

Moderating Effect of Covid-19 On E-Learning Predictors: An Empirical Study on Student's Perspective in Sindh, Pakistan

Imran Khan Keerio^{1*}, Asadullah Shah², Krishan Kumar Luhana³, Najhan Muhamad Ibrahim⁴, Hazwani Mohd Mohadis⁵

^{1,2,4,5}KICT International Islamic University Malaysia; E-mail: imran_keerio@yahoo.com

³Sindh University Laar Campus, Badin, Sindh, Pakistan

Abstracts: During the COVID-19 pandemic, e-learning has been crucial for maintaining educational continuity while adhering to safety protocols and using social distancing guidelines. The worldwide spread of the pandemic has significantly disrupted traditional face-to-face educational practices, compelling the rapid and extensive adoption of electronic learning alternatives. As a result, it is crucial to understand the key factors influencing e-learning adoption in developing countries such as Pakistan during COVID-19. This research aims to analyze the moderating role of COVID-19 on key e-learning predictors using the UTAUT model by including some external Constructs. This study employed a qualitative survey-based methodology, with a sample size of 460 responses from students who engaged in e-learning during the period of the COVID-19 pandemic. The PLS-SEM technique was employed for data analysis utilizing the SmartPLS4 version 4.0.9.2 program. A Model was formed based on the UTAUT model by including some external variables. Empirical results revealed that during COVID-19 the most important factors predicting student behavior intention for e-learning adoption were, Computer anxiety, System characteristics, Facilitating conditions, Social influence, and COVID-19 itself. Furthermore, results also demonstrate that there was a sizable amount of COVID-19 moderating effect (0.022) on the association between social Influence and Behavior intention which somehow weakened the adoption of e-learning during COVID-19 time. The R-square value of the model is (0.677), which indicates that the model possesses substantial explanatory power, and the Q-square value is (0.662) indicating the establishment of Model predictive relevance.

Keywords: E-Learning, Moderating Effect, COVID-19, Sindh-Pakistan.

1. INTRODUCTION

The COVID-19 caused numerous problems in every aspect of life. By April 2020, approximately 50% of the global population adopted lockdown precautions. Nations worldwide took extreme safety measures to prevent the virus from spreading. These measures were very necessary otherwise the virus would have deep consequences for many aspects of human life. Approximately, 1.6 billion people were restricted to their homes, especially students delaying them from participating normally in their educational activities [1]. Even after immunization was available, students in higher education institutions faced several difficulties because of the COVID-19 outbreak. The challenge calls for a significant shift in how education is delivered and received. The only way to continue the educational activities was to transfer from traditional face-to-face classes to virtual classes through e-learning using available platforms. So most educational institutions, including universities, shifted their education to e-learning [2,3]. This shift caused several challenges as most of the students in higher education institutions were experiencing life in an entirely new setting, anxious with extreme difficulty [4,5,6]. Understanding students' challenges when adapting to a new e-learning system can better evaluate their learning and progress [7–8]. e-learning is a process in which education is achieved with the involvement of electronic devices such as Laptop, PCs, and Tablets, these devices need an internet connection by which they can communicate with each other, in this process, the physical distance between students and teacher exist as they can be far apart from each other [9]. Communication between teacher and student can be established with the help of software that runs on electronic devices through the internet connection; Several software applications provide this type of facility. Some well-known applications are Zoom, MS Team, and Google Classrooms. All these types of software provide education on distance as they have flexibility. Along with several advantages of the e-learning system, there are also diverse e-learning challenges, especially from students' perspectives due to the involvement of technology. The study's primary objective is to design a framework highlighting students' major problems during the COVID-19 epidemic to use e-learning technologies. Some of the problems highlighted by the literature review are Computer Anxiety, System Characteristics, Social

Influence, Facilitating Conditions, Computer self-efficacy, and Covid-19 itself. The literature review section of this study will enlighten these problems in detail.

2. LITERATURE REVIEW

In this study, a detailed literature review was undertaken using reliable sources to identify the important factors that predict students' behavior toward the adoption of e-learning during COVID-19. The subsequent section discussed some of the past research conducted related to e-learning and psychological theories used for technology adoption.

2.1. Model and Theories

In the last few years, several theoretical models have been presented by researchers to know the behavioral intentions of users regarding the use of technology. In 2003 Venkatesh along with other researchers proposed a model called UTAUT by considering the previous models and theories [11] the main constructs of the UTAUT model are Facilitating conditions, Performance Expectancy, Social Influence, and Effort expectancy along with moderators such as voluntariness, gender, Age and Experience. The same model was upgraded in 2012 with the new name UTAUT2 by including three supplementary variables that were PV (Price-value), Habit, and HM (Hedonic motivation) [12]. The present investigation employs the Unified Theory of Acceptance and Use of Technology (UTAUT) model as its foundation, supplemented by incorporating external variables from other models and theories. In addition to the Unified Theory of Acceptance and Use of Technology (UTAUT), this discussion will explore several other models and theories employed in technology adoption. It is worth noticing that the UTAUT model has been derived from the following mentioned models and theories.

2.1.1. Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) is a psychological model that examines an individual's goals and attitudes to explain human behavior. Martin Fishbein and Icek Ajzen proposed the Theory in the late 1970s, proposing that humans are rational decision-makers who weigh many considerations when determining whether to engage in a particular behavior. (Fishbein & Ajzen, 1975).

2.1.2. Technology Acceptance Model

The Technology Acceptance Model, or TAM, is a popular theoretical model in IS and IT. Established by Fred Davis in the late 1980s, TAM seeks to understand and anticipate how people accept and use new technologies Davis (1989). TAM model was further extended by TAM2, which incorporates additional variables and factors to explain better the dynamics of technology adoption Venkatesh & Davis (2000). Moreover, TAM3 was expanded based on a theoretical study of TAM's usage in various situations. TAM3 is described by Venkatesh and Bala (2008) as a complete integrated method for measuring individual acceptability and usage.

2.1.3. Theory of Planned Behavior

Icek Ajzen's late-eighties psychological framework Theory of Planned Behavior (TPB) explains and predicts human activity, especially intentional and voluntary behavior. TPB, an extension of TRA, is used in psychology, social science, marketing, and health behavior studies. (Ajzen, 1991).

2.1.4. Innovation Diffusion Theory

The 1960s Innovation Diffusion Theory by Everett Rogers is a well-established communication and sociology theory. It describes how and why social systems and communities accept and spread innovations, such as new ideas, technology, items, and processes. The theory identifies key factors influencing adoption rates and divides people into different categories based on their behavior. Rogers, (1995)

2.2. Past Research

The objective of this study is to examine the factors affecting e-learning acceptance during the COVID-19 pandemic. Several scholars researched e-learning by expanding the UTAUT model some of the research studies are discussed as follows:

In a study conducted by Latip and others [13], the researchers examined the acceptability of e-learning in Malaysian higher education institutions. The work utilized the Unified Theory of Acceptability and Use of Technology (UTAUT) model to investigate the potential moderating influence of self-efficacy. The investigation included a total of 414 participants, primarily consisting of undergraduate and postgraduate students. The study findings indicate four distinct, independent variables, namely Perceived enjoyment, Social Influence, Performance expectancy, and self-efficacy, which substantially affect the acceptance of e-learning among students.

A study was undertaken in India by scholars Acharjya and others [14] to investigate the moderating effect of gender and age on e-learning during the COVID-19 epidemic. The researcher expanded the UTAUT model by including components related to computer anxiety, technological anxiety, and attitude. The outcomes of this research work reveal that several elements, such as anticipated performance, social impact, computer anxiety, favorable environment, attitude, and behavioral intention, significantly influence the utilization of e-learning throughout the COVID-19 epidemic. Furthermore, it was found that, in contrast to the female group, the male group moderates the association in-between Effort Expectancy and behavioral Intentions.

Scholars from Pakistan Kanwal, F., & Rehman, M [15] conducted a study to establish and investigate the online education system adoption and acceptability baseline by including crucial external variables in the technology acceptance model. Students at a virtual institution provided the study is given data evaluated using SEM (Structural Equation Modeling). According to the empirical results of this research work, computer-efficacy, IE (Internet experience), enjoyment, and SC (system characteristics) are all important determinants of reported ease of use, moreover, system attributes are also important predictors of PU (Perceived Usefulness).

Researchers from Qatar Middle East El-Masri, M., & Tarhini, A. [16] conducted a study investigating the primary elements that may limit or enable university students in Qatar and the USA countries to use e-learning technologies using the UTAUT2 model. A sample provided data from 833 students at the university through an online survey. The participants were enrolled in universities located in Qatar and the United States. The primary analytical method utilized in this investigation was SEM (Structural Equation Modeling). The results reveal that PE (Performance Expectancy), hedonic motivation, habit, and trust substantially impact Behavioral Intention (BI) in both samples. Conversely, in contrast to their initial hypotheses, the correlation in-between PV Pricing Value (PV) and Behavioral Intentions (BI) is statistically negligible. The results also show that effort expectancy and social influence contribute to the higher adoption of e-learning practices among students in developing countries. However, this relationship is not observed in developed nations. Furthermore, facilitating conditions enhance the use of e-learning in privileged nations rather than underprivileged countries.

3. PROPOSED MODEL

In light of the existing research work for this study, it has been observed that researchers worldwide widely utilize the UTAUT model to assess user acceptance and rejection behavior in the context of e-learning especially in COVID-19 pandemic situations. Even though this model is used a lot, experts continue to collaborate to figure out how combining various models and factors can predict how easy technologies are to use. Based on the thorough research analysis undertaken for this study, a set of crucial predictors has been identified and subsequently utilized to suggest a conceptual framework. The factors considered in this research are Social Influence, Facilitating Conditions, the influence of COVID-19, CA (Computer-Anxiety), SC (System Characteristics), and CSE (Computer Self-Efficacy), as outlined by the UTAUT (Unified Theory of Acceptance and Use of Technology) model. The associated mentioned Figure 3.1 the conceptual framework that highlights this investigation.

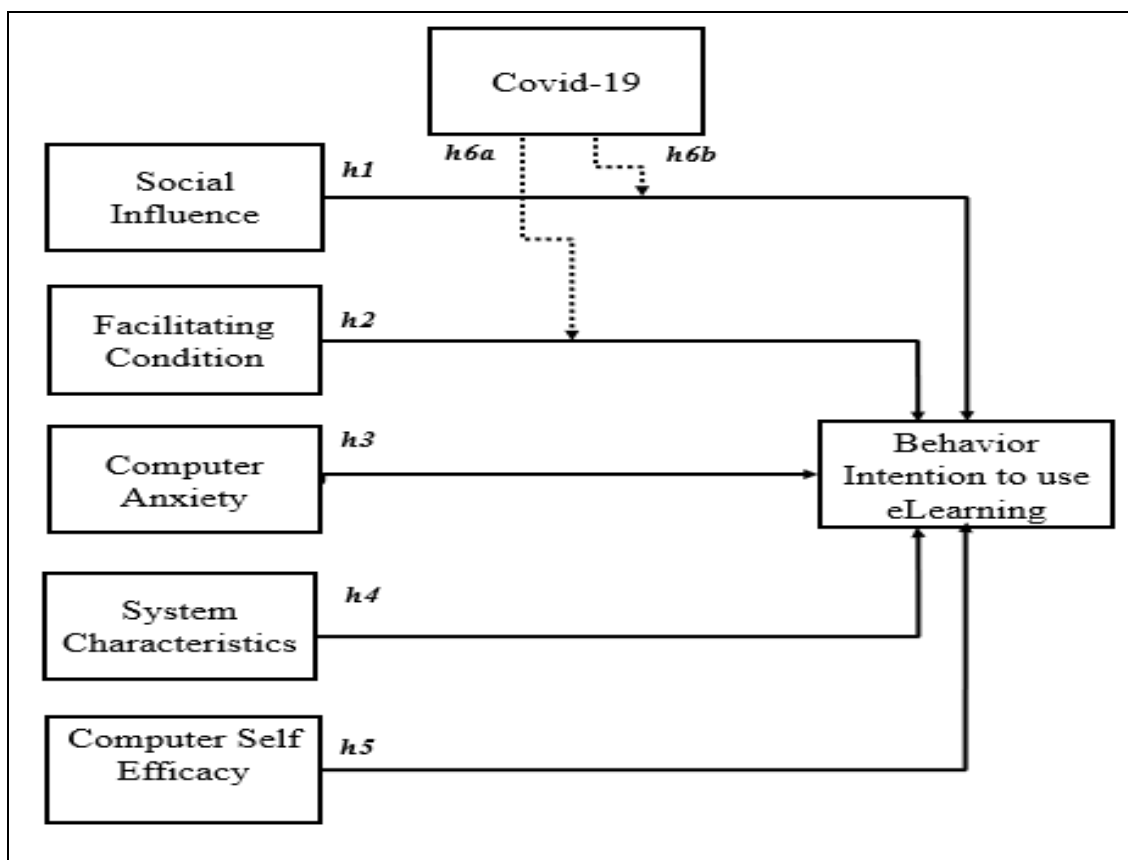


Figure 1: Proposed Framework

3.1. Predictors & Hypothesis Synthesis

The proposed model in Figure 3.1 will determine the relationship between the selected constructs; For this study, the behavioral intention construct is selected as a dependent variable to determine student intent to use e-learning through COVID-19 in Pakistan. This construct is extensively selected by many Investigators to find the behavior intention of users [13,14,15,16].

3.2. Social Influence

The concept of social influence (SI) can be referred to as the extent to which an individual feels that individuals around him believe that he or she should adopt and utilize the new system. The word "social influence" (SI) refers to how a person's immediate environment affects his or her thoughts and actions [12]. Social influence directly affects BI because people can be influenced by what others think, even if they do not want to. Venkatesh and Davis [19] say that the effect of SI only happens in places where it is required and has less of an effect in places where it is not. This study examines the influence of social influence's impact on students' adoption of e-learning through the COVID-19 epidemic, specifically from family, friends, and teachers. The hypothesis suggests the following:

H1. *Social influence will have a positive effect on behavioral intention to use e-learning.*

3.3. Facilitating Conditions

The concept of facilitating condition (FC) pertains to the extent to which an individual believes that an organizational and technological framework possesses the capacity to facilitate the utilization of a system effectively [12]. Simply, it provides the external resources required to support the accomplishment of a specific behavior [19]. Within this study, the measurement of FC will be based on the student's assessment of their capacity to acquire the

necessary resources and receive the needed assistance in utilizing the e-learning services. So, the hypothesis for FC is as follows.

H2. *Facilitating Conditions will have a positive effect on behavioral intention to use e-learning.*

3.4. Computer Anxiety

It is a psychological phenomenon shown by a person's hesitation or discomfort when using a computer [20]. In general, computer anxiety has a negative impact on computer use [21]. Although the development in the information technology sector is already mature enough, despite this using new interfaces and completing system-related tasks computer anxiety remains a significant obstacle. Many researchers have examined and supported computer anxiety's function from the e-learning perspective. Hence it is hypothesized as.

H3. *Computer anxiety will have a negative effect on behavioral intention to use e-learning.*

3.5. System Characteristics

In e-learning, system characteristics are important external variables influencing users' attitudes and adoption behavior. Scholars suggest and show that many system variables, such as system working mechanisms, interact with other systems and respond to changes, making it easier for users to adopt the technology [22, 23]. The system capability of an e-learning system is its capability to allow individuals to use it in a variety of ways [22]. Moreover, System Interactivity is one of the essential features because e-learning systems allow learners to work together with other individuals likewise teachers; the system should be interactive [24]. The system characteristics for this study are considered concerning its functionality, response time, and interactivity. Hence it is hypothesized as.

H4. *System characteristics will have a positive effect on behavioral intention to use e-learning.*

3.6. Computer Self-Efficacy (CSE)

Computer self-efficacy is an individual's position to accomplish IT (Information Technology) related tasks on a computer [25]. It has been established as the most important contributing factor in IS adoption and continuing use. Empirical evidence suggests that higher CSE increases one's confidence and motivation for adoption and acceptance of e-learning. Furthermore, those with greater CSE are keener to use e-learning systems and spend time-solving major challenges than people with low CSE.[26]. By considering the above literature in this study CSE is hypothesized as

H5. *Computer self-efficacy will have a positive effect on behavioral intention to use e-learning.*

3.7. Covid-19

The moderating influence of Covid-19 can be described as mitigating the influence of the Covid-19 epidemic through factors such as lockdown measures and fear associated with the virus. One of the research projects presented empirical evidence indicating that psychological strain and anxiety had a detrimental impact on adopting and adapting e-learning during the COVID-19 lockdown period [27, 28]. In this study, covid-19 was used as a moderating variable to investigate how it impacts facilitating conditions and social influence, so it is hypothesized as

H6a. *COVID-19 will negatively moderate the relationship between social influence and behavioral intention.*

H6b. *COVID-19 will negatively moderate the relationship between Facilitating Conditions and behavioral intention.*

4. Research Methodology

This study aims to determine the moderating effect of COVID-19 on e-learning predictors like Social Influence and Facilitating conditions and the probable correlation of e-learning predictors with behavioral intention. This study employs a quantitative survey approach to validate the things above experimentally. The SEM approach is used with SmartPLS4 software to validate the study model and test hypotheses. Previously, several scientists used this method to analyze the measurement and structural Model [31].

4.1 Data Collection

This study examined e-learning predictors and students from higher education institutions in Sindh, Pakistan, who used e-learning during the COVID-19 epidemic. Due to limited resources, only Sindh province's university samples could be collected. A cluster-based sampling technique was used to collect data from students in urban areas of public sector universities such as Sindh Madressatul Islam University, University of Sindh, and Sukkur IBA. The universities are located in Karachi, Hyderabad, and Sukkur, which are highly populated province cities that house a sizable amount of the province's population.

The study employed a Sven Point Likert scale consisting of 41 items in the survey form. Among these items, 36 were focused on the construct being investigated, while the remaining 5 items pertained to demographic information. Items that are based on constructs were derived from prior research conducted by [32, 33, 16]. A digital survey in the form of an online Google form was created for data collection. The distribution of this survey was carried out through popular communication platforms such as WhatsApp and email. A final sample size of 460 replies was obtained for data analysis, representing a reduction of 100 responses from the initial pool of 560 due to the exclusion of biased responses. The next section presents a demographic analysis of the study.

4.2. Demographic Analysis

The subsequent figure 2 illustrates the demographic analysis of the study. The data reveals that male participation in the survey was much higher, accounting for 71.3%, compared to female involvement. Furthermore, regarding age distribution, a significant majority of 69.5% fell within the 21-30 age bracket. Notably, a substantial proportion of individuals, specifically 77.1%, were pursuing undergraduate courses. The majority stake of 43.8 is attributed to SMIU, given its location in Karachi, the most densely inhabited metropolis in the province and the country.

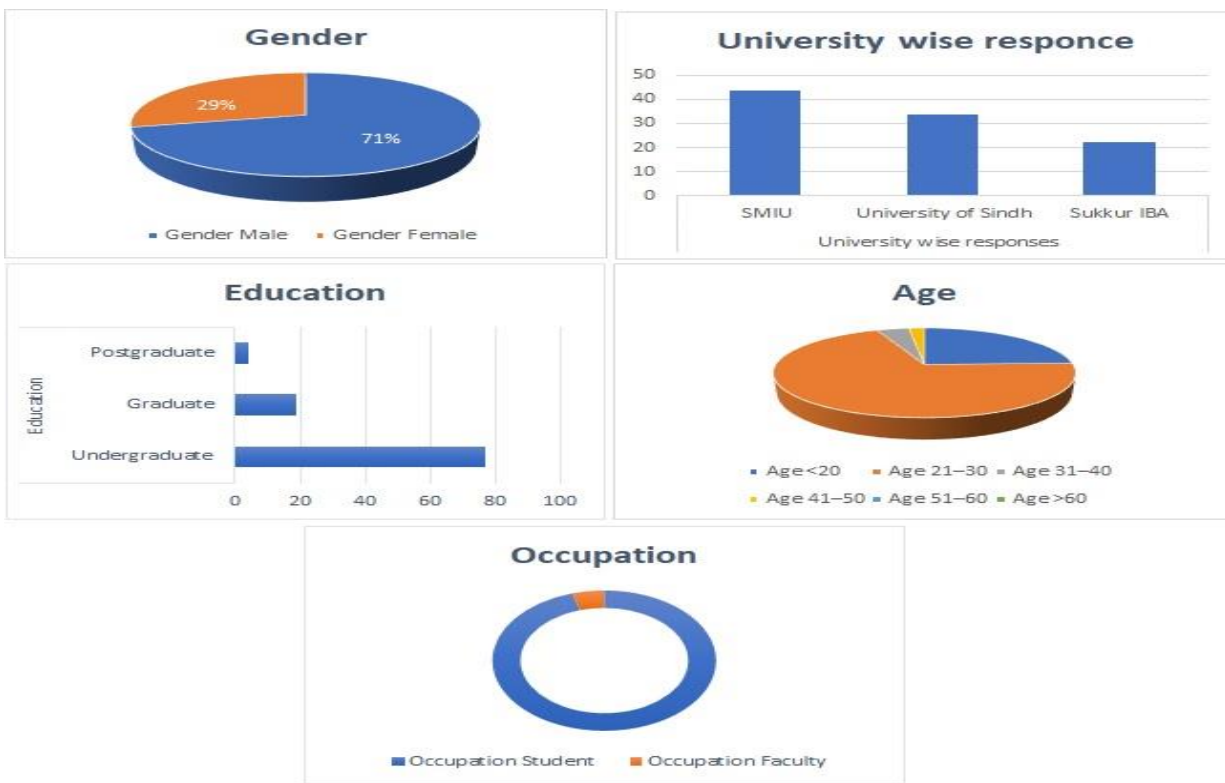


Figure 2: Demographic Analysis

5. Data Analysis

The data analysis for this investigation was divided into two sections. The first section is the Measurement model, which determines the model's validity and reliability, and the second section is the Structural model, which evaluates the testing of hypotheses and the moderating influence of COVID-19.

5.1. Measurement Model

The measurement model assesses the measurement's reliability and validity. Internal consistency (Cronbach's alpha), composite reliability, convergent validity (average variance reduced), and discriminant validity are all quality measures. To evaluate the measurement model, the Partial Least Squares (PLS) algorithm was executed. [34]. Table 1 presents the reliability and convergent validity of statistical measures. Based on the findings, the values of Cronbach's alpha and composite reliability exceed the established criterion of 0.7, as shown by Hair [34]. Furthermore, the observed values for crossover loading and average variance retrieved fall within the expected range of values greater than 0.70 and 0.50, respectively [34]. Therefore, based on the results, this study has successfully demonstrated reliability and convergent validity.

Table 1: Reliability Analysis

Items	Loading	Alpha	CR	AVG
BI1	0.872	0.932	0.948	0.785
BI2	0.894			
BI3	0.897			
BI4	0.875			
BI5	0.893			
CA1	0.822	0.876	0.910	0.669

CA2	0.851			
CA3	0.818			
CA4	0.776			
CA5	0.819			
CSA1	0.740			
CSA2	0.739			
CSA3	0.830	0.852	0.894	0.629
CSA4	0.804			
CSA5	0.846			
CVD2	0.833			
CVD3	0.891	0.904	0.933	0.777
CVD4	0.907			
CVD5	0.893			
FC1	0.740			
FC2	0.749			
FC3	0.796	0.780	0.859	0.603
FC4	0.819			
SC1	0.891			
SC2	0.902			
SC3	0.900			
SC4	0.864	0.950	0.959	0.768
SC5	0.876			
SC6	0.882			
SC7	0.819			
SI1	0.875			
SI2	0.865			
SI3	0.881	0.941	0.953	0.773
SI4	0.869			
SI5	0.891			
SI6	0.894			

Discriminant validity is achieved for this study using two tests, Fornell Larcker and the Heterotrait Monotrait Ratio (HTMT). Based on the Fornell Larcker criterion, it is recommended that the square root of the Average Variance Extracted (AVE) for each factor should exceed the association values between the variable under consideration and other variables. According to Henseler [35] the HTMT value for an effect should not exceed 0.90. The findings indicate that the observed HTMT values were below 0.90 (see Table 2). Moreover, the (AVE) of the Fornell Larcker criterion is above the required range (see Table 3) Based on the obtained results, the study has successfully demonstrated discriminant validity.

Table 2: HTMT Analysis

	BI	CA	CSA	CVD	FC	SC	SI
BI							
CA	0.657						
CSA	0.722	0.546					
CVD	0.584	0.288	0.558				
FC	0.714	0.613	0.621	0.380			
SC	0.688	0.462	0.680	0.563	0.603		

SI	0.744	0.580	0.778	0.435	0.631	0.638	
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Table 3: Fornell Larcker Analysis

	BI	CA	CSA	CVD	FC	SC	SI
BI	0.886						
CA	-0.598	0.818					
CSA	0.653	-0.483	0.793				
CVD	-0.538	0.26	-0.49	0.882			
FC	0.609	-0.509	0.516	-0.323	0.777		
SC	0.649	-0.429	0.62	-0.524	0.521	0.877	
SI	0.697	-0.53	0.712	-0.404	0.542	0.604	0.879

5.2. Structural Model

The structural model is used for testing and examining the relationships between latent constructs based on theory and prior research. For this study, a bootstrap procedure was applied using a sample size of 500 [34]. The results of path coefficient parameters such as β Coefficient, Std-deviation, T-Statistics, and P-Values along with Models Explanatory Power predictor R square, F square, and Q square are presented in Table 4 and (see Figure 3). A total of seven hypotheses were proposed in the model. According to the results six hypotheses **H1** ($\beta= 0.262$, $t= 4.696$, $p= 0.000$), **H2** ($\beta= 0.179$, $t= 4.203$, $p= 0.000$), **H3** ($\beta= -0.202$, $t= 4.851$, $p= 0.000$), **H4** ($\beta= -0.155$, $t= 3.172$, $p= 0.002$), **H6a** ($\beta= -0.095$, $t= 2.532$, $p= 0.011$), **H6b** ($\beta=0.086$, $t= 2.227$, $p= 0.026$) are supported while one hypothesis **H5** ($\beta= 0.084$, $t= 1.749$, $p= 0.080$) was rejected. According to Hair [34], the hypothesis acceptance requirement is based on its p-value which should be less than or equal to 0.50. Concerning models' explanatory power, researcher Cohen, [36] states that a value of 0.02 for the effect size f^2 is generally regarded as modest, while a value of 0.15 is considered medium, and a value of 0.35 is considered high. Revealed results presented in Table 1 indicate that all the factors have satisfactory f^2 effect sizes except computer self-efficacy with an effect size of 0.009 and Covid moderating effect on facilitating conditions with an effect size of 0.018 are below the satisfactory requirement. The study's results indicate that a considerable proportion, precisely 62%, of the variation in Behavioral Intention may be accounted for by factors including computer anxiety, computer self-efficacy, facilitating conditions, social influence, system characteristics, and the impact of COVID-19. According to Choen [36], when the r square value is above 0.26, it indicates that the model possesses substantial explanatory power. Moreover, for predictive relevance, Hair [37] states that if the value of Q-square is more than (0.35) it will be assumed high, (0.15) moderate, and (0.02) weak. In this investigation, it was found that the Q-square value of BI is more than zero, indicating the establishment of predictive relevance.

Table 4: Hypothesis Test Analysis

Hypo	Paths	β	Std-dev	T-Stat	P-Values	f^2	R ²	Q ²	Result
H1	SI -> BI	0.262	0.056	4.696	0.000	0.088	0.677	0.662	Accepted
H2	FC -> BI	0.179	0.042	4.203	0.000	0.059			Accepted
H3	CA -> BI	-0.202	0.042	4.851	0.000	0.081			Accepted
H4	SC -> BI	0.155	0.049	3.172	0.002	0.036			Accepted
H5	CSA -> BI	0.084	0.048	1.749	0.080	0.009			Rejected
H6a	(SI*CVD) -> BI	-0.095	0.037	2.532	0.011	0.022			Accepted
H6b	(FC*CVD) -> BI	0.086	0.039	2.227	0.026	0.018			Accepted

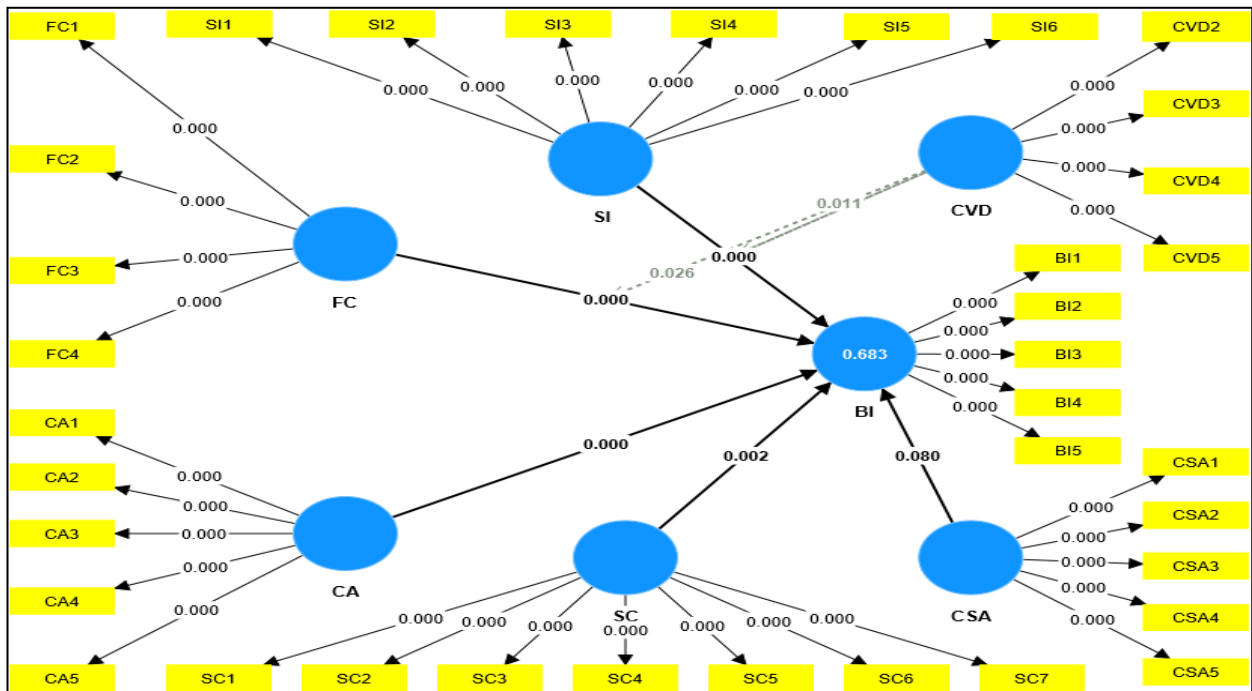


Figure 3: Structural model with Bootstrapping

5.3. Moderating Effect

The object of this study is to find the moderating effect of COVID-19 on e-learning predictors such as Social Influence and Facilitating conditions. The subsequent section enlightens on the revealed results.

(SI*CVD) -> BI: When the moderating effect of (SI*Covid-19) was not considered, the R-squared value for Behavioural Intention was 0.647, showing that social impact changes behavioral intention 64.7%. The inclusion of the interaction term boosted R-Sq to 0.677%. The dependent variable, behavioral intention, increased 3%. The moderating influence was also examined in this study. The study found that COVID-19 significantly moderated the relationship between SI and BI ($\beta = -0.095$, $t = 2.532$, $p = 0.011$), supporting Hypothesis H6a, indicating that the correlation between SI and BI weakens as COVID-19 (concerning stress and confinement) increases. Cohen's [36] research states that 0.02, 0.15, and 0.35 are small, medium, and big effect sizes of moderation, respectively. The f-square effect size was 0.022. There is a balancing effect that is medium negative and significant. This shows that the moderating effect contributes significantly to explaining the endogenous construct of BI as shown in Table 4. Additionally, slope analysis helps to understand moderating effects. In Figure 4, the red line shows the COVID-19 effect minus one standard deviation of low, the green line high, and the blue line mean. The red line is steeper than all others, indicating that social influence will affect BI more with low COVID-19 effects. In simple terms, the higher effect of COVID-19 will weaken the impact of SI on BI.

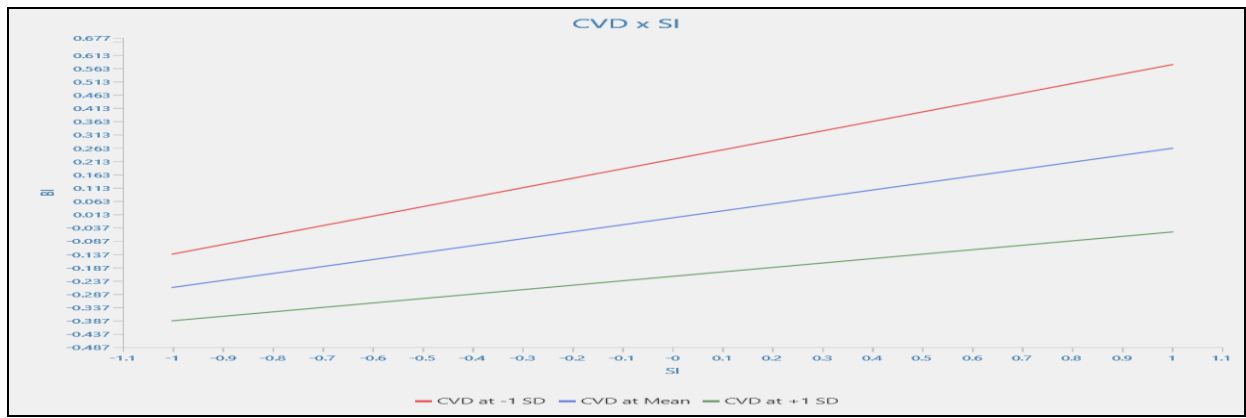


Figure 4: Slope Analysis for (SI*CVD) -> BI

(FC*CVD) -> BI: Analysis of COVID-19's moderating influence on FC and BI, the R-squared value for BI was 0.67 without the moderating influence of FC*Covid-19. This shows that FC impact changes in BI by 67%. The coefficient of determination (R-sq) increased to 0.683% when adding the factor interaction term. The results show that the dependent variable, BI, has become 1.3% more varied. The moderating influence was also examined in this study and found that COVID-19 positively moderated the relationship between FC and BI ($\beta = 0.086$, $t = 2.227$, $p = 0.026$), supporting the alternative Hypothesis H6b. The f-square size of COVID-19 in this association is 0.018 which is negligible and does not provide any sufficient impact. Moreover, the slope analysis presented in Figure 5 predicts that all lines are almost parallel with a slightly steeper redline which indicates an almost insignificant moderating effect despite the significance of the hypothesis.

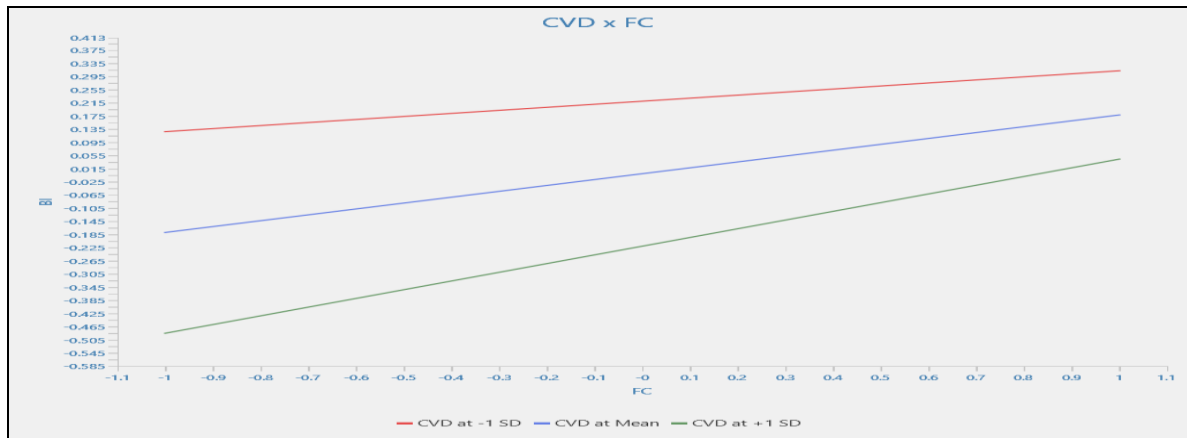


Figure 5: Slope Analysis for (FC*CVD) -> BI

6. Discussion

This study aims to investigate the moderating effect of COVID-19 on e-learning predictors according to the revealed results for H1, which is significantly accepted. The results indicate that students were considering the recommendations their friends, family members, and teachers provided to adopt e-learning during the COVID-19 era. The same sort of results were also revealed by past studies such as Alami [38] Moving on, H2 related to facilitating conditions was accepted and predicted that the availability of infrastructure such as continuous power, internet facility, and relevant required IT hardware will ultimately increase student intention to use e-learning. Similar results were received in research conducted by MUSYAFFI [39].

Moreover, H3 was also accepted, predicting that computer anxiety negatively influences the extent to which individuals adopt e-learning during the COVID-19 pandemic. The possible reasons for this can be the student's fear

of making mistakes or having problems when utilizing technology for learning can cause anxiety. Students may worry about falling behind on assignments or exams; another reason is that students with little computer or online learning experience may feel uncomfortable about new digital environments and tools. The findings presented for H3 in this study are supported by previous research conducted by Alkhuwayldee [40].

Furthermore, H4 related to system characteristics is positively accepted by this study; the possible reason behind this result could be the perception of students for e-learning software systems that have a user-friendly interface and sufficient amount of function required to conduct or take online classes along with its always availability and fast response time. Studies such as Kanwal [41] report the significance of system characteristics.

In addition, H5, which predicted that computer self-efficacy would play a role in students' adoption of e-learning during COVID-19, was rejected. The rejection reason could be that students were required to use computers and tablets for online coursework regardless of their comfort level with such technology, students with less technology experience may have reduced self-efficacy in using computers for learning. It was supported in previous studies [42].

Hypothesis 6a deals with the moderating effect of COVID-19 in a correlation between SI and BI. According to the statistical results, the hypothesis was accepted, proving that during the COVID-19 pandemic, students were stressed and anxious during online classes. One possible reason for this stress could be the frequent deaths in families and surroundings, which divert their behavior intention to adopt e-learning. Another reason could be social isolation; students' mental health was negatively impacted by the isolation and stress brought on by the pandemic. Several studies in the past predicted the COVID effect on social life, such as Roman [38].

Finally, hypothesis 6b related to the moderating effect of COVID-19 on the association between FC and BI was accepted; according to the statistics results, there is a negligible moderating effect of COVID-19 on said association, but as the alternative hypothesis was accepted so one explanation for the positive impact could be the efforts taken by the government to provide desired facilities for online classes during pandemic, which ultimately improve the behavior intention of the students to adopt e-learning.

6.1. Theoretical Implications

Regarding e-learning adoption predictors during COVID-19, this study presents theoretical implications such as an extension of the UTAUT2 model by incorporating the external variables in the context of e-learning, especially in Sindh Pakistan. The model's explanatory and predictive efficacy is enhanced by moderating external variables like COVID-19. Moreover, SmartPLS4 data analysis will provide theoretical implications to the literature.

6.2. Practical Implications

Due to the COVID-19 epidemic, several countries switched to e-learning as their main education method. This transformation affected students, educators, educational institutions, and policymakers.

One implication is that E-learning enables institutions to teach and support students after campuses close. This allowed learning during lockdowns and restrictions. Digital textbooks, multimedia information, and online libraries were available through e-learning. This increased educational materials. changed classes, augmented reality, and interactive simulations were used to engage students online. Online evaluations like proctored exams and alternate assessments required educators to adapt. Maintaining academic honesty was hard. E-learning requires policymakers and governments to change rules. This covered accreditation, licensing, and privacy. These implications emphasize the necessity of using technology to address access, equity, quality, and education support.

6.3. Limitations and Future Directions

This study used a cross-sectional quantitative approach for data collection, Data was collected only from urban areas of Sindh with a limited sample size that is 400, for future approaches rural areas should be considered and the sample size should be increased. Additionally, it is recommended to incorporate additional constructs into the

model to augment its predictive capacity. These constructions may include factors such as students' satisfaction and teachers' pedagogy.

CONCLUSION

Finally, this study has led to the conclusion that in response to the COVID-19 pandemic, educational institutions universally shifted to an e-learning mode due to the compulsory deployment of social distancing measures. Several critical determinants for the successful implementation of e-learning were identified in this study, including computer fear, system characteristics, social influence, and supportive surroundings. Furthermore, the current global pandemic has greatly influenced students, resulting in increased stress and worry. Additionally, the findings indicate a significant COVID-19 moderating effect (0.022) on the relationship between social influence and behavior intention, leading to a reduction in the adoption of e-learning during the COVID-19 pandemic. The model's R-square score of 0.677 suggests that it has a significant level of explanatory power. Also, the Q-square value of 0.662 indicates that the model has established predictive relevance.

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