must be implemented immediately (Almaiah et al., 2020).

Although there were students who were reportedly happy about the closure of campuses owing to the COVID-19 outbreak, many professors at reputable universities were also pleased to embrace online education. Teachers are receiving certification in online teaching to conduct lectures online and help students complete e-learning successfully. Face-to-face instruction was the norm prior to the pandemic's outbreak, but it has now been replaced by an electronic learning system utilizing various online learning platforms. During pandemics, e-learning or online education was undoubtedly helpful. However, there were considerable concerns about its quality (Sahu, 2020). Furthermore, current research has yet to adequately analyze or describe students' e-learning experiences. Almaiah et al. (2020) stated that an e-learning system is the optimal alternative for instructors to manage, prepare, deliver, track, and even measure learning outcomes. In addition to the system, E-learning resources play an important role by assisting colleges, universities as well as the students they serve.

In addition to COVID-19, contemporary technologies have changed conventional learning strategies to new ones, such as learning through artificial intelligence (Di Vaio et al., 2020). E-learning, which uses technology-based learning through various learning portals, websites, mobile apps, video conferencing, YouTube, or other comparable online learning platforms, is another contemporary method of education. Along with improving student understanding, digital learning makes it easier for academic professionals and those employed in sectors to gain skills online

(Adams et al., 2018). The global e-learning market was valued at \$300 billion USD in 2015 (Global Market Insights, 2019) due to higher education being profitable globally (Palvia et al., 2018). More than 95% of higher education institutions in the United Kingdom have effectively implemented e-learning in their main programs (Tarhini et al., 2017). Islam et al. (2015) emphasized that there are numerous approaches, frameworks, and factors to consider when analyzing utilization and adoption rates of online instruction in universities that are physically operational and e-learning-ready. Numerous studies (Jefferson & Arnold, 2009; Radovi-Markovi, 2010; Alexander, Truell, & Zhao, 2012; Dumford & Miller, 2018; Hiranrithikorn, 2019; Salleh et al., 2020; Bczek et al., 2021) have explored the disadvantages of e-learning. Several theories and their respective models examined the adoption of technology and its characteristics in numerous industries.

Numerous theories have also been added to the Technology Adoption Model theory, but “the Unified Theory of Acceptance and Use of Technology” (UTAUT), UTAUT 2, and UTAUT 3 theories presented the ideal technology adoption with behavioral goals. Venkatesh et al. (2003) introduced the UTAUT theory, which has been applied to evaluate computer use in education, mobile services and technologies, social influence, and workplace technology adoption (Koivumäki, Ristola, & Kesti, 2008; Eckhardt, Laumer, & Weitzel, 2009; Curtis et al., 2010; Verhoeven, Heerwegh, & De Wit, 2010). According to Huang and Kao (2015), the UTAUT2 is useful for analyzing and explaining how people interact with new Information Technology (IT) products. However, the UTAUT 3 theory highlights technology adoption concerning e-learning in the context of the teaching sector (Farooq et al., 2017; Gunasinghe et al., 2019). The adoption of technology in the teaching sector had previously been primarily disregarded.

Businesses were not the only sector impacted by COVID-19; educational institutions felt its effects as well. Therefore, just like consumers, students focused on e-learning or technology adoption in order to avoid face-to-face interaction and learn while preserving social distance. Although students are also the customers, the focus of the Technology Adoption Model theory and the theory of Reasoned Action mostly concerns ordinary customers’ adoption of technology. Even though the bulk of the affected countries have since recovered from the pandemic, students are still favoring online learning and embracing it. As a result, this research combined the ideas behind UTAUT and UTAUT 3 theories to examine the significance of e-learning. In order to conceptualize the impact of effort expectancy, performance expectancy, social influence, and facilitating factors on behavioral intention to utilize e-learning, certain irrelevant determinants from the UTAUT 3 theory were removed. In addition, the relationship between e-learning adoption behavior and behavioral intent to use it was highlighted.

An assessment of UTAUT 3 components (effort expectancy, performance expectancy, social influence, and facilitating conditions) that can affect behavioral intentions to use e-learning after COVID-19 is currently lacking, according to a thorough review of the literature and extensive research. Therefore, this research aims to close this gap by establishing the relationship between the previously described variables. Following are the research queries that this study addressed:

- 1- Does performance expectancy influence the behavioral intention to use e-learning?
- 2- What is the effect of effort expectancy on behavioral intention to use e-learning?
- 3- What is the potential relationship between social influence and behavioral intention to use e-learning?

- 4- What is the effect of facilitating conditions on behavioral intention to use e-learning and e-learning adoption behavior?
- 5- What is the effect of behavioral intention to use e-learning on e-learning adoption behavior?

2. LITERATURE REVIEW

Farooq et al. (2017) introduced the UTAUT-3 framework, which is an extension of the UTAUT-2 model which includes eight determinants of technology acceptance. These determinants are hedonic motivation, effort expectancy, social influence, performance expectancy, affordability, facilitating conditions, habit, and personal innovativeness in information technology. The UTAUT-3 model has an explanatory power of 66% in predicting technology acceptance. Gunasinghe et al. (2019) attempted to empirically validate the UTAUT-3 model to understand academics' adoption of e-learning. However, their study found non-significant relationships between some indicators. Therefore, the most relevant generic items of the UTAUT-3 scale that could help analyze students' and teachers' e-learning recipient attitudes were extracted. The UTAUT-3 framework was used to understand the adoption of various technologies, including e-learning, and the determinants identified in the model can help to examine student and teacher adoption practices. The UTAUT-3 framework provides a comprehensive framework for understanding technology adoption, and its implications can be used to develop strategies to promote technology adoption in a variety of settings.

The UTAUT-3 model has been widely applied in a variety of technological contexts, including e-learning, online banking, and mobile health applications (Lantu et al., 2023). The determinants of the model have been shown to have different effects on the technology adoption process depending on the context (Tewari et al., 2023). A study by Gunasinghe et al. (2019) found insignificant relationships between some of the determinants in the case of student adoption of e-learning. However, their study identified important determinants of UTAUT-3 theory that can help analyze student and teacher e-learning adoption behavior. The broad framework of the UTAUT-3 model provides a valuable tool to understand technology adoption, using its measures to develop strategies on adoption attitudes and practices that can help researchers and practitioners understand the factors that influence technology adoption and provide resources for interventions to promote technology adoption. Overall, the UTAUT-3 model provides a valuable framework for understanding technology use and can be used in a variety of contexts to promote technology use.

This study focused on performance expectancy, effort expectancy, social influence and facilitating conditions towards behavioral intention and adoption behavior.

2.1. Performance Expectancy

Performance expectancy is defined as “the extent to which an individual believes that adopting a particular technology will provide benefits in performing an activity” by Venkatesh et al. (2012). However, They also modified this definition and stated that performance is “the degree to which technology adoption and usage will deliver benefits to customers in carrying out certain activities.” Performance expectation could be defined as the conviction that the intended technology will enable users to make more accurate assumptions. Numerous studies focusing on technology adoption concepts in a variety of contexts have described and defined the concept of performance

expectation. The UTAUT model was utilized by San Martin and Herrero (2012) to explain the correlation between performance expectations and traveller intention to visit. Performance expectancy, according to Hong and Kang (2011), is a significant and prospective predictor of behavioral intention to use online travel. The individual's intention to use or accept new technology may be predicted by performance-related criteria (Schaupp et al., 2010). Similar to this, performance expectancy from the standpoint of the educational sector refers to academics' faith that e-learning will help them complete their duties (Gunasinghe et al., 2019). Therefore, the behavioral intention to use e-learning following COVID-19 can be influenced by performance expectancy. Hence, the following idea was generated:

H1: There is a positive effect of performance expectancy on behavioral intention to use e-learning.

2.2. Effort Expectancy

Effort expectation is described by Venkatesh et al. (2003) as "the degree of ease derived while using a particular system in place." According to them, effort expectancy refers to a person's perception of how trouble- or hassle-free their interactions with technology are. Similar to this, Mohsen et al. (2019) explained that customers always choose technology that is user-friendly and capable of providing optimal efficiency. Customers are more likely to adopt new technology if it is simple to understand, and learning about it requires little effort (Kang, 2014). Similarly, Schaupp et al. (2010) argued that simple or convenient technology favorably influences users' attitudes and behavioral intentions. In the context of education, effort expectancy refers to academicians' perceptions of how simple or comfortable e-learning platforms are to use (Gunasinghe et al., 2019). Technology will be more convenient for both students and teachers to employ if it is easy to use or adopt. In light of this, we proposed the following theories:

H2: There is a positive effect of effort expectancy on behavioral intention to use e-learning.

2.3. Social Influence

Ajzen (1991) defined social influence as societal pressure that compels a person to carry out or refrain from carrying out a behavior. El-Gayar et al. (2011) contended that social influence is a crucial factor in determining a person's behavioral goals. The adoption of smartphone technologies has a societal impact on travelers' travel behaviors, as Gupta and Dogra (2017) noted. Similarly, social impact was defined by Venkatesh et al. (2012) as "the extent to which customers perceive using a particular technology to be important as others believe they should be using it." According to Shereen et al. (2020) and Tan (2013), the fundamental goal of social influence is to draw attention to essential roles and viewpoints in our lives, such as those of our family, friends, and coworkers. Yang (2010) asserted that the social effect of consumers' social groupings is driving the expanding trend of online purchasing. The social influence of customers and behavioral intentions should be positively correlated (Leong et al., 2013). As a result, it is claimed that social influence is the outcome of various conceptions, including interpersonal influence, peer and superior influence, and other external factors. For instance, Schepers and Wetzels (2007) demonstrated how subjective norms have moderated how each individual approaches use particular technology. According to Venkatesh et al. (2003), a subjective norm has a substantial impact on how effectively a job is seen to be performed. In contrast, Maldonado et al. (2011) and Keong et

al. (2012) found that social effects, learning motivation, and consumer behavioral intentions have a favorable association. According to research by Gonzalez et al. (2012), social pressure from peers or higher authorities has a substantial impact on how quickly customers adopt new technologies. Gonzalez et al. (2012) also found that pressure from higher authority plays a more prominent role in influencing a person's decision to embrace or use new technologies. These arguments lead us to the following hypotheses:

H3: Social influence is positively related to behavioral intention to use e-learning.

2.4. Facilitating Conditions

Facilitating conditions are defined as the extent to which a person believes that a technological and organizational framework exists to make using the system easier (Mtebe & Raisamo, 2014). Triandis (1980) asserted that the absence of enabling variables in the environment prevents the emergence of well-intentioned activity. Bhattacharjee (2000) defined an enabling condition as an external restraint that identifies attitudes toward resource availability as encouraging specific conduct. Facilitating conditions are resources that are made available to an organization to make it easier to integrate and use digital technology (Venkatesh et al., 2003). The availability of a suitable learning environment and infrastructure to facilitate the usage of the technologies under examination is referred to in this study as a facilitative condition. These prerequisites include the students' own abilities and expertise as well as a setting that stimulates and supports their usage of online learning. Accessibility to digital equipment, a steady internet connection, and other related tools are all crucial elements in the context of e-learning. If a person has easy access to resources like computers, smartphones, internet connections, support chat rooms, phone lines, or other favorable circumstances, their inclination to use e-learning will likely improve. This means that a student's comprehension of the support services and technologies available to offer e-learning may have an impact on his or her decision to adopt and use e-learning. According to previous research (Venkatesh et al., 2003; Venkatesh et al., 2012; Chauhan & Jaiswal, 2016), enabling conditions have a considerable impact on behavioral intention. The acceptability of e-learning systems has been demonstrated to be impacted by supportive conditions in numerous research examining the impact of technology adoption (Teo, 2010; Sharma et al., 2016; Tarhini et al., 2016, 2017). According to Venkatesh et al. (2003), one of the most critical variables affecting how people use technology is the facilitating condition. Therefore, the following hypothesis was formulated:

H4: Facilitating conditions is positively related to behavioral intention to use e-learning and e-learning adoption behavior.

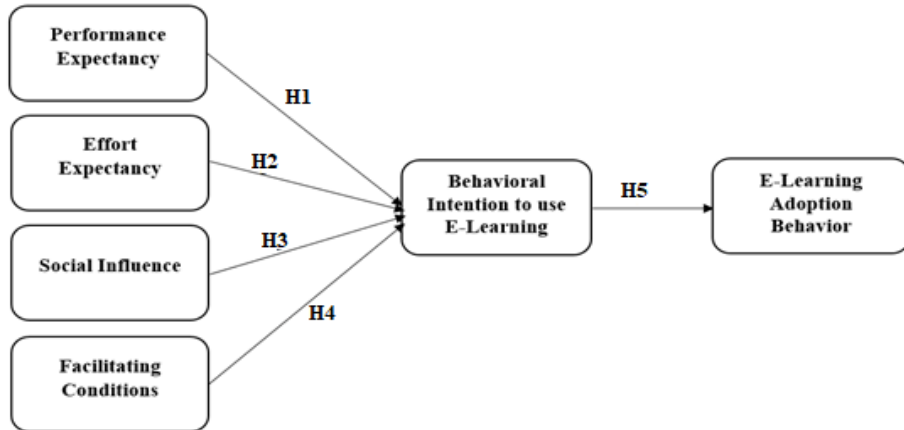
2.5. Behavioral Intention and Adoption Behavior

A user's inclination to employ self-service technologies (SSTs) is defined as a behavioral intention by Venkatesh et al. Behavioural intention has consistently been examined and found to be the most potent predictor of individual behavior pertaining to the technology adoption stream (Ajzen, 1985; Venkatesh et al., 2003). Furthermore, previous research (Jarauwachirathanakul & Fink, 2005; Martins et al., 2014; Shih & Fang, 2004) has supported consumer intention as a key predictor of actual user activity. Therefore, it was hypothesized in the current study that behavioral intention to use is a significant predictor of users' adoption behavior. So, we proposed the following theories:

H5: Behavioral intention to use e-learning leads to e-learning adoption behavior.

The model for the current study is shown in Figure 1:

Figure 1: Conceptual UTAUT-3 Model



3. METHODOLOGY

This research focused on the comprehensive concept of e-learning and technology adoption post-COVID-19. The conceptual model provided by this research highlighted some functional determinants that can influence e-learning or technology-adopted learning, particularly in e-learning systems. Therefore, the methodology section of this research provided the details of the research instrument, data collection, and data analysis techniques.

3.1. Research Instrument

The current study is quantitative, and to collect the data, a structured questionnaire was used. To overcome the validity issue, questionnaire items were adopted from valid past studies. The study comprised six constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention to use e-learning, and e-learning adoption behavior. The construct of performance expectancy was measured with a 3-item measurement scale adopted from the studies of Nahla and Bashair (2020), and Venkatesh et al. (2012). Each construct of effort expectancy, social influence, and facilitating conditions was measured with a scale of 3 items, adopted from the study of Venkatesh et al. (2012). The construct of behavioral intention to use e-learning was measured with a 3-item scale adopted by Venkatesh et al. (2012) and Maldonado et al. (2011). Moreover, the construct of e-learning adoption behavior was also measured with a 3-item scale adopted from the study of Cohen (2010), and Islam (2013). A 5-point Likert scale (5=strongly agree, 1= strongly disagree) was used to measure all items.

3.2. *Data Collection & Analysis Techniques*

Data type and research design determine how the data are collected. Data gathering techniques differ between qualitative and quantitative research methodologies. The self-administered questionnaire was made for quantitative research. Data used in qualitative research may come from interviews or reputable secondary sources such as books, journals, websites, and other secondary sources. Similar to that, gathering information from literature is a crucial procedure while carrying out qualitative studies. Data were gathered utilizing a structured questionnaire because the current study is quantitative in nature. Data were collected from 303 students who were chosen using an easy sample procedure. The target demographic of the study was university students who were still utilizing e-learning systems after COVID-19. PLS-SEM was used to analyze the collected data with SmartPLS.

4. RESULTS

4.1. *Descriptive Statistic and Test of Normality*

Though PLS-SEM is a non-parametric and does not need normal data (Henseler et al., 2009), it is better to access the data normality before further analysis (Hair et al., 2014). As recommended by Kline (2015), Skewness and Kurtosis statistics were used to test the normality. Kline (2015) suggested that the Skewness value should be less than 3, and the absolute value for Kurtosis should be less than 10. Results shown in Table 1, reveal that both Skewness and Kurtosis statistics have values well within the recommended criteria. The average mean of the data is also 3.27 on a 5-point Likert scale, indicating respondents' agreement.

Table 1: Descriptive Statistics and Test of Normality

	Mean	SD	Skewness	Kurtosis
Performance Expectancy	3.73	0.65	0.02	-0.82
Effort Expectancy	2.77	1.30	0.15	-1.57
Social Influence	2.90	1.08	-0.08	-0.74
Facilitating Conditions	3.06	1.22	0.18	-1.17
Behavioral Intention to Use e-Learning	3.26	1.05	-0.18	-1.02
E-learning Adoption Behaviour	3.91	0.76	-0.63	-0.36

4.2. *Measurement Model Assessment*

Due to the fact that the constructs are reflective, the measuring model was examined for internal consistency, indicator reliability, convergent validity, and discriminant validity (Esfahani et al., 2019). Table 2 displays the results of the measurement model assessment for the criterion values of composite reliability (CR), outer loading, and average variance (AVE). According to Maghsoudi et al. (2018), the reliability and validity assessments of reflective constructs are required. With CR [98], the internal consistency can be assessed. According to Bagozzi and Yi (1988), CR values above 0.7 are necessary. Because the CR value in this study is greater than 0.7, it was determined

that each of the study variables is reliable and that the study complies with the standards set by Hair et al. (2016).

Table 2: Measurement Model

Constructs	Items	Loading	CR	AVE
Performance Expectancy (PE)	PE1	0.800	0.810	0.588
	PE2	0.756		
	PE3	0.742		
Effort Expectancy (EE)	EE1	0.935	0.943	0.847
	EE2	0.920		
	EE3	0.906		
Social Influence (SI)	SI1	0.975	0.983	0.950
	SI2	0.975		
	SI3	0.974		
Facilitating Conditions (FC)	FC1	0.894	0.891	0.731
	FC2	0.830		
	FC3	0.839		
Behavioral Intention (BI)	BI2	0.808	0.838	0.722
	BI3	0.890		
	AB1	0.900		
Adoption Behavior (AB)	AB2	0.809	0.859	0.672
	AB3	0.743		

According to Hair et al. (2016), all suggested loadings have values of 0.7 or higher for every item. Due to their low loading values, all items with loading values lower than 0.7 were disqualified from consideration. The AVE must be used to assess convergent validity (Maghsoudi et al., 2018). According to Amin et al. (2016), the degree to which various questions measure the same concept that is included in the agreement is referred to as convergent validity. The constructs have attained convergent validity when all of the AVE values in Table 3 are greater than the minimal value of 0.5. The fact that all AVE values above the required minimum level serves as clear evidence of this (Fornell & Larcker, 1981). “Discriminant validity” refers to an item’s capacity to distinguish between several constructions or evaluate distinct concepts (Amin et al., 2016). Table 3 illustrates the evaluation of discriminant validity using the HTMT criterion. This study has proven the validity of such constructs by indicating that they exhibit discriminant validity.

Table 3: Discriminant Validity (HTMT)

VARIABLES	Adoption Behavior (AB)	Behavioral Intention (BI)	Effort Expectancy (EE)	Facilitating Conditions (FC)	Performance Expectancy (PE)	Social Influence (SI)
Adoption Behavior (AB)						
Behavioral Intention (BI)	0.088					
Effort Expectancy (EE)	0.229	0.268				
Facilitating Conditions (FC)	0.279	0.122	0.114			
Performance Expectancy (PE)	0.351	0.271	0.240	0.179		
Social Influence (SI)	0.079	0.280	0.450	0.056	0.351	

4.3. Structural Model Assessment

4.3.1. Collinearity Assessment

According to Yoo et al. (2014), the multicollinearity problem occurs when two or more variables are not independent. This can be established by the measurement of collinearity using the variance inflation factor (VIF). VIF of 5 or greater, according to Hair et al. (2011), suggests probable collinearity issues. Table 4’s findings show that all variables’ VIF values are below 5, which suggests that none of the study’s variables have a significant degree of correlation. As a result, there is no collinearity issue.

Table 4: Result Of Collinearity Assessment

LATENT VARIABLES	VIF
Behavioral Intention (BI)	1.000
Effort Expectancy (EE)	1.234
Facilitating Conditions (FC)	1.020
Performance Expectancy (PE)	1.101
Social Influence (SI)	1.283

To determine whether an omitted variable has a significant impact on the dependent variable, researchers can utilize the effect size of f^2 , which measures the change in R^2 when a specific independent variable is removed from the model (Hair et al., 2014). The f^2 results for the study’s independent variable are shown in Table 5. As the value of the effect size is less than 0.02, the recorded findings show that all the factors do not show any effect of the predictive relevance for the dependent variable (Hair Jr et al., 2016).

Table 5: Result of Effect Size (f^2) for Independent Variable

	Adoption Behavior (AB)	Behavioral Intention (BI)
Behavioral Intention (BI)	0.004	
Effort Expectancy (EE)		0.014
Facilitating Conditions (FC)		0.005
Performance Expectancy (PE)		0.013
Social Influence (SI)		0.014

4.4. The Hypotheses Testing

Path coefficients were used to determine whether the developed hypotheses should be accepted or rejected. The results of path coefficients are shown in Table 3. The results reveal that there is a significant impact of performance expectancy on behavioral intention to use e-learning ($\beta=0.115$, $T=2.117$, $P<.05$). Moreover, there is a significant impact of effort expectancy on the behavioral intention to use e-learning ($\beta=0.125$, $T=2.380$, $P<.05$). Furthermore, there is also a significant impact of social influence on the behavioral intention to use e-learning ($\beta=0.129$, $T=2.069$, $P<.05$). As a result, hypotheses H1, H2, and H3 are accepted. However, the results indicate an insignificant impact of facilitating conditions on behavioral intention to use e-learning and e-learning adoption behavior, and also an insignificant impact of behavioral intention to use e-learning leads on e-learning adoption behavior. Therefore, H4, and H5 are not supported by the study data and hence both hypotheses are rejected.

Table 6: Hypothesis Testing

Relationships	Std. Beta	Std. Error	t-Value	Decision
H1 Performance Expectancy → behavioral intention to use e-learning	0.115*	0.055	2.117	Supported
H2 Effort Expectancy → behavioral intention to use e-learning	0.125*	0.053	2.380	Supported
H3 Social Influence → behavioral intention to use e-learning	0.129*	0.062	2.069	Supported
H4 Facilitating Conditions → behavioral intention to use e-learning	0.068	0.054	1.270	Not Supported
H5 Behavioral intention to use e-learning → E-learning adoption behaviour	0.061	0.085	0.713	Not Supported

Note: * $p>0.05$

5. DISCUSSION

In order to predict the use and acceptability of electronic learning for academic and technological learning, particularly in the post-COVID-19 setting, the current study aims to test the UTAUT-3 model of Gunasinghe et al. (2020), as shown in Figure 3. Through the use of an information system, the UTAUT aims to provide clarity to the user’s objectives (Gupta & Dogra, 2017). To encourage

more academicians to use e-learning in a pandemic conditions like COVID-19 and continue to do so after pandemics, this study sought to ascertain whether the (UTAUT-3) model is appropriate for comprehending academician adoption. Eight determining elements for technology acceptance were included in the UTAUT-3 model developed by Farooq et al. (2017) and Gunasinghe et al. (2020), which included “performance expectancy, effort expectancy, social influence, facilitating conditions, habit, hedonic motivation, prize value, and personal innovativeness in IT.” The current study, however, only integrated four factors because they were considered more pertinent in the e-learning setting: “performance expectancy, effort expectancy, social influence, and facilitating conditions.” Due to the COVID-19 pandemic, e-learning has temporarily displaced traditional methods, such as traditional face-to-face instruction. When comparing the developed and developing worlds, it was found that the latter experienced issues such as poor internet connection, the lack of knowledge about using ICT, and shortcomings in content production (Aung & Khaing, 2015). For instance, many educators still lack experience in creating material, such as films and other applications, even at the postsecondary level in wealthy nations. This new tendency calls for improved technology and a change in educators’ working cultures. It is crucial to consider whether the students can succeed online before adding e-learning (Watkins et al., 2004; Guglielmino & Guglielmino, 2003). In order to understand the shift in behavioral adoptions following situations such as COVID-19, the study examined the appropriateness of UTAUT-3 for e-learning adoption determination.

This study’s first hypothesis was to demonstrate the beneficial influence of performance expectations on behavioral intention to use e-learning. The findings showed that performance expectancy still impacted behavioral intentions to use e-learning following COVID-19. Additionally, by supporting H2 and H3, the study’s findings showed that students’ post-COVID19 behavioral intentions towards using e-learning were significantly influenced by effort expectations and social influence. The fourth hypothesis (H4) was proposed to investigate the positive effects of favorable conditions on behavioral intention to use e-learning and e-learning adoption behavior. The data showed no correlation between “facilitating conditions and behavioral intention to use e-learning” and “facilitating conditions and e-learning adoption behavior.” This hypothesis was thus rejected. These findings differed from earlier research that concentrated on the use of technology during COVID-19. The H5 was also constructed to investigate the relationship between behavioral intention to use e-learning and e-learning adoption behavior. However, the results refuted this hypothesis by showing that there was no significant relationship. The majority of studies using UTAUT, UTAUT-2, and UTAUT-3 showed a favorable association between various behavioral intentions to utilize particular technologies and the adoption of technologies, but this research produced different results from the previous studies. This discrepancy in results may be due to the study’s context, which concentrated on a post-COVID-19 situation.

6. CONCLUSIONS AND IMPLICATIONS

Due to COVID-19, educational institutions across the globe were shut down. As a result, more than 1.2 billion children are not enrolled in educational institutions. With the emergence of e-learning, which involves remote teaching and the use of online platforms, education has undergone significant changes.

Studies showed that studying online improves information retention and takes less time, suggesting that the changes brought about by the coronavirus are permanent. Many people are questioning if online learning acceptance will continue after the pandemic and how such a revolution may affect the global educational system in light of the abrupt shift away from the classroom in many parts of the world. At the outset, well before COVID-19, e-learning expenditures attained a global peak of \$18.66 billion in 2019; by 2025, the total market for online education was anticipated to reach US\$350 billion. Since COVID-19, the use of instructional modules, virtual counselling, videoconferencing, and online learning software has increased dramatically. Significant global events such as COVID-19 frequently catalyses rapid innovation. This pandemic has illuminated the significance of knowledge exchange across industries, companies, and all aspects of society. If online learning technology plays a role in this, everyone must maximize its potential.

The UTAUT-3 framework was used in the study to examine the impact of behavioral intention to utilize e-learning on effort expectancy, performance expectancy, social influence, and enabling factors. By assessing the UTAUT-3 model's applicability for comprehending e-learning adoption in the context of COVID-19, this research adds to the theory. The current study verifies the UTAUT-3 paradigm proposed earlier [29] as key predictors of e-learning adoption, including effort expectancy, performance expectancy, social influence, and facilitating environments. As a result, this study makes an important contribution to the idea of technology adoption, particularly to the contemporary post-COVID-19 era's acceptance and adoption of e-learning. The study's findings will aid in the planning and execution of both learners' and learning providers' online strategies, as well as the decision-making of policymakers on how to increase user acceptance of e-learning.

By implementing e-learning effectively, we can circumvent a number of problems associated with traditional learning, such as physical presence, human resources, time, and space. Through enhanced performance management and capability development, e-learning expands the geographic and temporal boundaries of learning while concurrently improving output quality and overall performance (Ali, 2018). As a result, it is advised that decision-makers consider the implications of the aforementioned findings when formulating plans for expanding the use of e-learning. Depending on the political structure and degree of commitment to integrating technology into education, several approaches to e-learning policies are decided upon around the world. Generally speaking, developing a national e-learning policy that covers all public education is more challenging in nations where education is overseen by the state or provincial governments located within those nations. This study will serve as a guide for national or worldwide governing bodies as they develop comprehensive e-learning policies.

Only UTAUT3 emphasized the significance of e-learning in its research on the UTAUT, UTAUT2, and UTAUT3 theories, which largely concentrated on the technology adoption behaviors of the average consumers. As a result, this study will assist university leaders, decision-makers, and school administrators in developing efficient policies to acquaint students with the most recent online learning tools and techniques. National or international governing authorities can simplify and expedite the learning process for future pandemics or epidemics by focusing on this study.

7. LIMITATIONS AND RECOMMENDATIONS

Although the study concentrated on the broad viewpoint of UTAUT 3 in the context of adopting e-learning in the current post-COVID-19 period, it still has some shortcomings that should be taken into account by future studies. First, only the first four components of UTAUT 3—performance expectancy, effort expectancy, social influence, and facilitating conditions—were utilized in this study. Future studies may have an impact on other factors to emphasize behavioral goals and e-learning adoption behaviors. Second, future research can concentrate on other learning technologies as the study solely focused on adopting e-learning.

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