

FACTORS AFFECTING THE ADOPTION OF E-LEARNING
DURING COVID-19: AN EMPIRICAL STUDY IN
PAKISTAN

BY

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ABSTRACT

E-learning enables an environment in which educational activities are delivered through online platforms using computing devices to empower learning facilities anywhere and anytime without geographical boundaries. During the COVID-19 crisis where social distancing was mandatory, many e-learning platforms were adopted by institutions around the globe. Experiences show that for the adaptation of E-learning, several challenges were faced by educational institutions, among them some of the core challenges are Cost, System Quality, System Complexity, Infrastructure, Social influence, COVID-19 effect, and Student learning motivation. Therefore, this research aims to find the factors affecting the adoption of E-Learning during COVID-19 in Pakistan. To achieve this, a proposed hypothetical model has been formed based on well-known IT/IS acceptance models such as extended TAM, UTAUT, M&D, TRA, and IDT. Keeping problems in mind, an extensive literature search has been completed. In this study, constructs like Perceived Cost, System Quality, Complexity, Social Influence, Facilitating Condition, COVID-19 (Lockdown and COVID fear); Student learning motivation; Perceived Ease of User (PEOU), and Perceived Usefulness (PU) are the most significant variables to impact Behavior Intention (BI) to use e-learning in Pakistan, are measured. The hypothesized correlations were investigated using Smart-PLS software and Structural Equation Modeling (SEM). The correlational paths between constructs are studied using a quantitative methodology (survey questionnaire). A cluster sampling methodology was employed to gather a comprehensive dataset of 461 responses from students who utilized e-learning throughout the COVID-19 epidemic. The research findings indicate a significant statistical relationship in 13 out of the 15 hypotheses tested, while the other 2 did not yield statistically significant results. The research findings suggest that a significant portion, specifically 61.1%, of the change in Behavioral Intention may be reported by factors such as PU, PEOU, SI, SQ, CS, and COVID-19. Likewise, PEOU factors explained 39% of the variance, and Perceived Usefulness explained 54.7% in descending order of importance. Furthermore, the Cost and COVID-19 factors involved in adopting e-learning during COVID-19 negatively correlate with behavioral intention. Thus, Cost and COVID-19 were considered obstacles to adopting e-learning in the COVID-19 pandemic. This study contributes to identifying the significant factors influencing the behavioral intentions of Pakistani students for e-learning adoption during the COVID-19 pandemic, it also proposes an integrated research model to investigate the adoption of e-learning. Moreover, it offers practical and theoretical implications of its findings for stakeholders, including policymakers, educators, researchers, and industry practitioners involved in developing and implementing e-learning initiatives in Pakistan.

ملخص البحث

البيئات التمكينية للتعليم الإلكتروني يتم فيها تقديم الأنشطة التعليمية من خلال منصات إلكترونية تستخدم أجهزة حاسوبية لتمكين مرافق التعلم في أي مكان وزمان دون حدود جغرافية. خلال أزمة فيروس كورونا (كوفيد-19) حيث كان التباعد الاجتماعي إلزامياً، تم اعتماد العديد من منصات التعلم الإلكتروني من قبل المؤسسات في جميع أنحاء العالم. تشير التجارب إلى أنه من أجل تكييف التعلم الإلكتروني، واجهت المؤسسات التعليمية العديد من التحديات، من بينها بعض التحديات الأساسية وهي التكلفة، وجودة النظام، وتعقيد النظام، والبنية التحتية، والتأثير الاجتماعي، وتأثير كوفيد-19، وتحفيز تعلم الطلاب، والتي يمكن البحث فيها في البلدان النامية مثل باكستان. ولذلك يهدف هذا البحث إلى إيجاد أهم العوامل التي تؤثر على بقاء اعتماد التعلم الإلكتروني خلال أزمة كوفيد-19 في باكستان. لتحقيق هذا، تم تشكيل نموذج افتراضي مقترح بناءً على بعض نماذج قبول تكنولوجيا المعلومات/نظم المعلومات المعروفة مثل Extended TAM ، وUTAUT، وM&D، وTRA، و IDT. مع أخذ المشكلات في الاعتبار، تم الانتهاء من بحث مكثف في الدراسات السابقة وتم الانتهاء من المتغيرات الأكثر صلة بمشكلة البحث والإعدادات السياقية. في هذه الدراسة، يتم استخدام بنى مثل التكلفة المدركة، وجودة النظام، والتعقيد، والتأثير الاجتماعي، والظروف الميسرة، وكوفيد-19 (الإغلاق والخوف من كوفيد)؛ دافعية تعلم الطالب؛ تعد سهولة الاستخدام المدركة (PEOU)، والفائدة المدركة (PU) من أهم المتغيرات التي تؤثر على نية السلوك (BI) لاستخدام التعلم الإلكتروني في باكستان. تمت دراسة الارتباطات المفترضة باستخدام برنامج Smart-PLS ونمذجة المعادلات الهيكلية (SEM). تتم دراسة المسارات الارتباطية بين التركيبات باستخدام منهجية كمية (استبيان المسح).

تم استخدام منهجية أخذ العينات العنقودية لجمع مجموعة بيانات شاملة مكونة من 461 استجابة من الطلاب الذين استخدموا التعلم الإلكتروني طوال فترة وباء كوفيد-19. وتشير نتائج البحث إلى وجود علاقة ذات دلالة إحصائية في 13 فرضية من أصل 15 فرضية تم اختبارها، في حين لم تسفر الفرضيتان الأخريان عن نتائج ذات دلالة إحصائية. تشير نتائج الدراسة إلى أن جزءًا كبيرًا، على وجه التحديد 61.1%، من التغيير في النية السلوكية قد تكون بسبب عوامل مثل PU، وPEOU، وSI، وSQ، وCS، وCOVID-19. وبالمثل، أوضحت عوامل 39% PEOU من التباين، وفسرت الفائدة المدركة 54.7% بترتيب تنازلي من حيث الأهمية. بالإضافة إلى، إن عوامل التكلفة وفيرس كورونا (COVID-19) المرتبطة باعتماد التعلم الإلكتروني خلال فيروس كورونا (COVID-19) لها علاقة سلبية مع النية السلوكية. وبالتالي، تم اعتبار التكلفة وفيرس كورونا (COVID-19) بمثابة عقبات أمام اعتماد التعلم الإلكتروني في ظل الوباء. علاوة على ذلك، تعتبر نتائج هذه الدراسة مهمة جدًا لأصحاب المصلحة الذين يستثمرون في تطوير وتنفيذ مبادرات التعلم الإلكتروني. إن الفهم الأكبر وإعادة النظر في هذه الجوانب قد يؤدي إلى فوائد لأصحاب المصلحة المحتملين. يسعى البحث الحالي إلى تحديد العوامل الرئيسية التي لها تأثير على التعلم الإلكتروني. ستوفر النتائج فهمًا قيمًا لتطوير وتنفيذ أنظمة التعلم الإلكتروني، لا سيما في سياق حالات الوباء، مع الهدف النهائي المتمثل في تعزيز اعتماد التعلم الإلكتروني على نطاق واسع. تساهم هذه الدراسة في تحديد العوامل الهامة المؤثرة على النوايا السلوكية للطلاب الباكستانيين لاعتماد التعلم الإلكتروني خلال جائحة كوفيد-19، كما تقترح نموذج بحث متكامل لدراسة اعتماد التعلم الإلكتروني. علاوة على ذلك، فإنه يقدم آثارًا عملية ونظرية لنتائجه لأصحاب المصلحة، بما في ذلك صناع السياسات والمعلمين والباحثين وممارسي الصناعة المشاركين في تطوير وتنفيذ مبادرات التعلم الإلكتروني في باكستان.

APPROVAL PAGE

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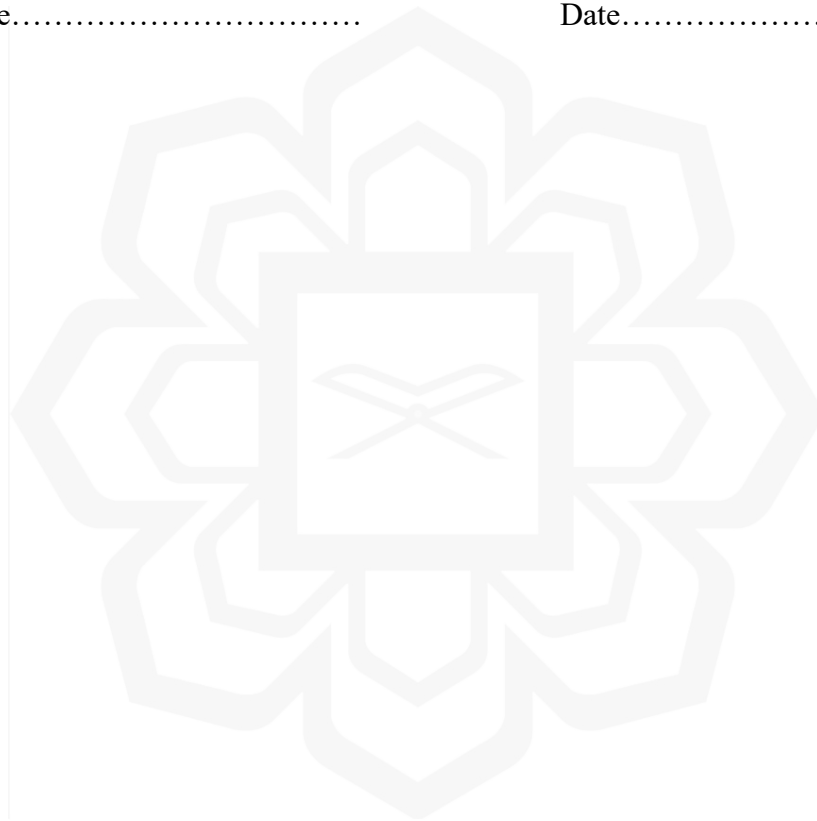
DECLARATION

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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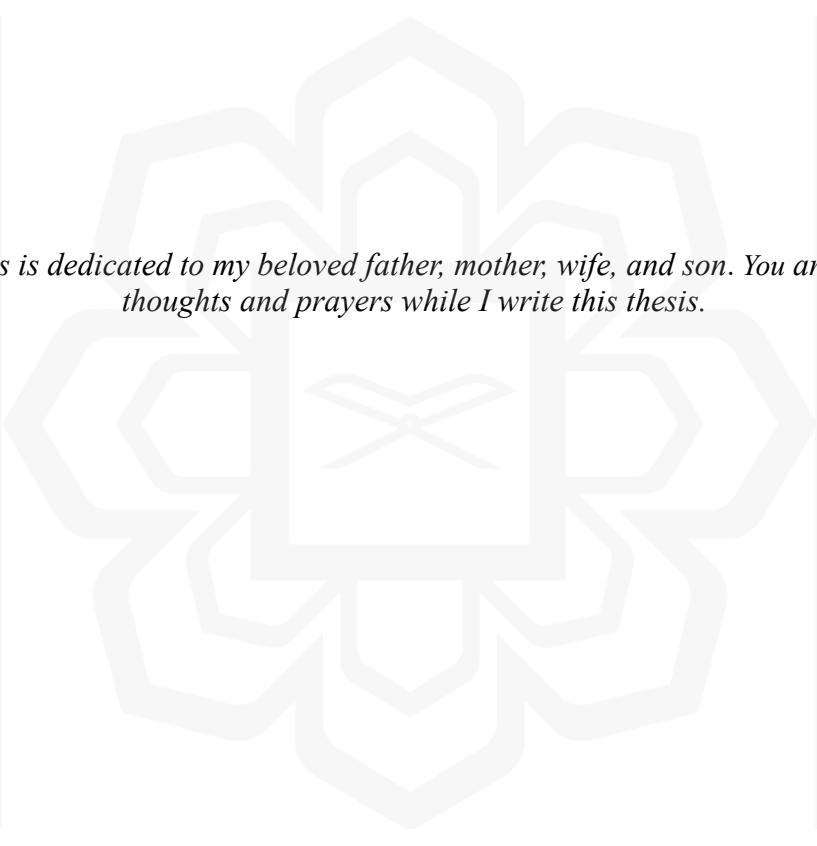
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This thesis is dedicated to my beloved father, mother, wife, and son. You are all in my thoughts and prayers while I write this thesis.

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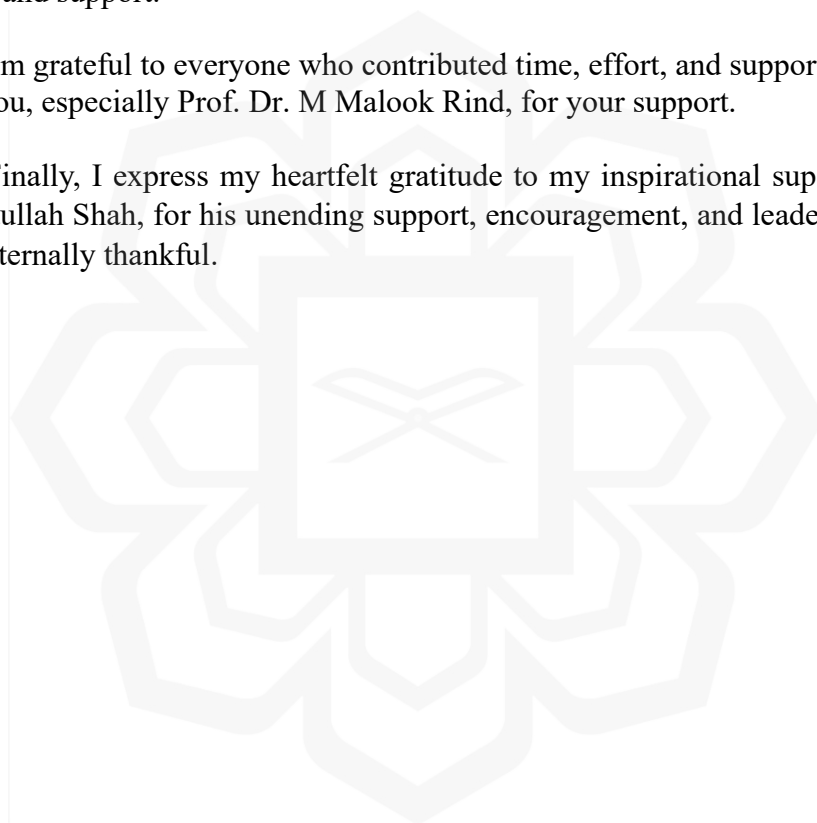


TABLE OF CONTENTS

Abstract	ii
Abstract In Arabic	iii
Approval Page	v
Declaration	vi
Copyright	vii
Dedication	viii
Acknowledgments	ix
List of Tables	xiv
List of Figures	xvi
List of Abbreviations	xvii
CHAPTER ONE: INTRODUCTION	1
1.1 BACKGROUND OF STUDY	1
1.1.1 Adoption of e-learning in Pakistan	2
1.2 PROBLEM STATEMENT	4
1.3 RESEARCH AIM AND OBJECTIVES	6
1.4 RESEARCH QUESTIONS	6
1.5 RESEARCH SCOPE	6
1.6 SIGNIFICANCE OF STUDY	7
1.7 CONTEXT OF STUDY: PAKISTAN	7
1.8 RESEARCH METHODOLOGY	8
1.9 THESIS STRUCTURE	9
1.10 CHAPTER SUMMARY	10
CHAPTER TWO: LITERATURE REVIEW	11
2.1 INTRODUCTION	11
2.2 BACKGROUND	11
2.3 E-LEARNING	12
2.4 E-LEARNING IN COVID-19	13
2.5 BENEFITS OF E-LEARNING	14
2.5.1 The Flexibility of Time and Location	14
2.5.2 Saving Cost	14
2.5.3 Collaborative Learning	15
2.5.4 Instructors' Ease of Access	15
2.5.5 Personalized Education	15
2.6 BARRIERS IN E-LEARNING	16
2.6.1 Instructors Barriers	16
2.6.2 Student Barriers	17
2.6.3 Infrastructure Barriers	18
2.6.4 Environment and Space Barrier	18
2.6.5 COVID-19 As Barrier	19
2.6.6 Absence of e-learning resources	19
2.6.7 E-Learning Challenges in Pakistan during COVID-19 and Beyond	20
2.7 THEORIES AND MODELS USED FOR ADOPTION IS/IT	23

2.7.1	Theory of Reasoned Action (TRA).....	24
2.7.2	Innovation Diffusion Theory (IDT)	25
2.7.3	DeLone and Mclean Model.....	26
2.7.4	Unified Theory of Acceptance and use of technology (UTAUT).....	27
2.7.5	Technology Acceptance Model (TAM).....	29
2.8	Past Research on E-Learning Adoption In COVID-19.....	34
2.9	CHAPTER SUMMARY	47

CHAPTER THREE: PROPOSED RESEARCH MODEL DEVELOPMENT 48

3.1	INTRODUCTION	48
3.2	THE RESEARCH MODEL.....	49
3.3	DEVELOPMENT OF HYPOTHESES	53
3.3.1	Behaviour Intention Dependent variable (BI).....	53
3.3.2	Perceived Usefulness Mediating variable (PU)	54
3.3.3	Perceived Ease of Use Mediating variable (PEOU)	54
3.3.4	Perceived Cost external variable (PC)	55
3.3.5	System Quality external variable (SQ)	56
3.3.6	Complexity external variable (CO).....	56
3.3.7	Social Influence external variable (SI).....	57
3.3.8	Facilitating conditions external variable (FC).....	58
3.3.9	Covid-19 external variable external variable (CVD).....	59
3.3.10	Student Learning Motivation external variable (SLM).....	60
3.4	CHAPTER SUMMARY	60

CHAPTER FOUR: RESEARCH METHODOLOGY 62

4.1	INTRODUCTION	62
4.2	RESEARCH PARADIGMS	63
4.2.1	Positivism.....	64
4.2.2	Post-positivism.....	64
4.2.3	Critical Theory	64
4.2.4	Constructivism	65
4.3	POSITIVIST AND INTERPRETIVISM RESEARCH APPROACH.....	66
4.4	RESEARCH METHODS FOR INFORMATION SYSTEMS.....	67
4.5	DATA SOURCE.....	69
4.5.1	Quantitative Research Method.....	69
4.5.2	Qualitative Research Method.....	70
4.5.3	Choice of Research Method.....	70
4.6	SELECTION OF SURVEY AS THE RESEARCH STRATEGY	72
4.7	RESEARCH DESIGN	74
4.7.1	Purpose of the Study: Hypotheses Testing	77
4.7.2	Type of Investigation: Correlational Study.....	77
4.7.3	Study Settings: Non-contrived.....	77
4.7.4	Unit of Analysis: Individuals	78
4.7.5	Time Horizon: Cross-sectional	78
4.8	POPULATION AND SAMPLING	78
4.8.1	Population	79
4.8.2	Sampling	79
4.8.3	Sampling Method for this Research.....	80
4.9	DATA COLLECTION PROCEDURE: QUANTITATIVE.....	82

4.10	INSTRUMENTS/QUESTIONNAIRE DEVELOPMENT	84
4.10.1	Questionnaire Wording.....	84
4.10.2	Response Formatting	88
4.10.3	Scale Development For this study	88
4.11	PRE-TESTING AND PILOT STUDY	89
4.11.1	Pre-testing.....	89
4.11.2	Pilot Study.....	90
4.11.3	Reliability Test.....	91
4.11.4	Respondents Demographic Profile of Pilot Study	92
4.12	DATA ANALYSIS PROCEDURE	94
4.12.1	Initial Data Analysis	94
4.12.2	Missing Data	95
4.13	STRUCTURAL EQUATION MODELING	97
4.13.1	Selection Reasons for PLS-SEM	98
4.13.2	Partial Least Square (PLS).....	100
4.13.3	Measurement Model	100
4.13.4	Structural Model (SM).....	102
4.14	ETHICAL CONSIDERATION.....	103
4.15	CHAPTER SUMMARY.....	104
CHAPTER FIVE: DATA ANALYSIS.....		106
5.1	INTRODUCTION	106
5.2	RATE OF PARTICIPATION.....	108
5.3	DATA SCREENING	108
5.3.1	Identification and Handling of Missing Data.....	108
5.3.2	Outliers Examination	108
5.4	DEMOGRAPHICAL DATA ANALYSIS	109
5.5	DESCRIPTIVE ANALYSIS	111
5.8.1	Behavioral Intention Construct (BI)	111
5.8.2	Perceived Usefulness Construct (PU).....	112
5.8.3	Perceived-Ease of Use Construct (PEOU).....	113
5.8.4	System Quality Construct (SQ).....	113
5.8.5	Cost Construct (CS)	114
5.8.6	Application Complexity Construct (CO)	114
5.8.7	COVID-19 Construct (CVD).....	115
5.8.8	Social Influence (SI)	115
5.8.9	Facilitating Conditions (FC)	116
5.8.10	Student Learning Motivation (SLM)	117
5.6	NORMALITY OF DATA FOR LATENT FACTORS	117
5.7	MEASUREMENT MODEL	119
5.8.11	Factor Loading.....	119
5.8.12	Indicator Multicollinearity.....	120
5.8.13	Reliability Analysis.....	123
5.8.14	Construct Validity.....	124
5.8.15	Convergent Validity.....	124
5.8.16	Discriminant validity	125
5.8.17	Fornell and Larcker Criterion	125
5.8.18	Cross loading	126
5.8.19	Heterotrait-Monotrait Ratio (HTMT)	127
5.8	STRUCTURAL MODEL ASSESSMENT.....	128
5.8.1	Mediation Analysis.....	134

5.8.2	Explanatory Power.....	139
5.8.3	Changing the Structural Model by Removal Non-Significant Paths	142
5.9	CHAPTER SUMMARY.....	145
CHAPTER SIX : DISCUSSION		147
6.1	INTRODUCTION	147
6.2	RESULTS DISCUSSION.....	147
6.2.1	Rate of Participation	147
6.2.2	Demographical Characteristics of Respondents.....	148
6.2.3	Constructs and Items.....	149
6.2.4	Relationships in-between Predictor Variables and the Outcome Variable	155
6.2.5	Results of Hypotheses Testing.....	156
6.2.6	Mediation	165
6.3	CHAPTER SUMMARY.....	169
CHAPTER SEVEN: CONCLUSION		171
7.1	INTRODUCTION	171
7.2	REVIEW OF THE RESEARCH CONTEXT AND OBJECTIVES.....	171
7.3	CONTRIBUTIONS TO THEORY AND METHODOLOGY	176
7.4	RESEARCH IMPLICATIONS.....	178
7.4.1	Practical Implications.....	178
7.4.2	Theoretical Implications	182
7.5	LIMITATIONS.....	183
7.6	RESEARCH FURTHER DIRECTIONS.....	184
7.7	CHAPTER SUMMARY.....	185
REFERENCE.....		186
APPENDIX A.....		225
APPENDIX B.....		227
APPENDIX C.....		255

LIST OF TABLES

Table 2.1	E-Learning Barriers/Challenges in Pakistan	20
Table 2.2	Eight Models /Theories	28
Table 2.3	Summary of key research studies on E-learning during COVID-19	38
Table 4.1	Received response distribution	83
Table 4.2	Survey Questionnaire associated with variables.	86
Table 4.3	Reliability Statistics	91
Table 4.4	Demographic analysis for a pilot study with sample size=55	92
Table 5.1	Respondents' Demographic Details	110
Table 5.2	Behavioural Intention (BI) Descriptive Analysis	112
Table 5.3	Perceived Usefulness (PU) Descriptive Analysis	112
Table 5.4	Perceived-Ease of Use (PEOU) Descriptive Analysis	113
Table 5.5	System Quality (SQ) Descriptive Analysis	114
Table 5.6	Cost Descriptive Analysis	114
Table 5.7	Complexity (CO) Descriptive Analysis	115
Table 5.8	COVID-19 (CVD) Descriptive Analysis	115
Table 5.9	Social Influence (SI) Descriptive Analysis	116
Table 5.10	Facilitating Conditions Descriptive Analysis	116
Table 5.11	Student Learning Motivation Descriptive Analysis	117
Table 5.12	Data normality test.	118
Table 5.13	Constructs Descriptive Analysis	118
Table 5.14	Factor loadings results	119
Table 5.15	Multicollinearity VIF results.	121
Table 5.16	Composite-Reliability & Cronbach's-Alpha results.	123

Table 5.17	Convergent construct validity AVG	124
Table 5.18	Discriminant validity F & L	125
Table 5.19	Factor Cross Lading.	126
Table 5.20	Discriminant validity HTMT	127
Table 5.21	Construct Relationship and Hypothesis Testing	129
Table 5.22	Mediation analysis for Perceived-usefulness and Perceived-ease of use	136
Table 5.23	Explanatory Power	141
Table 5.24	Revised Construct Relationship and Hypothesis Testing.	143
Table 7.1	Achievement of Research Objectives	174

LIST OF FIGURES

Figure 2.1	Theory of Reasoned Action	24
Figure 2.2	Innovation Diffusion Theory	26
Figure 2.3	DeLone, W. H., & McLean Model	27
Figure 2.4	(UTAUT) Unified theory of acceptance and use of technology	29
Figure 2.5	Initial TAM Technology Acceptance Model	30
Figure 2.6	TAM without Attitude	31
Figure 2.7	TAM 2	32
Figure 2.8	TAM3	33
Figure 3.1	A Proposed Framework for Research	50
Figure 4.1	Significant steps required for research design	76
Figure 5.1	Flow Chart for the Data Analysis	107
Figure 5.2	Model Reliability and Validity Using PLS-SEM Algorithm	122
Figure 5.3	Structural Model. 1st Bootstrap through SmartPLS4	130
Figure 5.4	Structural Model	131
Figure 5.5	Revised Structural Model. 2nd Bootstrap through SmartPLS4	144
Figure 5.6	Final Structural Model	145

LIST OF ABBRIVIATIONS

BI	Behavior Intention
CO	Complexity
CS	Cost
CVD	COVID-19
DTPB	Decomposed Theory of Planned Behaviour
D&M	Delone and Mclean model
FC	Facilitating Condition
HEC	Higher Education Commission of Pakistan
ICT	Information and Communication
IP	Internet Protocol
IS	Information System
IT	Information Technology
IDT	Innovation diffusion theory
LMS	Learning Management System
MM	Motivational Model
MOC	Movement Control Order
MOOC	Massive Open Online Courses
MPCU	Model of PC Utilization
MTP	Mobile-Teaching Platform
PERN	Pakistan Education and Research Network
PC	Personal Computer
PDA	Personal Digital Assistant
PEOU	Perceived ease of use
PLS	Partial Least Squares
PU	Perceived usefulness
QR	Quick Response
SEM	Structural Equation Modeling
SI	Social Influence
SP	Service Provider
SQ	System Quality
SCT	Social Cognitive Theory
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviors
TRA	Theory of Reason Action
UTAUT	Unified Theory of Acceptance and Use of Technology
UNESCO	United Nations Educational, Scientific and Cultural Organization
VIF	Variance Inflation Factor
Web 2.0	World Wide Web version 2.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF STUDY

Learning is the process of developing new understanding, knowledge, behaviour, and skills. Suppose this process is achieved with the help of electronic devices; it is called e-learning. The history of e-learning is brief; Elliott Masie, a technical expert, stated in 1995, "Online learning refers to the employment of network technology for the purpose of designing, delivering, selecting, administering, and extending the process of learning." (Cross J, et al. 2004). Online education offers students access to convenience and comprehensiveness; It offers on-demand and distance learning. (Saxena, et al. 2021) It is a situation in which teachers and students can be far apart but connected with the help of technology (Liaw, 2008).

E-learning has many commercial applications, such as distributed learning, online learning, web-based training courses, virtual learning, etc. (Alla et al., 2013). Along with these commercial applications, there are many platforms for e-learning such as "Massive Open Online Courses", "Mobile Learning System", "Microsoft Teams", "Google Classroom", "Moodle e-learning," Web 2.0," YouTube," "Zoom," "Fusion learning platform," and learning management systems "LMS" (Mastan, et, al. 2022). All these platforms provide distance learning using ICT technology. Several universities and institutions also delivered recorded lectures to enhance and improve their students' learning skills. According to some researchers, only listening and watching content is insufficient for students to improve their knowledge and cannot be compared with face-to-face learning; instructors should engage their students with the help given assignments, quizzes, and debate forms. (Saxena, et al., 2021).

The adoption of online education relies on certain elements, for example, training the human resources, developing the related knowledge, motivating the instructor, preparing course content as per the standards, providing material to the students, and selecting the proper tool to deliver the knowledge. Several efforts have been made to adopt e-learning in emerging countries around the globe. It provides an essential role in helping governments achieve their targets (Uppal, M. A. 2017). As the COVID-19 epidemic appeared in 2019 in Wuhan, China, it created much concern about public health; countries were affected politically, economically, culturally, and educationally (Rehman, et al., 2021), social distancing was mandatory, so the borders were closed by imposing the Lockdown or MOC (Movement Order Control). Among all sectors, the education sector was affected the most. As per the statistics figures of UNESCO, this pandemic affected almost 1.6 billion students across the globe.

This pandemic forced all educational institutions to shut down their face-to-face educational activities, as social distancing was mandatory (Dhawan, S. 2020). Education institutions were trying to find a solution by which their activities could be restored. In that situation, e-learning was the only option to continue educational activities by maintaining social distance; e-learning was a requirement rather than a choice. It had several advantages during COVID-19; for example, it provided flexibility, which means that it can be accessed anytime from anywhere if there is connectivity. It saves time, and expenditure means there is no need for a particular place, just like schools and universities, so the running cost for these places can be saved (Soni, V. D. 2020).

1.1.1 Adoption of e-learning in Pakistan

Despite the number of benefits, the adaptation of e-learning has many challenges, particularly in underdeveloped countries like Pakistan; even before COVID-19, the pace of e-learning adaptation was relatively lagging due to the number of problems faced by the country. Pakistan is a multi-lateral, multilinguistic country in the subcontinent of South Asia that made several efforts to implement information technology in the country so that e-learning can be adopted smoothly (Hussain, Wang & Rahim, 2013). Nevertheless, despite

several efforts, Pakistan experienced several socio-economic issues being a developing country due to the rapid increase in its population.

The government of Pakistan is making efforts to promote education in every part of the country by initiating several distance learning programs for instance, the establishment of the Alama Iqbal open university, Virtual University of Pakistan, IP-based online lectures through video conference system, National Digital Library, and PERN (Pakistan education and research Network) (Siddiquei, et al., 2020). For the actual implementation of these initiatives, the country faces several challenges identified by researchers from time to time. For example, one study by (Majoka, Fazal, and Khan, 2013) revealed that due to power outbreaks, teachers should use laptops for distance learning programs to execute the education process uninterruptedly.

Another study (Noreen, et al., 2016) revealed that the unavailability of ICT tools and proper material related to distance learning is challenging for its adoption. Pakistan faces diverse challenges due to its multiculturalism, which requires different measurements and values for teachers and students to adopt distance learning (Rizvi, et al., 2016). Higher education students are familiar with e-learning, but a proper process is required to accomplish their requirement for full access to the resources (Nasir, M. 2017). Students with a user-friendly application interface can understand and adopt the e-learning software system (Mir, K. 2017).

Moreover, students face problems in Pakistan regarding the acceptability of ICT in the universities, such as power shortfall, slow internet speed, and lack of IT equipment like projectors (Arshad, et al., 2017). Students are not interested in adopting e-learning in developing countries like Pakistan as several critical factors are involved (Farid et al., 2018). Among the different age groups of students, there is a negative attitude toward accepting technology (Nisar, 2018). Efforts are required to promote online education in Pakistan at the university level. (Akhter, et al., 2018). Based on the above evidence, researchers can predict that the adoption of e-learning in Pakistan was lagging even before

COVID-19 due to several problems, as discussed. All these problems are still researchable in Pakistan, especially in any pandemic conditions like COVID-19 and beyond.

So, considering the adaptation of e-learning in the IT and IS field, the researchers have presented several models in order to comprehend, examine, and forecast the user's adoption and usage patterns. The TAM, developed by Davis (1989), is a widely used model for predicting the user's adoption and usage behavior due to its Perceived-ease of use (PEOU) and Perceived-usefulness (PU) factors. These factors help to find the individual perception and influence for adaptation of technology or usage. (Davis, et al., 1989). Later, scholars further investigated that despite the robustness and simplicity of the model, having factors of PEOU and PU as main predictors are inadequate to explain the IS/IT system's user adoption/acceptance. More constructs need to be added to the model to ascertain the genuine behavioral intention of students toward technology adoption (like e-learning in COVID-19), which is the focus of this study. Thus, for a clear understanding of the potential adoption of e-learning in COVID-19, this study used TAM extended as a base reference model, along with the constructs of other models such as the Unified Theory of Acceptance and Use of Technology (UTAU), Innovation Diffusion Theory (IDT), theory of planned behavior (TPB) and Delone and Mclean model(D&M).

1.2 PROBLEM STATEMENT

During the pandemic COVID-19, when strong social isolation measures were in place, e-learning proved to be essential as it provided students with the flexibility to study at their convenience and location of choice. E-learning was the sole option to keep the educational process running smoothly even when universities were temporarily closed. likewise other developing countries Pakistan also faced massive disruptions in these crises, and in March 2020 National Command and Operation Center decided the close educational institutions throughout the country. The Higher Education Commission of Pakistan (HEC) directed universities to shift their educational process to distance learning using several available e-learning options.

The primary purpose of the HEC directive was to ensure the continuity of education through those e-learning platforms. As a developing country, the shift towards an e-learning environment brought several challenges in technology adoption for the Higher education community. One of the significant challenges was the cost, as most of Pakistan's population belongs to the lower middle class; with limited financial resources, purchasing e-learning-related hardware and internet packages was an additional burden on their budgets, especially in circumstances where the government had imposed lockdown-type restrictions, which was creating further financial problems as mentioned in UNESCO (Case Study of Pakistan 2019).

The second challenge was the complexity of e-learning applications, every e-learning application was not adaptable, so the application interface matters. Less complex applications have more chances for adoption than complex ones. The third challenge was System quality referring to the system's availability, reliability, and response time which could influence the adoption of e-learning. Along with these challenges, some more challenges need to be addressed, such as Student learning motivation, power shortfall, COVID-19 pandemic, internet connectivity problems, and institutional pressure on students and teachers to shift to e-learning as quickly as possible, even without experience and proper training (Rehman, 2021; Abid, et al, 2021; Khan, Z. H., & Abid, M. I. 2021; Siddiqui et al, 2020; Mseleku, Z. 2020; Aini, et al, 2020; Almaiah, et al, 2020; Adnan, M., & Anwar, K. 2020; Noor, et al, 2020; Qazi, et al, 2020; Farooq, et al, 2020).

Considering the aforementioned limitations, this study aimed to propose a research model based on the construes highlighted in the literature review such as Cost, COVID-19, System quality, System complexity, Social Influence, Facilitation conditions, PEOU, PU, and student learning motivation. The model is empirically examined and analyzed to find the adoption of e-learning throughout the COVID-19 situation in Pakistan. Moreover, it was also addressed how successfully thesis factors impact on eLearning on the overall quality of education.

1.3 RESEARCH AIM AND OBJECTIVES

This research focuses on finding the most critical factors affecting e-learning's adoption during COVID-19 using a framework that provides outcomes of distinct beliefs. This research study aims to accomplish the following objectives based on the issues mentioned in the problem statement.

1. To determine the significant factors influencing e-learning adoption during COVID-19.
2. To design a research model based on the Extended Technology Acceptance Model (TAM).
3. To analyze the hypotheses in the suggested research model of e-learning adoption in COVID-19.

1.4 RESEARCH QUESTIONS

To achieve all research objectives related to the adaptation of e-learning during COVID-19 in Pakistan subsequent research questions need to be answered:

1. What are the key factors influencing the adoption of e-learning during the COVID-19 pandemic in Pakistan?
2. How student behavior influences the adoption of eLearning during the COVID-19 epidemic in Pakistan.
3. How to statically validate the proposed research model for identifying the significant factors influencing e-learning adoption during the COVID-19 pandemic.

1.5 RESEARCH SCOPE

This study can be approached from various angles. Initially, it centers on the implementation of e-learning as a response to the COVID-19 crisis. The introductory section elaborates on the importance of e-learning during this period. The rationale behind

selecting the study location is outlined within its context. A review of the literature reveals numerous research articles from prominent journals, originating from diverse countries. Consequently, the intention is to apply the technology adoption model in Pakistan to elucidate the factors contributing to the sluggish uptake of e-learning during the COVID-19 pandemic.

1.6 SIGNIFICANCE OF STUDY

This study aims to enrich both theoretical and empirical literature concerning the adoption of Information Systems/Information Technology (IS/IT), with a primary focus on elucidating the key factors influencing the adoption of e-learning among the higher education community in Pakistan amidst the COVID-19 pandemic, utilizing the Technology Acceptance Model (TAM). The findings and recommendations derived from this research work are expected to offer valuable insights to educational institutions, supporting them in enhancing e-learning practices in Pakistan, particularly in times of pandemics necessitating social distancing measures.

1.7 CONTEXT OF STUDY: PAKISTAN

During COVID-19, Pakistan faced massive disruptions. This period has made things not as good as for Pakistan, a country still trying to improve its position economically, politically, or in terms of education. In March 2020, the National Security Committee decided to close educational institutions. The Higher Education Commission of Pakistan directed universities to shift their educational process to distance learning using several available e-learning options. The main object of this exercise was to ensure the continuity of education (Nasir, et al. 2021). In the world ranking concerning population, Pakistan has the fifth position with over 227 million population, more than 220 universities, and 2 million students enrolled in higher education; due to COVID-19, the annual GDP growth rate declined from 1.9 percent in 2019 to 1.5 percent in 2020 (UNESCO Pakistan case study), HEC (Higher Education Commission of Pakistan).

COVID-19 brought many challenges to Pakistan; one of the significant challenges was trying to sustain learning while closing educational institutions, as cited above. The solution for this challenge was a shift in the education system to deliver education using ICT technology such as e-learning. However, shifting to e-learning was not an easy task, as the country was facing several problems with the adoption of e-learning, which are already discussed in the problem statement. According to the literature review for this study, problems for the adaptation of e-learning in emerging countries are somewhat different in a situation like COVID-19 as in Pakistan; timely adaptation of e-learning needs immediate attention for solutions to problems and proper guidance for future purposes.

1.8 RESEARCH METHODOLOGY

The research methodology employed in this study is quantitative, in which data is collected from respondents' feedback through a Seven-point Likert scale instrument, initiating from strongly disagree (1) to strongly agree (7). Rensis Likert introduced the seven-point Likert Model in 1932 to take feedback from the respondents as per their level of agreement. The researcher widely adopts this scale in academics due to its high reliability, relevance, and popularity (Chandio et al., 2011; Davis, 1989; Rutherford, 2010; Sekaran, 2016; Zikmund et al., 2012). Before proceeding with the complete survey, it is necessary to conduct a pre-testing to avoid ambiguity, error, or misunderstanding in questions. Through this practice, the target respondent can answer the questions without confusion. Following the pre-testing phase, researchers highly support conducting pilot testing to assess the psychometric features of the measurement question.

To cover the country's entire higher education student population, a clustered sampling approach was adopted to collect the data for this study. All the questionnaire questions were converted into Google Forms, and its link was shared via WhatsApp and email by adopting an online survey approach. An equal number of questions were distributed in all identified clusters of Pakistan universities, i.e., Punjab, Khyber Pakhtunkhwa, Baluchistan, and Sindh, a total of 567 responses were received from across the country. From the received responses some respondents were biased, and their

responses were removed by calculating the standard deviation recommendation which is any response with a less than 0.25 score should be eliminated Collier, J. E. (2020). Therefore 461 valid responses were finalized for data analysis.

1.9 THESIS STRUCTURE

This dissertation has seven chapters that have been designed to fulfill the study's aim and objectives. These chapters include an Introduction, Literature Review, Proposed research model development, Research Methodology, Data Analysis, Discussion, and Conclusion.

Chapter One presents an introductory overview and identifies the research problems, specifically focusing on the factors influencing the adoption of e-learning in Pakistan throughout the COVID-19 pandemic. This chapter presents a summary of the research background, problem statement, research questions, objectives, scope, significance, context, research methodology, and the data analysis methods employed in this study.

Chapter Two presents an extensive examination of the existing literature, which subsequently identifies a research gap that demands further investigation. The discussion commences with a discussion on the historical background of e-learning, after exploring its application during the COVID-19 pandemic and examining its advantages and obstacles. Subsequently, an in-depth analysis was conducted on prominent theories and models about adopting innovation, including the TRA, TAM, extended versions of TAM (TAM2 and TAM3), TPB, IDT, M&D, and UTAUT. This analysis aimed to ascertain the key factors, construct the study model, and propose the hypotheses. Additionally, this work presents a comprehensive analysis of previous research undertaken in various geographical locations within the framework of e-learning during the COVID-19 epidemic.

Chapter Three provides a comprehensive overview of the research model that has been developed. This model extends the TAM and incorporates further external factors, namely COVID-19, Cost, System Quality, and Application Complexity. Furthermore, this

chapter presents the research approach and proposed hypotheses that aim to analyze and measure the extent to which students adopt e-learning during COVID-19 time.

Chapter Four presents a comprehensive examination and justification for this research's methodological framework and data analysis techniques. Additionally, this work offers a concise analysis of selecting research paradigms and research design. Furthermore, the present study includes a comprehensive examination of many methodological aspects, including sample selection, data collection procedures, scale item selection, questionnaire construction and execution, pre-testing procedures, pilot study implementation, and, ultimately, the ethical considerations.

Chapter Five of this work offers the result revealed after data analysis, by employing several data analysis tools that have been explained and verified in chapter four. Furthermore, this chapter presents descriptive and inferential data analysis outcomes.

Chapter Six thoroughly examines the main findings derived from the analysis of descriptive statistics and the hypotheses assessed in Chapter Five. This chapter also analyses the many factors that influenced COVID-19-related e-learning adoption and use.

Chapter Seven of this study presents a comprehensive overview of the research background and objectives, and a detailed account of the procedures used to accomplish these objectives. Furthermore, this work provides a concise overview of the research outcomes and its theoretical and methodological implications. This study acknowledges its shortcomings and identifies potential opportunities for future studies.

1.10 CHAPTER SUMMARY

This chapter offers an overview of the problem statement addressed in the research, as well as an exploration of the scope and significance of the study. The study's aims and questions were articulated and presented clearly. In addition, the purpose of e-learning in COVID-19 was explained. The study's purpose and implications in Pakistan's setting were elucidated at length to facilitate understanding.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter aims to respond to the first research question of this study. What are the key factors influencing the adoption of e-learning during the COVID-19 pandemic in Pakistan? By reviewing the literature review on e-learning during COVID-19 and by use of in-depth analysis, this chapter will also elaborate on the many advantages of online education and the challenges that negatively impact its adoption. The objective of this chapter is to ascertain the factors that influence the adoption of e-learning and the models and theories used for finding users' behavior intentions during COVID-19. The acceptance or usage of e-learning has been under research for a decade and is considered essential for further improvement and innovation in that technology. The research community has been keenly interested in finding the vital factors affecting the students and teachers to adopt, accept, or reject the use of e-learning. Similarly, government and higher education institutions need to solve related problems and provide all required facilities to take e-learning and understand users' perceptions. Identifying significant factors also guides policymakers in making a policy that may rapidly enhance the adoption and usage of e-learning in any future pandemic situation.

2.2 BACKGROUND

The beginning of e-learning appeared when ICT (information and communication technologies) was getting popular and was frequently used by institutions to modify their system (Westera, 2004). It has become more dominant in educational institutions as a substitution solution to face-to-face learning (Ma, Zheng, 2010; Clark, 2011), providing education at an affordable cost and can be accessed anytime, anywhere Engelbrecht (2005). The increasing use of information technologies in universities, and the utilization in higher

education institutions for administrative purposes, content development, and delivery will ultimately and effectively enhance the education and information provision to the students (Westera, 2004). The replacement of face-to-face teaching delivery can be done using a more complex mode of teaching (Kalanidhi, 2010). New technology brings several challenges to its adoption, and to deal with these challenges, proper planning is required. Researchers are trying to understand the more complex factors responsible for the adoption of e-learning, especially in a pandemic situation like COVID-19, where social distancing is mandatory (Dhawan, S. 2020).

2.3 E-LEARNING

E-learning technology is expanding and is being adopted by several educational institutions and countries to enhance their educational effectiveness. However, the successful adoption of any system depends upon its users, who face the minimum barriers to its adoption. Technology adoption is a very complex subject, especially for students striving to gain knowledge using traditional methods like face-to-face learning; hence it needs further in-depth exploration. Several terms are used for learning with electronic devices: computer-based, collaborative, distance, technology-enhanced, digital, virtual, online, computer-assisted, web-based, distributed, and distributed learning e-Learning. All these terms are interrelated with each other. For this study, the term e-learning will be used to expand it further and to discuss the use of e-learning by the student, especially in situations like COVID-19.

E-learning is penetrating very fast in education, so learning effectiveness is growing more intense (Naresh & Reddy, 2015). This also points to future education planning for the smooth availability of network services and low-cost equipment (Wang et al. 2012). Several scholars in the literature present the definition of e-learning: for example, according to Alonso et al. (2005), the use of new technologies like as multimedia and the Internet can improve learning standards by enabling the use of resources and services, as well as distant sharing and cooperation. Wels et al. (2003) define e-learning as the process of providing information and instruction in the workplace by employing computer network technologies,

particularly the Internet. E-learning is defined by Raymond et al. (2012) as a tool that uses computer network technology, namely electronic media such as the internet, intranets, extranets, and others, to provide learning materials to users. e-learning also includes web-based communication, collaboration, and knowledge-sharing capabilities. All the above definitions represent that e-learning presents a ubiquitous learning environment that is flexible, interactive, and collaborative, which is available in a variety of formats and languages.

2.4 E-LEARNING IN COVID-19

As the COVID-19 crisis emerged in 2019 in Wuhan, China, it affected almost every aspect of life (Adnan and Anwar, 2020). It had a significant impact on the education sector, emerging as the most severely afflicted area due to the unexpected shift from conventional face-to-face learning to online education, as social distancing was mandatory in this health crisis (Toquero, 2020). This sudden shift brought several challenges for the students and instructors as they needed to be more mentally prepared for this transformation (Doghonadze, 2020; Straub, 2020; Aristovnik et al., 2020). For the students and instructors, this time was unavoidably very stressful to conduct educational and pedagogical processes such as coaching classes, seminars, meetings, and exam supervision through online mode (Hodges et al., 2020; Bao, 2020). Although this change for the institutions was not new, adopting education through online learning was under process for many decades. Still, due to health emergencies during COVID-19, all the institutions were forced to shift their learning mode (Van Nuland et al., 2020).

In the education sector, by dissemination of information technology, and the activities of e-learning are easily executable, and it emerged as the standard of modern education (Sun et al., 2008). During the COVID-19 situation, as the world was shifted into quarantine, e-learning was the optimal solution for educational institutions to conduct their activities (Radha et al., 2020). To understand the behavioral intention of students to adopt e-learning during COVID-19, it is necessary to find the benefits and barriers /problems/factors they faced during this pandemic.

2.5 BENEFITS OF E-LEARNING

Compared to traditional learning, e-learning has several benefits; the researcher discusses these benefits in their research from time to time. Some of the most appropriate benefits selected for this study are discussed below.

2.5.1 The Flexibility of Time and Location

Education through electronic devices overcomes the problem of location and distance by providing a virtual learning facility. People who want to continue their studies and work can benefit from this facility. This facility also helps people with medical issues who cannot take face-to-face classes (Zhang, 2003; Koller, 2008). e-learning also offers instant access to learning stuff which means students can refer to the internet if they need help understanding their subjects (Kruse, 2002). e-learning offers an environment where students are flexible; they can continue their studies with what they want to learn at their chosen time.

2.5.2 Saving Cost

The cost-benefit of e-learning is significant. It can save organizations time and money by eliminating the need for physical classrooms, travel expenses, and instructor fees. It also allows learners to access content anytime, anywhere, and at their own pace. Through e-learning, the running cost borne by the institution can be saved; for example, building maintenance costs and electricity costs can be reserved by the institution (Soni, V. D. 2020). It is a cheaper method than the traditional method, which requires ongoing expenses, and over time this method increases the cost burden on the institution (Uppal, M. A. 2017). So, the institution and the student bear the cost of various types, which can be saved through e-learning.

2.5.3 Collaborative Learning

One of the main benefits of e-learning is the ability to facilitate collaborative learning. With e-learning, students can collaborate in virtual classrooms, share resources, and collaborate on projects. Students can ask questions freely as fellows do not surround them; they also have the facility to ask questions privately from the instructors, which provides them with privacy (Hiltz & Benbunan-Fich, 1997; Uppal, M. A. 2017). A study by Arbaugh (2000) revealed that students showed a high interest in learning by spending more time on web-based learning. e-learning generally provides an environment where students can work on a single project even if they are far apart. This type of learning encourages students to think critically and develop solutions for problems.

2.5.4 Instructors' Ease of Access

E-learning offers instructors a great deal of ease of access. Instructors can access course materials and student work from anywhere with an internet connection. This makes it easier for instructors to stay connected with their students and provide feedback on assignments. Students can also contact their instructors if they need help with their studies. e-learning presents an excessive prospect for teachers to communicate with their students as associated with traditional face-to-face classes (Hiltz, 1997; Kim, 2005). Students and instructors can be in touch with each other using email, WhatsApp, and other related technologies, which provide them with easy access.

2.5.5 Personalized Education

Personalized education in e-learning is a form of learning tailored to each student's needs. It is based on the idea that each student learns differently and has different needs and interests. Personalized education in e-learning can include artificial intelligence, which significantly improves e-learning systems through personalized content provided to the learner (Murtaza, et al, 2022). Through this system, a learner can practice enhanced

learning through personalization, as the e-learning system sets the delivery of contents according to the strengths and limitations of the learner.

Using e-learning presents various advantages that can address the challenges within the education industry. However, when we look at the actual situation, it seems like it should be more successfully adopted. This is due to the number of barriers its users face during its implementation. The subsequent section enlightens the challenges/barriers faced by the students in adopting e-learning during COVID-19 and before.

2.6 BARRIERS IN E-LEARNING

Higher education institutions around the globe faced several challenges in implementing online education during COVID-19, as social distancing was mandatory. Many universities successfully achieved their targets as they were well-established and had formal online learning and teaching systems. However, this success needs to be improved, as most of the higher education institutions worldwide confront several challenges, which are discussed below.

2.6.1 Instructors Barriers

Due to the sudden shift in education, most institutions needed to prepare for a complete change to online learning as there needed to be more time to adapt to the new environment and platforms (Wang et al., 2020; Burgess, 2020; Chen et al., 2020). Furthermore, one of the studies found that there needed to be more knowledge related to information technology to understand online teaching (Chen et al., 2020). As a result, instructors faced several problems in conducting online classes. Among them, some of the issues were the arrangement of online class schedules, the Selection of the proper software tool, and the establishment of a system to maintain quality and vigilance (Goh, 2020; Chen et al., 2020).

Another problem for the instructors was engaging with students via online platforms while maintaining the same level of communication as there was during physical classes

(Jegade, 2020; Ratten, 2020). According to Bryson & Andres (2020), it is challenging to replicate the physical classrooms experienced with online courses to obtain the desired learning results. Due to sudden shifts, proper training was not provided to instructors related to online learning tools, and most were familiar with how to deal with them (Chang & Fang, 2019; Donitsa-Schmidt & Ramot, 2020). Another study suggests that the unavailability of the online software system can produce a problem for instructors while having an online class (Chen et al., 2020). During online courses, student assessment is also a challenge; faculty members need special training to detect plagiarism during examinations (Sahu, 2020). Other than plagiarism, Self-discipline, and learning attitude are also difficult issues for faculty members who need online education experience (Bao, 2020). So, these are a few difficulties faced by instructors during COVID-19.

2.6.2 Student Barriers

During the COVID-19 epidemic, students faced numerous difficulties, similar to those experienced by their teachers, in the context of online education. According to Ronnie et al. (2020), It is difficult for students to pay proper attention while having online courses due to several factors, such as home responsibilities and deprived communication between students and instructors; students need more time to be ready for online learning. Researchers also found that social issues, lecturer issues, and online software platform issues generally affect students' desire to learn online (Rapanta et al., 2020; Chung, 2020; Aboagye et al., 2020). Other than these concerns, if the technical problem faced by the student in the middle of online classes, there wasn't any support available to resolve it (O'Keefe, 2020).

The availability of IT hardware such as laptops, PC, tablets, and internet access were also significant issues (Adnan & Anwar 2020; Dhawan, 2020; Moawad 2020). In underprivileged countries, online education is unavailable, especially for those families who cannot afford its required cost. A study conducted by a researcher in West Bengal Indian state found that 30.6% of students were trying to have an education by reading textbooks through their efforts and were not joining e-learning classes due to the

unavailability of relevant infrastructure (Kapasias et al., 2020). Another scholar, (Dawadi et al. 2020), concluded that online learning access for some students was an issue due to their socioeconomic and education/literacy problems.

2.6.3 Infrastructure Barriers

The Internet is one of the critical components required for conducting online education; a reliable Internet connection is necessary for the smooth operation of e-learning. If this facility is available to students, their e-learning teaching would be unaffected. Barriers related to internet connectivity were highlighted in most countries during the COVID-19 pandemic (Bao; Berezhna; Dawadi; and Jena, 2020). According to Ronnie et al. (2020), access to a fast and reliable internet connection was a significant issue for device owners and technical capacity. Internet as the major challenge is also reposted in the literature section of the study conducted by (Naciri, 2020; Mamun et al., 2020); according to the literature, the primary cause for the nonparticipation of students in e-learning during COVID-19 was the Internet problem.

Furthermore, the unavailability of required hardware and software was also identified as a barrier to conducting online classes (Crawford et al., 2020). Countries having weak infrastructure of ICT and telecommunication face frequent disconnection of internet problems (Aboagye et al., 2020). Researcher Chang Fang (2020), states in his article that most educators, ranging from 60% to 70%, agreed that the quality network's bandwidth and stability were substandard. So, considering the above literature, weak infrastructure, including (Slow internet and lack of PCs, Laptops, and Tablets) creates a critical challenge for students to adopt e-learning education in a situation like COVID-19.

2.6.4 Environment and Space Barrier

The unavailability of a proper environment and separate space to take online classes has become challenging for some students during COVID-19. Students from the lower middle class do not have a separate room to take lessons with peace of mind (Ronnie et al., 2020).

According to the study conducted by Kapasia et al. (2020), it was found that among a total of 232 students, 103 of them do not own a dedicated space for participating in online classes. Students could not concentrate on their studies in this depleted environment, which further affected their educational productivity (Chang & Fang, 2020) According to Daniel (2020), institutions must take special consideration for student who belongs to underprivileged families. Taking an online class in this type of unconducive environment was challenging during COVID-19. Which negatively affects the learning outcome.

2.6.5 COVID-19 As Barrier

Sudden change in education from in-person to online in COVID-19 brings stress, anxiety, and depression to students as there is uncertainty about what will happen in the future (Rajkumar; Ronnie; Rossi; Tandon; and Xiong 2020). Dropout ratio, education loss, and tricky qualifying were the significant factors produced by COVID-19 in education. This scenario gives rise to a societal disruption for the whole public and particularly intensifies the challenges students face (Dorn, 2020). The students whose family background was not financially strong were affected by stress, anxiety, and depression due to the sudden increase in expenditure required for the execution of online classes, which further affected the motivation of students to adopt e-learning (Cao; Husky; Son; Wu; Zolotov; 2020). In China, due to COVID-19, 24.9% of students have experienced anxiety as their relatives or friends were infected by the coronavirus (Pragholapati, 2020).

2.6.6 Absence of e-learning resources

The lack of facilitating resources for conducting online is a crucial concern for instructors and students. According to Kerres (2020), several educational institutions do not have proper software tools to execute online classes. A limited license for accessing the online library is an example of a lack of resources. Additionally, the unavailability of required broadband connection and IT-related hardware for taking online classes also weakened the intention towards online classes (Azorín, 2020). Along with instructors who were facing difficulties in working from home related to online learning, the parents of students also

felt the additional burden as they needed to arrange laptops, PCs, and other related hardware for their children to continue their education from home (Garbe et al., 2020; Sahu, 2020). Power failure was also reported as a significant issue for students in deep rural areas (Verawardina et al., 2020; Atabhtor et al., 2020; Sarwar et al., 2020). These issues related to facilities for online learning are highlighted in the literature, which needs significant attention by the institution to deal with any future pandemic situation like COVID-19.

2.6.7 E-Learning Challenges in Pakistan during COVID-19 and Beyond

Besides these challenges, this study's context is Pakistan. So, it is essential to highlight the need to conduct this study. For this purpose, the following summarized table has been formulated with information related to the most frequent barriers/challenges/issues faced by students while having online education during the pandemic in Pakistan. Researchers from different areas of the country found several problems that need attention from the government and higher education institutions to deal with future challenges like COVID-19.

Table 2.1 E-Learning Barriers/Challenges in Pakistan

Author	Article Title	Factors Identified	Description
(Rehman, 2021)	"Student Experiences of ICTs in Online Learning during COVID-19 in Pakistan"	Power shortfall, Internet connectivity.	According to this study, students and teachers from rural places faced significant difficulties during online sessions due to inadequate internet connection and a shortage of electricity.
(Umbreen, et al., 2021)	"Perceptions of Students Regarding Web Based/E-Learning during COVID-19 at Nursing College Lahore, Pakistan"	Student Motivation, Social Influence.	The findings of this study indicate that students recognized the need for e-learning education, but they were not ready to utilize it due to social isolation.
(Abid, et al, 2021).	"Online Teaching Experience during the	Social Influence, Facilitating	This study demonstrates that the COVID-19 pandemic poses

	COVID-19 in Pakistan: Pedagogy–Technology Balance and Student Engagement”	condition. COVID-19	significant difficulties for students enrolled in online courses, mostly because of higher levels of stress, depression, anxiety, limited family assistance, and insufficient internet connectivity.
(Adnan, M., & Anwar, K. 2020).	“Online Learning amid the COVID-19 Pandemic: Students' Perspectives.”	Internet Issue, Interaction with the instructor, Curriculum design,	During the COVID-19 pandemic, students encountered many obstacles in online learning, including as limited internet access, minimal engagement with instructors, delayed teacher response times, and the development of curriculum design for online learning in Pakistan.
(Farooq, et al, 2020)	“Challenges of online medical education in Pakistan during COVID-19 pandemic”	Low-Income (Cost), Faculty Training, Internet support, Connectivity issues, Student Involvement, Student Assessment,	Medical students of low-income countries like Pakistan faced challenges while having online classes during the COVID-19 period: "lack of faculty training and institutional support, internet connectivity issues, maintaining student engagement, online assessments, and problems with understanding the unique dynamics of online education."
(Mukhtar, et al., 2020)	“Advantages, Limitations, and Recommendations for online learning during COVID-19 pandemic era.”	Faculty Training, Faculty load, Interaction with the instructor	The limitations of online learning during COVID-19 were the faculty training as per online study requirements, developing proper lesson plans, minimizing the cognitive load, and increasing the interactivities.
(Ansar, et al, 2020)	“Undergraduate students' perception and satisfaction regarding online learning system amidst COVID-19 Pandemic in Pakistan”	Interaction with the instructor, Student Assessment	As per the developed scale of the researcher, 78% of students are not satisfied with online learning during COVID-19 due to concerns such as “student-instructor communication, fairness of examination, and difficulty in understanding concepts.”
(Khan, Z. H., & Abid, M. I. 2021).	“Distance learning in engineering education: Challenges and opportunities during COVID-19 pandemic crisis in Pakistan.”	Low-Income (Cost), Internet Infrastructure	This study points out distance learning challenges faced by engineering students in developing countries like Pakistan, challenges like slow internet services and low income are the issues due to limited

			resources accessible to the large community.
(Qazi, et al, 2020).	“Conventional to online education during COVID-19 pandemic: Do developed and underdeveloped nations cope alike”	Low-Income (Cost), Social Influence	This study deals with face-to-face vs. online learning during COVID-19 in developing countries like Brunei and underdeveloped countries like Pakistan. The researcher found that students of Brunei are more satisfied compared with students of Pakistan when having online classes due to high- and low-income factors. The other is the involvement of family and friends in using online resources influenced Pakistani students during COVID-19.
(Noor, et al, 2020).	“Performance of online classes in Lahore, Pakistan during Covid-19. Performance Improvement,”	Social Influence, Low-Income (Cost)	In this study, the researcher revealed students' performance by taking online classes during COVID-19 and found that they faced environmental problems at home, unfamiliarity with modern IT equipment, and cost.
(Nisar, 2018)	“Students' Attitude towards the Use of Mobile Telephone Technology in Distance Education”	Student Attitude	In this study, researchers worked on students' attitudes towards e-learning and found a negative attitude toward accepting the online learning technology among the different age groups of students.
(Arshad, et al., 2017)	“Availability and problems relating to the accessibility of information and communication technologies (ICTs) among university students.”	Internet speed, Power shortfall, Lack of IT equipment	This study revealed problems faced by the students in Pakistan regarding the acceptability of ICT in the universities, such as power shortfall, slow internet speed, and lack of IT equipment such as projectors.
(Mir, K. 2017).	“Design and development of online student support system”	Application Complexity	This study discussed the design issue of applications for online learning and found that Students can understand and adopt the e-learning software system, which has a user-friendly interface.
(Rizvi, et al., 2016)	“Cultural diversity in higher education benefits and challenges”	Social Influence	This study focused on the cultural issues of Pakistan for adaptation to distance learning and found that the country is facing diverse challenges due to its multiculturalism which has

			different measurements and values for teachers and students to adopt distance learning.
(Noreen, et al. 2016)	“Challenges of digital learning for distance universities of Pakistan”	Lack of IT equipment	In this study, the author suggests that the inaccessibility of ICT tools and the development of e-learning material used for distance learning is challenging.
(Majoka, Fazal, and Khan 2013)	Implementation of Information and Communication Technologies (ICTs) in Education Course	Power shortfall,	This study examines education IT implementation, and points out the problems teachers face, and suggests that teachers should use laptops for smooth implementation of the course due to power outbreaks.

2.7 THEORIES AND MODELS USED FOR ADOPTION IS/IT

Over the last few decades, technological adaptation through individuals or organizations has seen massive progress. So, it is crucial to determine why users are hesitant to use information systems and emerging technologies. The investigation is necessary to decide on the applied techniques to measure and estimate the user's intention for the adaptation of new information technology systems in IS/IT (Davis, 1989; Jurevičiūtė, et, al. 2013).

The literature review associated with information system models and theories suggests that several attempts are made to measure the user's adoption intention for the different products and services belonging to information technology. Several research models and theories are intensely associated with several academic disciplines, including psychology. The two most essential disciplines, sociology and Information Systems are used to analyze and measure the users' intentions and behaviors by finding critical factors Davis (1989) and Jureviciute (2011). So, it is essential to find the necessary practical technique to know the student's adaptation intention toward e-learning during COVID-19. Researchers in the field have presented several models of IS/IT, which explain about 40 percent of the change in distinct intention to use the technology. Scholars face various models and either choose a better model or choose some of the constructs from the existing

models (Venkatesh et al., 2003). The literature for these models and theories was searched using keywords like e-learning, COVID-19, Models, frameworks, and theories from several scientific databases through online search engines, Results suggest that several studies have been done related adoption of technologies through models and social psychological theories. By considering the main objectives of this study which intends to find the most important factors affecting the adoption of e-learning during COVID-19. This section demonstrated the common models and theories related to the field of IS/IT that are available for the adoption and usage of technology.

2.7.1 Theory of Reasoned Action (TRA)

Fishbein and Azjenin presented this theory TRA in 1975 and it is extensively used as a social psychology general theory to examine the behavior related to technology adoption (Abu Ghannam, 2011; LaCaille 2013). This theory predicts the individual behavior of the user. The idea behind this theory is that humans are rational decision-makers who make wise use of all the information at their disposal Fishbein and Ajzen, (1975). Figure 2.1 exhibits the TRA model and the relationship among their constructs. i.e. (Actual use, Beliefs, Subjective norms, Attitudes, and Intentional behavior)

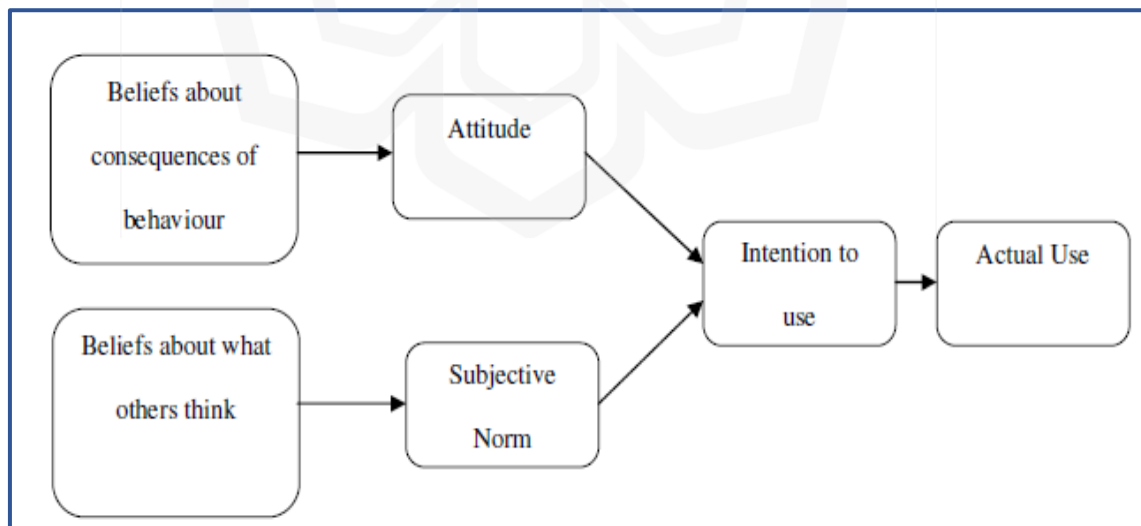


Figure 2.1 TRA. Source: Fishbein and Ajzen, (1975)

In the above figure the term attitude implies to personality's like or unlike feelings for acting on behavior in a question. In contrast, norms refer to social pressure on the individual to do a job. According to Fishbein and Ajzen (1975), it is believed that norms and attitudes produce an influence on the personal behavior for adoption of any technology. This theory has been extensively used for finding individual behavior toward new technologies and criticized by the research community that this approach is insufficient in certain conditions due to limitations in the context and not suitable in some situations (Malook, M. 2016).

2.7.2 Innovation Diffusion Theory (IDT)

In 1995 a professor of psychology, E.M Rogers, discovered a theory regarding the adaptation behavior of new products. According to this theory, innovative attributes such as complexity, advantages, trainability compatibility, and observability can influence technology transmission, followings are the definitions of these attributes.

Relative Advantage: It is the extent to which it is perceived as being better than current substitutes.

Compatibility: It is the degree to which two or more ideas, concepts, or beliefs can be combined or integrated into a single system

Trainability: A learner can acquire knowledge and skills through instruction.

Observability: It is the ability to observe the effects of a given stimulus on a person's behavior.

Complexity: It refers to the idea that the process of diffusion is not a simple, linear process but rather a complex, dynamic process that involves multiple factors and influences.

According to Rogers (1995), Karahanna et al. (1999), Agarwal, Sambamurthy, and Stair (2000). This concept has found extensive application across various academic areas, including but not limited to education, agriculture, Here the term innovation refers to an idea, job or practice that is new for individual until he adopts it and on the other side the concept of diffusion refers to the mechanism via which innovation is disseminated among individuals within a social system via certain communication routes (Rogers 1995, p. 11,5).

This theory comprises five primary elements: innovators, early adopters, early majority, late majority, and laggards, as seen in the accompanying diagram. This theory is widely utilized by researchers in Information Systems/Information Technology (IS/IT). Figure 2.2 illustrates the attributes of theory.

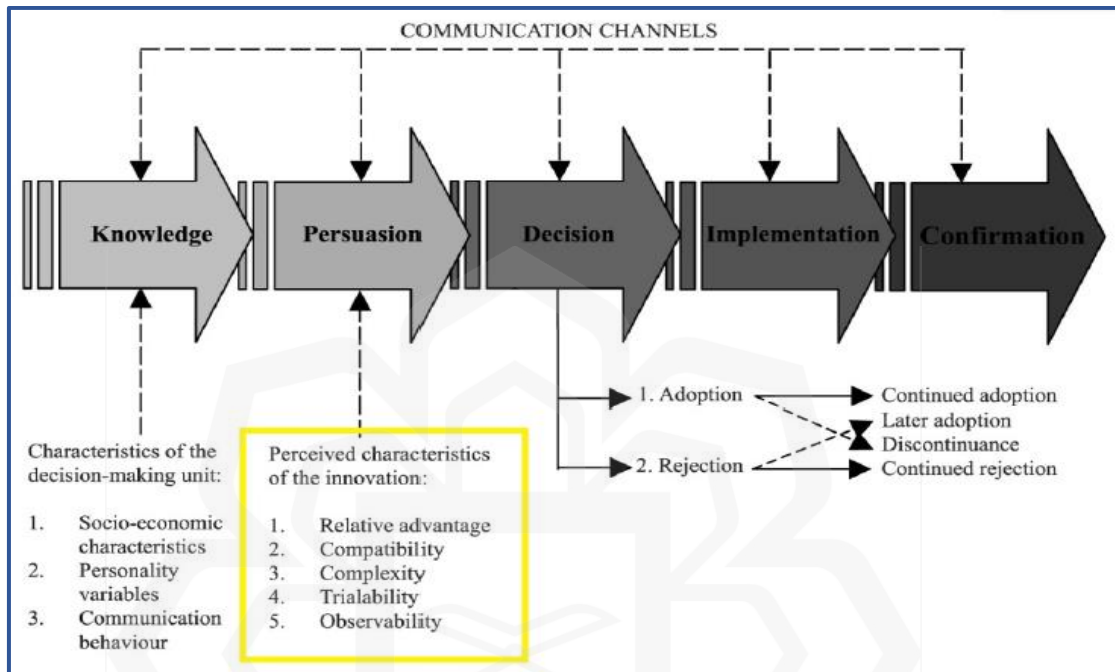


Figure 2.2 Innovation Diffusion Theory (IDT) Source: (E.M Rogers, (1995)

According to Wu & Wang (2005) some constructs IDT and TAM are closely similar with each other, due to successful result both theories supplement each other. The main disadvantage of this theory is its focus on individuals rather than organizations (Ratts, et al., 2011). To get the optimal result researchers successfully integrated IDT with other theories like TAM to find the users actual intention for adoption of technology (Hardgrave, 2003; Wu, 2005; Chang, 2008).

2.7.3 DeLone and Mclean Model

In Information Systems/Information Technology, "DeLone and Mclean" proposed a model for user satisfaction. This model is extensively used by the researcher along with other models to find the adaptation of information system-related technologies. For example, (Adeyemi, I. O., & Issa, A. O. 2020) Found the student's satisfied with the compulsory use

of portalsrtal. There are three main self-regulating variables (Service Quality, System Quality, and Information Quality) in the model, as show Figure 2.3.

System Quality: It is a measure of the degree to which a system meets the needs of its users.

Information Quality: It is the extent to which information meets the needs of its meant purpose. It is a measure of how accurate, complete, reliable, and timely the information is.

Service-Quality is the overall measure of how well a service meets and exceeds customer expectations. It is based on a combination of factors, including the aspects of the product or service provided, the timeliness of delivery.

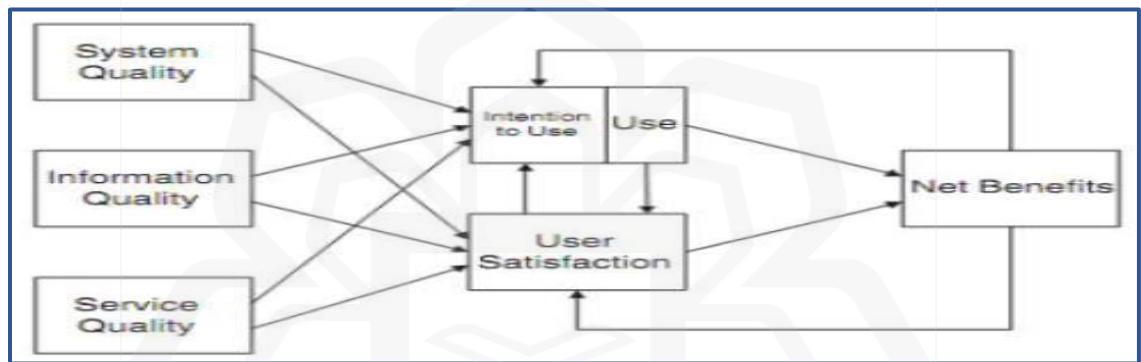


Figure 2.3 DeLone, W. H., & McLean, E. R. (2003)

The main disadvantage of this model is that it has only three independent variables, and for the complex, multidimensional, and independent nature of systems it is difficult to test them using this model (DeLone. et al., 2003).

2.7.4 Unified Theory of Acceptance and use of technology (UTAUT)

Venketash and other in the year 2003 derived a model called uthe nified theory of acceptance and use of technology. This model is derived from the previous eight models by comparing the similarities and differences among them.

Table 2.2 Eight Models /Theories

Model / Theory	Proposed By
Theory of Reasoned Action (TRA)	Fishbein and Ajzen (1975)
Innovation Diffusion Theory (IDT)	(Rogers, 1995)
Theory of Planned Behaviour (TPB)	Ajzen (1991)
Technology Acceptance Model (TAM)	Davis (1989)
Decomposed Theory of Planned Behaviour (DTPB)	Taylor and Todd (1995)
Model of PC Utilization (MPCU)	Thompson et al (1991)
Social Cognitive Theory (SCT)	Compeau and Higgins (1995)
Motivational Model (MM)	Davis et al (1992)

Now a days this is the most famous framework to recognize the user's adaptation of technology. The reason behind the creation of this model was to predict the power of user acceptance. It has the best characteristics for the adoption of technology. It consists of mainly critical deterministic and moderators (PE) Performance-Expectancy, (EE) Efforts-Expectancy (SI) Social-Influence, and (FC) facilitating-condition along with age, gender, and voluntariness as additional factors.

Effort expectancy: It is the ease associated with using the system.

Efforts Expectancy: One's confidence in the system's ability to improve one's performance on the job.

Social Influence: The degree pertains to an individual who believes that their colleagues and colleagues believe they need to utilize the method.

Facilitating condition: The concept pertains to the extent of an individual's belief in the accessibility of technological infrastructure associated with a certain system to provide support.

The main drawback of this model is that it can clarify 70% of the change in user determination, and the disadvantage is that it does not access the actual usage of a particular technology. It represents only one organization's culture or country and can be measured at one point at a time, which is difficult to generalize the result (Min et al., 2008; Hakami, et al, 2014). The following Figure 2.4 illustrates the constructs and their relation in the model.

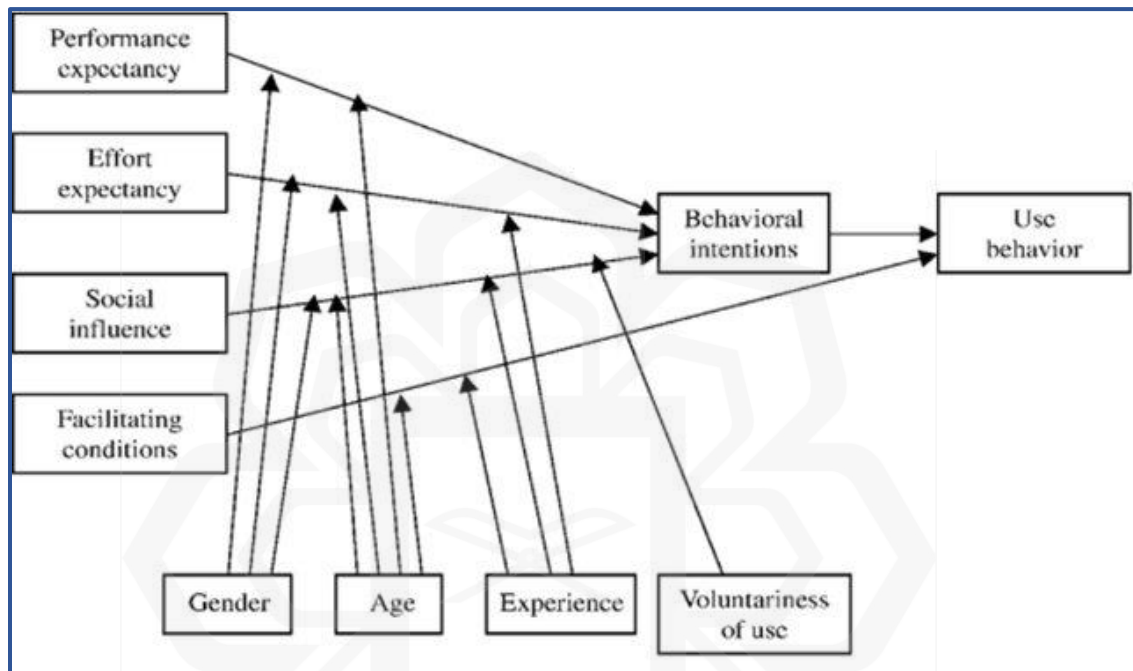


Figure 2.4 (UTAUT);Source (Venkatesh et al., 2003)

2.7.5 Technology Acceptance Model (TAM)

The TAM model was proposed in late 1980 by (F-Davis) and it is used to forecast the usage and acceptance/adaptation of any new technology by human beings. This model predicts that humans' adoption of any new technology depends upon several factors such as Age, Gender, experience, and perception of a particular technology. It is a basic model based on two principles usefulness and easiness of technology. This model is extensively used to forecast the acceptance of IS/IT-related technologies. It has been broadly used for the World Wide Web (Agarwal and Prasad, 1997), and various other software such as digital libraries and word processing systems (Davis, 1989, 1997), Shopping through the Internet (Shih, 2004), E-commerce (Jiang et al., 2000) and telemedicine, (Karahanna et al., 1999).

According to (Eze, 2008) TAM proved a robust model for predicting how people would adopt new technologies for a variety of IS/IT-associated fields. Several scholars used this model for the analysis of diffusion innovation. (Al-Somali, 2011). As per the nature and context of technology, this model has been modified by adding or removing some of the constructs.

TAM Initial Version: The original version of TAM was introduced by Fred Davis for his post-graduate dissertation, he published two research papers, and his research model was appreciated around the globe (Davis, et al., 1989). He attempted to find the user's intention for acceptance of computer technology by evaluating his model with the theory of reasoned action intended by Ajzen and Fishbein's (1975). Figure 2.5 indicates the initial version of the model TAM.

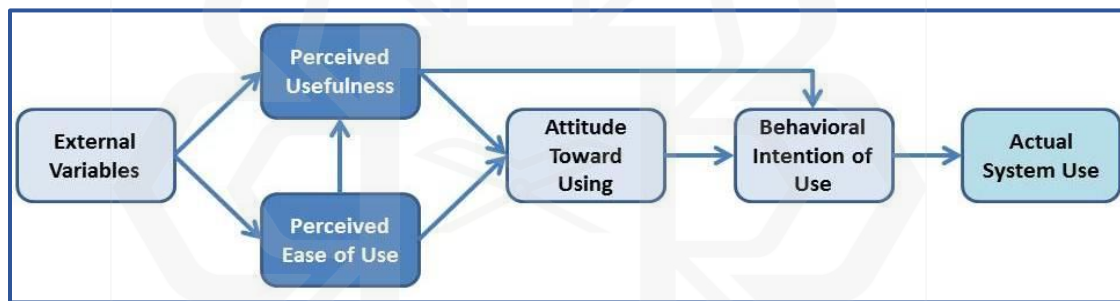


Figure 2.5 Initial TAM. Source: (Davis, 1989)

The external factors of initial TAM model such as training, system characteristics, and development process have indirect effect on the actual uses of the system the effect of these factors can be measured through mediating variable i.e., PEOU and PU these tow mediating variables are useful for finding the individual perception for acceptance and rejection of technologies. The term PU refers as “the extent to which an individual has the belief that the utilization of a specific system will enhance their overall performance.” and the other term PEOU refers to a fact that less effort is required to use the particular system. The predictor attitude will be jointly ascertained by PU and PEOU, therefor behavior intention will be determined by PU and attitude and in final the actual system usage can be found (Davis, 1989). This model has some disadvantages; one is that TAM has a limited

explanation of intention variance. It does not address the voluntariness of use and facilitating factors. It fails to express the individual difference (Hakami, et al., 2014).

Removal of Attitude construct from TAM: Venkatesh and Davis in 1996 made some alteration in the earliest TAM model by removing the predictor Attitude. In the earliest model this predictor had a mediating effect on PEOU and PU. Following figure 2.6 depicted the improved version of TAM without attitude.

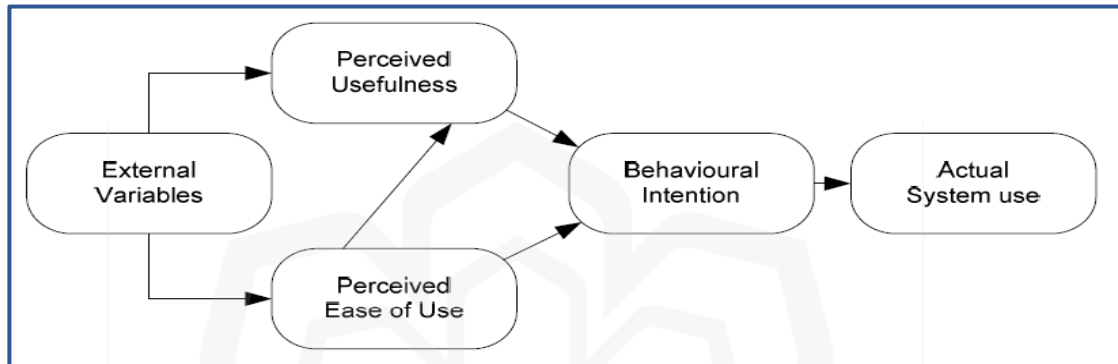


Figure 2.6 TAM without Attitude (Venkatesh and Davis, 1996)

Further extension of TAM appears in the form of TAM2 and TAM3 by including some more constructs which are discussed in following sections.

Technology acceptance model two (TAM2): TAM2 was proposed by Venkatesh and Davis (2000) by incorporating cognitive instrumental process (PEOU, output quality, job relevance, and result demonstrability) and social influencing process (image, voluntarism, and subjective norm). These processes, along with PU and PEOU, indirectly affect the user's behavior and intention to accept the technology.

TAM2 was considered more robust than the original TAM, but over time, some researchers identified specific weaknesses in the model, such as its dependence on highly subjective self-reported data and lack of attitude variables (Obeidat, et al, 2013; Raeisi, et al 2016). The subsequent Figure 2.7 reveals the TAM2.

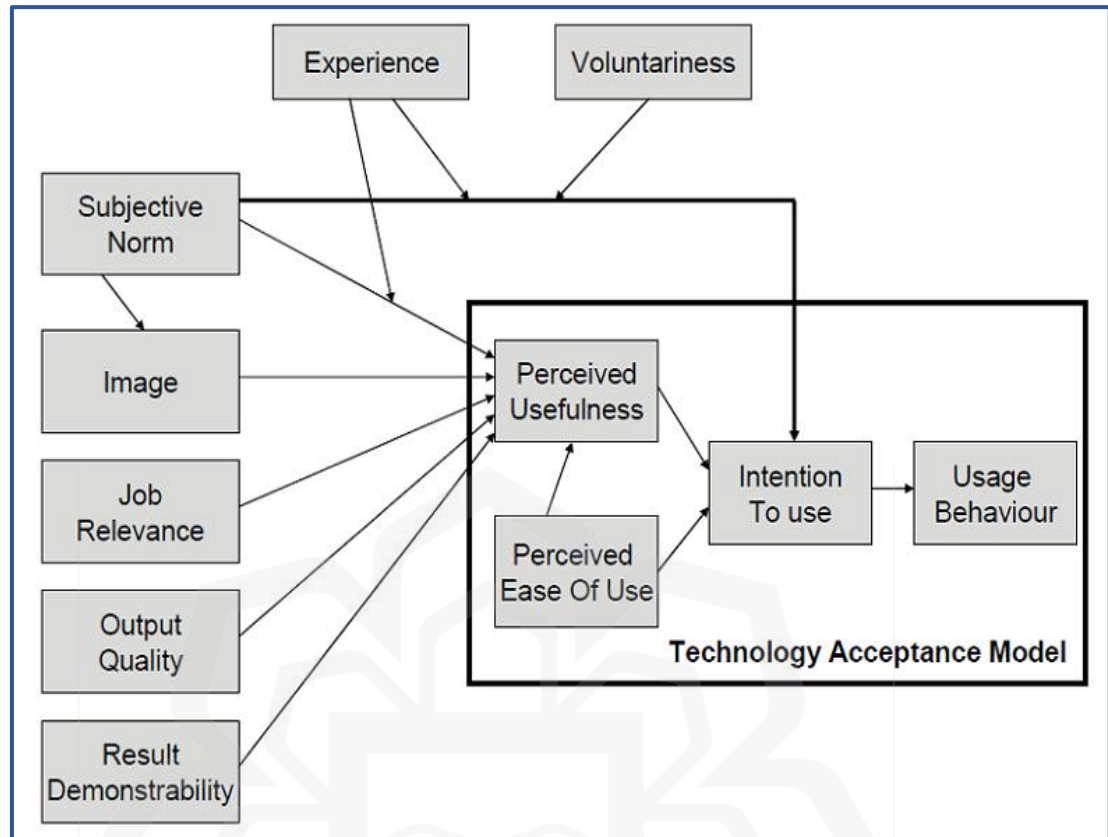


Figure 2.7 TAM 2; Venkatesh and Davis, (2000)

Technology acceptance model three (TAM3): By considering TAM2, Venkatesh, and Bala, (2008) suggest a new version of TAM2 called TAM3. It is the result of vast research conducted on original TAM and TAM2 Venkatesh and Davis (2000). The main objective for proposing this model was to prepare a broad nomological network of the factors of IS/IT adoption/usage (Connon, 2007). The theoretical framework proposed for TAM3 is shown in the following figure 2.8. The relation between constructs in the models are arranged, such as PEOU to behavioral intention, moderated by experience, Computer anxiety to PEOU, moderated by experience, and PEOU to perceived usefulness, moderated by experience.

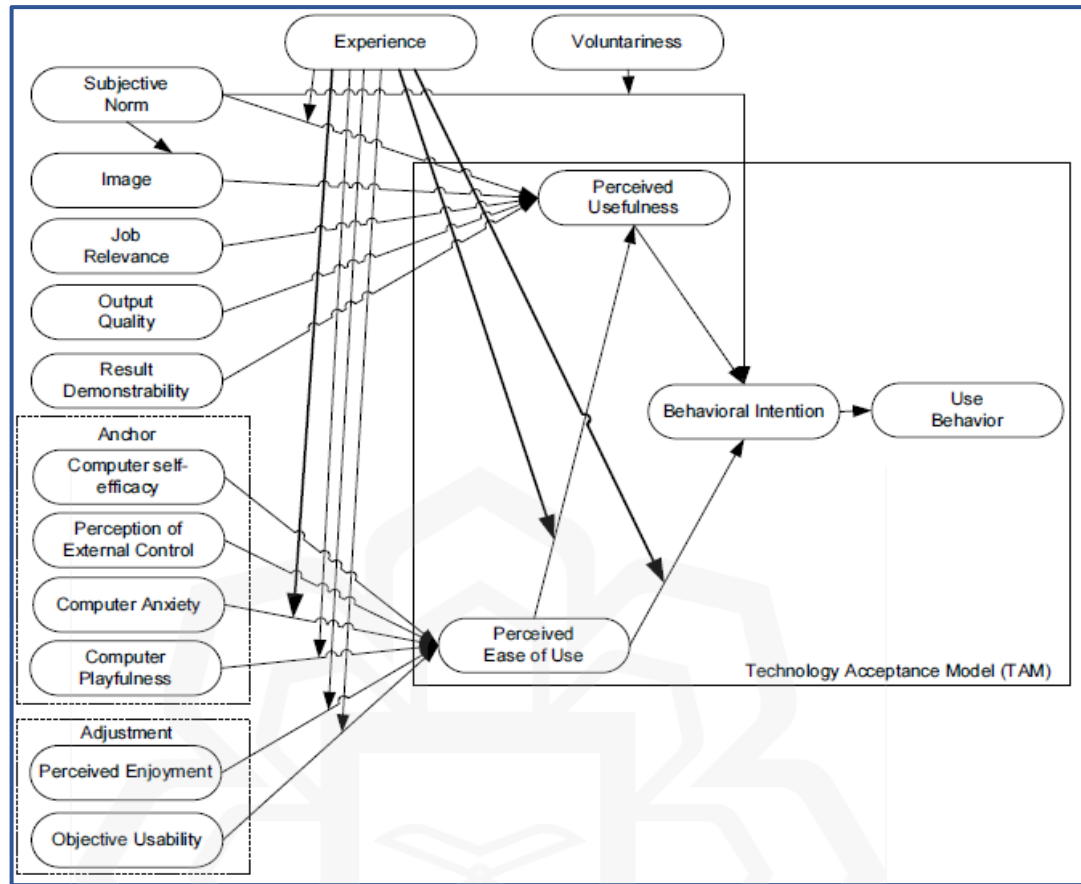


Figure 2.8 TAM3; Source: (Venkatesh and Bala, 2008)

Despite the number of improvements and changes, the researchers still believe that TAM alone is not suitable for all kinds of information technology and information system related settings (Min et al., 2008). According to (Al-Somali, 2011; Lu et al., 2005) TAM has very limited power and has only 40 percent ability to describe variance usage of information system. Other studies suggest that the predictive power of TAM can be improve by integrating other models with it (Wang, 2005; Jeyaraj et al., 2006). Due to the complicated nature of behavioral research scholars suggest that it is hard to assess human behavioral intention using only a single model or theory as every model and theory has its own limitation and does not match with other models (Chong, 2013).

2.8 Past Research on E-Learning Adoption In COVID-19

Since the start of COVID-19, the topic of e-learning adoption has been under research; the researchers have contributed enough literature for its adoption. Nevertheless, the need for finding further factors that help to predict individual trust about the adoption and usage of e-learning in different cultures and contexts needed to be identified (Almaiah, et al.2020). Research communities around the globe observed the use of some typical user's adoption theories and models such as TRA, TPB, IDT, TAM, UTAUT, and D&M to predict the user behavior intention for Information System. Among them, a few studies performed on e-learning in different scenarios, geographic locations, and cultures are discussed here.

In Indonesia (Mailizar & Damon Burg 2021) conducted a study on teachers' behavior intention for using e-learning during COVID-19 by proposing TAM extended model which is combination of TAM and IDT. The constructs selected for this model were intention to use, perceived usefulness, perceived ease of use, compatibility, complexity, relative advantages, observability, trialability and attitude for finding users' behavior intention. This study used a sample size of 161 respondents, and data were analyzed using structure equitation modeling. The findings of this research are that e-learning use and experience were the most important factors for predicting e-learning use during COVID-19 situation.

Another study in the same country was performed by (Fauzi, et al. 2021) on using an e-learning platform such as Google classroom in COVID-19. The model selected for this study was TAM, along with external variables such as Facilitating Condition and Price Value. This study used a sample size of 383 students, and methods of data analysis included SEM. The results of this study are that the facilities provided, such as the internet, devices, and the knowledge of how to use Google classrooms, sensitively affect the e-learning ease of use throughout COVID-19.

Moreover, in Saudi Arabia, Alturki, et al. (2022) researched "Students' willingness to use Mobile learning in Saudi Arabia throughout COVID-19" using the TAM model by

selecting constructs other than TAM such as Personal Innovativeness, Task-Technology-Fit, and Students' Satisfaction. An online survey was used to compile the data with a sample size of 300 respondents, and analysis was done using SPSS and Smart-PLS3.3.3. This work predicts the excellent and positive effect of mobile learning usage in COVID-19 situations regarding student satisfaction and behavior.

Aloulou et al. (2022) explored the social impact of video content as a newly raised area on e-learning adaptation throughout COVID-19 and proposed a model using TAM Model in UAE. The external variables used for this study are Instructor attributes (Instructor Attitude and Instructor interaction), Learner Attributes (Motivation, Computer anxiety, Collaboration,) and mediating constructs PEOU and PU, Contextual Information, and BI. This study used a sample size of 250 students; data were analyzed through PLS-SEM. The findings of this research paper are that instructor's attribute influences the readiness of the student to adopt the e-learning system; furthermore, the research outcomes are compelling causes for e-learning acceptance and understanding of the impact of the contextual information related to COVID-19 on the e-learning experience.

In Jordan, Mohammed (Habes and Mokhtar Elareshi, 2022) worked on the acceptance of video content by the user throughout COVID-19. The model selected for this study was (TAM) along with mediating construct online videos. There was a total of 332 respondents, and the data analysis technique was SEM for this study. This research finds that for shaping positive behavioral intentions PEOU and PU are the core factors. Further results indicate that online videos play a significant role in accepting e-learning in COVID-19.

Another study was executed by (Utami, et al. 2022) in Indonesia on Teacher's willingness to use the cloud-based learning system throughout pandemic period. The author proposed the TAM model by adding external variables, perceived risk (PR), and social influence (SI) to find the behavioral intention of the teacher to use cloud-based education. A total of 75 participants filled out the questionnaire using the online survey method, and then data analysis was done through Structured Equation Modeling (SEM) using

SmartPLS. The outcome shows that risk & social influence has a large impact on the teacher's willingness to learn technology. Factors such as family members and social support are also necessary.

In an effort to ascertain the essential variables for participation intent of students in e-learning throughout COVID-19 in Sweden, Nikou & Maslov (2021) proposed a model TAM by including external variables, Awareness of COVID-19, Perceived challenges, and perceived educational institutions' preparedness. The research method adopted for this work was qualitative and the data was gathered using an online survey from 131 respondents, and its analysis was done using PLS-SEM. In the end, the researcher found that the information related to the COVID-19 challenges situation was the most critical factor affecting e-learning. Being a student, if awareness related to COVID-19 increases, there are more chances for adapting to e-learning and achieving their educational goals.

In China, Mo, et al. (2021) Worked on finding the essential factors influencing online learning Continuance Usage throughout the COVID-19 epidemic by using TAM Model along with external construct and variables, i.e. (Task-Technology-Fit, Instructor-attitude, Family-Support). This study aimed to find the user's behavioral intention to use e-learning during the COVID-19 time. A total of 552 obtained valid responses from the students. The more accessible online platform may affect e-learning, PEOU is associated with the teacher's selection of platform, and its positive attitude toward teaching can also increase students' ease of use.

Elumalai, et al., (2021) worked on the COVID-19 epidemic and the acceptance of e-learning within university students in Sri Lanka. This work aimed to find the relationship among the seven constructs by proposing a framework, i.e. (Subject-Norms, Relevance, and Self-Efficacy Computer-Anxiety Experience Perceived-Usefulness PEOU Approach on the way to e-learning Behavioral-intention Facilitating-Condition Precipitating-Events) during COVID-19. The researcher in this study found that the attitude regarding e-learning and PEOU was established as the essential factor for explaining the behavior intention; however, the experience is more critical in PU and PEOU.

Another study in Indonesia by Mailizar. et al. (2021) was conducted to analyze the acceptance of the e-learning system in higher education throughout COVID-19 epidemic: Moderation Effect of Instructor Support: by integrating models TAM, TDD, and D&M along with their construct and predictors like System Quality (SQ) and e-learning Experience (XS); in this research, the finding is that there is a positive effect of three aspects suggested in the model on e-learning. The quality aspect is essential among the others. In addition, the support provided by the instructor positively adequate the association between the quality aspect and the student's adaptation.

In Saudi Arabia (Alassafi, M. O. 2021) worked on the willingness of the student to accept e-learning throughout COVID-19, using TAM and external variables (Knowledge-Quality, Information-Quality, Technology-Fit, Self-Efficacy, Perceived-Usefulness, Perceived-Ease, Social-Influence, Academic-Motivation, Behavioral-Intention) constructs. This research finds that BI is related to PU and PEP, Other factors like technology-fit and knowledge-quality are also essential factors that impact student adoption of e-learning. He also found that the association among Information-quality and PU, PEOU and behavior intentions, and social influence did not support due to insignificance association. Moreover, in subsequent section Table 2.3 demonstrate an overview of major e-learning research conducted for COVID-19 in the past.

Table 2.3 Summary of key research studies on e-learning during COVID-19

Study	Research Purpose	Model/Theory	Constructs used	Methodology	Findings
(Fauzi, et al. 2021).	To find the student's BI for acceptance of the Google Classroom platform for e-learning throughout COVID-19 in Indonesia.	TAM	External Variable(Facilitating Condition, Price Value) PU, PEOU, and Attitude.	Survey through questionnaire	The results of this study indicate that the implementation of Google Classroom has a significant effect on the advantages offered to students. The provision of services, such as internet access, significantly undermines the motivation to adopt the system.
(Weerathunga, et al. 2021)	What is the effect of the COVID-19 epidemic on students' willingness to accept e-learning? In Sri Lanka	TAM	Subject-Norms, Relevance, Self-Efficacy Computer Anxiety Experience PU, P EOU Attitude-toward e-learning BI, FC, Precipitating-Events	Online Survey questionnaire	The researcher of this study discovered that the attitude towards e-learning and PEOU emerged as a crucial determinant in explaining behavioral intention. However, in the context of PU and PEOU, experience plays a more significant role.
	To find the factors affecting the	TAM, TDD, and D&M	Usability (PEOU & PU), Interaction (student		The research reveals a favorable impact of three

(Altalbe, A. 2021).	student's actual use of e-learning throughout COVID-19 in Saudi Arabia		Interaction, Instructor Interaction, Content Interaction) Quality (System quality, Subject Knowledge, Content Vividness)	Quantitative Using Survey	suggested factors in the model on e-learning. The factor of quality is important compared to the others. Furthermore, the instructor's support significantly enhances the association's quality perspective and the students' adaptability to e-learning. However, poor contact with instructors has a detrimental impact on both usability and interaction.
(Abbad, M. M. 2021).	How UTAUT model can help in understanding the student's willingness Use e-learning. In Qatar	UTAUT	Performance-expectancy, Effort-Expectancy, Social-influence, Facilitating-condition, Behavioral-Intention	Quantitative Survey Questionnaires Distribution	In this research, researcher found that social influence taken as a construct in his model is not important to find out the BI that can influence the actual usage of the e-learning system.
(Asvial, et al. 2021).	To find the COVID-19 effect on the BI of students (junior school) to adopt the e-learning in Indonesia.	UTAUT	Performance-expectation, Effort-expectancy, Attitude, Social-Influence, Perceived-cost, Facilitating-Condonation	Quantitative Survey Questionnaires Distribution	The findings of this research are that all suggested hypothesis has an encouraging effect on the willingness to use e-learning in Indonesia except one, which is cost,

					as it hurts adaptation of e-learning.
(Prasetyo, et al. 2021)	What are the important factors influencing the usage of the e-learning platform throughout COVID-19? In the Philippines	ETAM M&D	System-quality, Information-quality, User-Interface, PEOU, and PU	Quantitative Survey Questionnaire	In this research, the researcher found that in the Philippines, the students are willing to adopt e-learning as there is only one factor that provides the hurdles: the provision of the internet.
(Almajali, et al. 2021)	To find the mechanism for acceptance of e-learning throughout the COVID-19 situation. In Jordon	TAM	PEOU, PU, Cultural-Knowledge - Management, Infrastructure, e-learning acceptance	Quantitative Survey Questionnaire	In this work all 7 hypotheses are supportive that e-learning can be accepted in Jorden. moreover, there is a powerful correlation is present between PEOU, perceived-benefit infrastructure, and cultural-knowledge
(Saxena, C. et al. 2021)	To develop a conceptual model to find out how variables can be affected the learner's satisfaction by	Hypothesized Research Model	Assurance, Empathy, Reliability, Responsiveness, Learning-Content, Website-Content, & e-learning-quality,	Quantitative Survey Questionnaire	This study indicates that factors related to quality can improve the e-learning provided by the institutions. The analysis predicts a path through a model that verifies the

	keeping social distance in mind in India.				learner's willingness. The results suggest that influencing e-learning quality is positively influenced by e-learning variables.
(Jie, S. et al. 2021).	To find the most important factors affecting the student behavior for adopting e-learning throughout COVID-19 in Malaysia	TAM	PU, PEOU, BI,	Quantitative online, Survey Questionnaire	A framework has been presented in this research paper, which has factors affecting the Intention of using an e-learning system throughout COVID-19 in Malaysia.
(Weerathunga, et al. 2021).	To find the effect of a COVID-19 epidemic, on e-learning in Sri Lanka.	TAM	Subject Norms, Relevance, Self-Efficiency, Computer anxiety, Experienced, PU, PEOU, Attitude, Facilitating Condition, BI, Participating Event COVID-19,	Quantitative Survey Questionnaire	This work suggests that there is no significant effect of moderating variable Participating Event COVID-19 on BI for Acceptance of E-learning. BI is important for usage and attitude, and EU are essential factors toward BI rest of the variables can effectively predict the attitude toward e-learning.

(Al-Rahmi, et al. 2019)	What are the possible factors influencing e-learning in Malaysia?	TAM and IDT	Relative-advantages, Trialability, observability, complexity, Perceived-compatibility, Perceived-enjoyment, PU and PEOU	Quantitative Survey Questionnaire	The findings are that these six perceptions positively affect students' BI, and these six are not worthy of PEOU. moreover, above perceptions have a powerful effect on PU
(Al-Marooof, et al.2021).	To find the most important factors inflecting on post-acceptance of e-learning platforms along with moderating effect of a COVID-19 vaccine in UAE.	TAM & UTAUT	Perceived Daily Routine, Self-Efficiency, PEOU, PU, Perceived-enjoyment, Critical mass, Mediating influence of Perceived-Vaccination-Fear	Quantitative online Survey Questionnaire	Finding No.1 all chosen variables dominant and are associated to independent variable No.2 Hypothesis PDR and PENJ are supportive No.3 CM and SE supported analysis in last vaccination fear statically is strong mediates as it has a powerful effect for E-learning platforms
(Raza, et al. 2021).	How social isolation and corona fear influence the acceptance of e-learning. In Pakistan	UTAUT	Performance-Expectancy, Effort-Expectancy, SI, FC, Social-Isolation, Corona-Fear BI	Quantitative Survey Questionnaire	There is a positive link among EE, SI, PE, and Social-Isolation on user willingness to use LMS Corona factor only moderate the link of performance.
(Alkhawaja, et al. 2021).	To find the influence of system	TAM and DeLone &	System Quality (adaptability availability Response Time		The findings are that the SQ Significantly affects the PU and the Intention

	quality on students to adopt the e-learning in Jordon.	McLean IS model	Reliability Usability) PU, Information to use, Actual Use,	Quantitative Survey Questionnaire	to use. Also, SQ does not have any influence on the e-learning use directly but indirectly through two other factors such as PU and IU.
(Younas, et al. 2021).	What are the effects of multiple designs attributes on learners' use of the e-learning system easily in Pakistan?	TAM	User-control, Connectivity, Personalization, Responsiveness, Information-quality, Navigation, Visual-Design, EOU, Trust, BI	Quantitative Survey Questionnaire	The findings of this study are that on learners' cognitive there is the influence of design attributes such as HCI; however, the navigation has partially influenced cognitive belief and cognitive construct PEOU and PU has strong determinant on trust
(Twum, et al. 2021).	To find the possible factors influencing the acceptance of e-learning throughout the COVID-19 epidemic in Ghana.	UTAUT	Personal Innovativeness in Information Technology, PE, EE, SI, FC, Hedonic Motivation, Habit, PFC, Intention to Use e-learning	Quantitative Survey Questionnaire	The findings of this research are Personal Innovativeness in IT PF cost Performance Expectancy, Hedonic motivation, and SI has more effect on the Intention of e-learning all other factors did not predict Intention on e-learning

(Sarosa, S. 2021).	What is the effect of cost on e-learning acceptance as it is mandatorily imposed on Indonesian students in COVID-19?	TPB and TRA	Attitude, Subjective Norms, PBC (perceived behavioral control), Intention, and P Cost.	Quantitative Survey Questionnaire Using Google form	This research proved that learning application behavior is affected by Intention, and Intention is affected by attitude, Subject norms, and PBC. Perceived cost negatively affects the PBC.
(Sukendro, et al. 2020).	To explore the issues affecting e-learning throughout COVID-19 in Indonesia.	Extended TAM	Facilitating-Condonation, PU, PEOU, Attitude, and BI.	Online Survey questionnaire	This work suggests that during an epidemic situation of COVID-19 students were facing many difficulties to accept the e-Learning such as lac facility conditions. So proven facilities are necessary for the adaptation of the system.
(Almaiah, et al.2020).	To find the critical and supported factors faced by e-learning throughout a COVID-19 situation in Jordan and Saudi Arabia.	Thematic analysis	Factors & challenges affecting e-learning system (Trust, Culture, social media, System Quality, Financial Support, Change Management, System Technical Issues)	Qualitative By Conducting interview	In this research, the researcher found that five main factors may critically affect the adaptation of e-learning systems: technological, System Quality, Cultural aspect, self-efficacy, and trust factors. Besides these, some challenges are also nominated, such

					as change management issues, system technical issues, and financial support issues.
(Siron, et al. 2020).	To predict the possible factors affecting the e-learning throughout COVID-19 in Indonesia	TAM	PU, PEOU, Students-Experiences, Perceived-Enjoyment, Computer-Anxiety, and Self-Efficacy	Online questionnaire	The suggestions of this work are that the number of variables comprising PE, SE, CA and PSE is accountable for the willingness of users to accept e-learning. This study also defines that PEOU and PU can explain students' objectives for utilizing the e-learning system.

The primary objective of this study is to investigate the determinants contributing to the adoption of e-learning in Pakistan during the COVID-19 pandemic. So, the higher education population faced several problems related to e-learning during COVID-19; the most frequent problems identified by the Pakistani researchers have been summarized in above Table 2.1 of section 2.6, i.e., Cost, System Quality concerning system's (availability, reliability, and response), Application Complexity, Social Influence, Facilitating Conditions concerning (power shortfall, internet availability, Internet connectivity problems), Student learning motivation, and COVID-19 (lockdown, Stress and fear). In order to ascertain the genuine behavioral intentions of the higher education population in Pakistan concerning e-learning during the COVID-19 pandemic, it is imperative to validate these aspects empirically.

To adopt different technologies, a massive amount of academic literature is available. Researchers continuously tried to extract the reason for e-learning's adaptation or refusal throughout the COVID-19 time. In the epidemic, education through e-learning was mandatory rather than a choice, so it is essential to predict the user's behavior to accept or adopt e-learning during that situation. The research community also tests several adoption models to discover the essential factors for the adoption of e-learning. Based on literature summarized in Table.2.3 and section 2.8 it can be assumed that TAM is a popular framework for implementing e-learning systems during COVID-19. In addition, research on user adoption of IT/IS systems shows that TAM has high predictive potential, DuPree (2015). Several empirical studies reveal that PEOU and PU are major determinants in COVID-19 behavioral intention to use e-learning. Past studies like (Mailizar & Damon Burg, 2021; Sarosa, S., 2021; Alkhawaja et al., 2021; Al-Marroof et al., 2021; Al-Rahmi et al., 2019; Prasetyo et al., 2021; Sukendro et al. 2020; Liao et al., 2007; Wang and Barnes, 2007) highlighted the necessity to add external factors to the TAM to improve its illumination.

2.9 CHAPTER SUMMARY

This chapter seeks to identify the most relevant factors experienced by users during COVID-19, as well as the most essential theories and models employed by the researcher to determine the user's behavioural intention towards e-learning during COVID-19. This chapter also gives a theoretical background to the literature for this research. The first section 2.1 is rated as the introduction of the chapter, the second section 2.2 provides a background of the study, the third section 2.3 describes e-learning, the fourth section 2.4 suggests the importance of e-learning during COVID-19, the fifth section 2.5 points out the benefits of e-learning, and the sixth section 2.6 finds the e-learning challenges globally and especially in Pakistan during COVID-19. The seventh section, 2.7, went into great detail about the theories and models used to determine behaviour intention. Finally, section 2.8 gives a comprehensive assessment of previous research to identify the linked theories, models, and elements that have been most commonly employed in measuring e-learning adoption behaviour.

CHAPTER THREE

PROPOSED RESEARCH MODEL DEVELOPMENT

3.1 INTRODUCTION

The most common models used for the IS/IT adoption theories and research identified by Algethmi (2014) are (TAM, TRA, TPB, IDT, and UTAUT), the model of motivation, PC utilization, and the theory of social cognition. A massive discussion is available in the literature regarding the best-fit model to find the essential factors influencing the user's adoption of a particular technology. According to Jureviciute (2011) and (Wei et al., 2009), most of the research for finding factors was conducted on TAM (Davis, 1989), IDT (Rogers, 1995), and TPB (Ajzen, 1991). Despite the significant contribution made by these theories and models in the context of the IS and IT fields, none of these theories alone is 100% suitable to answer all the research questions. Most of the theories and models individually can only identify 40% of the variance in the setting of IS and IT model-based research (Algethmi 2014; Venkatesh et al. 2003). Despite the number of resemblances in these commonly used theories and models, each has its weaknesses and is not balanced by another (Venkatesh et al., 2003). Considering the limitation, of each model usually, some of the vital constructs from these models are selected with additional external constructs to measure the user adoption behaviour related to any system or product (Venkatesh et al., 2003).

TAM is the most frequently used model among all IS /IT theories and models. The TAM model is beneficial for understanding user behaviour for implementing any information system. Several researchers have tested this model in their empirical research and consider it an instrument that is more consistent in extracting Statistical results. Although the TAM is being used in different contextual settings for explaining the new system adoption by the users, it has a specific limitation as it is so simple and over-studied (Barki, 2007; Legris et al, 2003; Min et al., 2008; Lopez et. al., 2008). According to Davis

(1989), to enhance the predictive capabilities of this approach, the global research community should conduct further investigations by integrating additional variables such as perceived usefulness (PU) and perceived ease of use (PEOU). This enables the model to effectively explain the adoption of specific technologies.

Therefore, many researchers extended this model by integrating the constructs of other models and theories to predict the best results (Mailizar & Damon Burg, 2021; Sarosa, S., 2021; Alkhawaja et al., 2021; Al-Maroofo et al., 2021; Al-Rahmi et al., 2019; Prasetyo et al., 2021; Sukendro et al. 2020; Liao et al., 2007; Wang and Barnes, 2007).

The main purpose of this chapter is to provide a thorough explanation of the research paradigm used in this study based on the previous information and the extensive literature review presented in chapter two. After the introduction, the next section of this chapter provides details regarding the model development and justification related to the interrelationship between dependent and independent variables. In the third section, there is a detailed explanation related to exogenous and endogenous variables to affect the e-learning selected for this study using the literature review of chapter two. Tentative hypotheses are also suggested in this section, and at the end, there is a summary of this chapter.

3.2 THE RESEARCH MODEL

Several models have been proposed and adopted by the research studies to find the adoption and intention behaviour of the user toward specific technology. The researcher suggests the most appropriate models for adopting technology in each study. For each study, the selection of its base model depends upon the different contexts and the country in which it will be tested (Lai, 2011). Currently, the most common models in the field of information systems / Information technology to find users' adoption behavior are UTAUT and TAM. The UTAUT is the most recently developed model and has gained massive attention from the research community. However, TAM is still a favorite choice of researchers due to its simplicity and fixability in adding extra constructs, which enhance its predictive power (DuPree, 2015). In a study conducted by Oshlyansky (2007), it was found that the inclusion

of demographic moderator variables, such as age, gender, experience, and voluntariness, in the UTAUT framework provides a convincing argument for its application in a wide range of research studies focused on measuring the adoption of new technologies or systems, particularly in the context of cross-cultural testing. The research model employed in this study is based upon investigating several IS/IT adoption theories and models already discussed in chapter two. The following Figure 3.1 reveals the research mode proposed for this study.

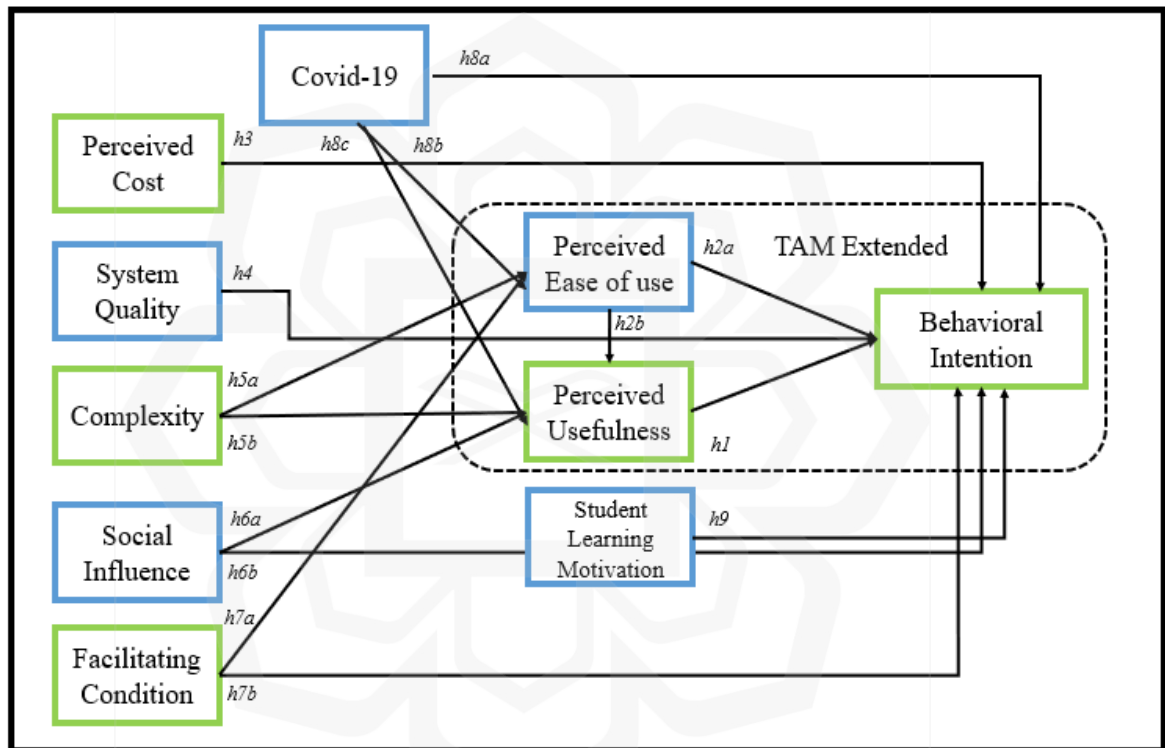


Figure 3.1: The Proposed Model for Research

The above figure represents the proposed research model for this study. In the suggested model TAM is used as a baseline along with constructs or variables of other well-known models and theories such as IDT, M&D, and UTAUT; these external variable integrations with TAM to enhance its analytical ability (Wang and Barnes, 2007). A total of ten constructs and fifteen hypotheses are proposed in the model out of fifteen hypotheses two hypotheses are negatively proposed and 13 hypotheses are positively proposed. The

behavioral intention construct represents a dependent construct, and the PEOU and PU constructs act as mediating constructs. The rest of the constructs such as Cost, COVID-19, System quality, Complexity, facilitating condition, student learning motivation, and social influence act as external constructs. The Behavioral intention to adopt E-Learning during COVID-19 will be jointly determined by PU, PEOU, Cost, System Quality, Complexity, Social Influence, Facilitating conditions, COVID-19, and Student Learning Motivation.

Moreover, the attitude construct used in the initial version of TAM is removed from the model as it was not recommended by (Venkatesh & Davis, 1996) in their TAM extended version. According to Davis (1989), the reason for its removal is that there is no effect of attitude among the behaviour intention and other primary predictors of TAM (PU and PEOU). Moreover, several studies in the past (Agarwal, 2000; Gefen et al., 2003a; Hong et al., 2002; Igbaria et al., 1995; 1997; Venkatesh & Davis, 1996; Venkatesh & Morris, 2000) suggest that the presence of an attitude does not have a mediating influence on principles of TAM that are PU and PEOU. Therefore, these are the inevitable facts that are the elimination cause of attitude from the proposed model of this study.

The main reason for selecting the TAM model as a baseline for this study is the past research conducted on e-learning during COVID-19, summarized in Table 2.3 of Chapter two; in these studies, researchers utilized TAM as the core model and extended it by adding extra variables from other theories and models; moreover, there are some other causes for choosing TAM as a baseline for this research work. It is one of the models supported by theory and verified by an array of psychometric tests; It is a simple and specific model that was developed to provide ample adoption prediction power around the user groups belonging to diverse contextual information system technologies. It revealed the outer aspects affecting users' opinions, feelings, and behavioural intentions. It also suggests the solid experimental backing for its main predictors, i.e., PEOU, and PU, in forecasting users' adoption of technology (Oyman, et al., 2022; Chandio, 2011; Davis, 1989; Gefen et al., 2003a; Mathieson, 1991).

The literature review conducted for this study in chapter two also suggests that model TAM has the edge over the other models due to its core construct, i.e., PEOU and PU, which are the most significant factors for finding the individual behaviour intention for the adoption of any technology. Moreover, Al-Emran and Grani conducted a bibliometric analysis in 2021 to examine the current relevance of the TAM. The study examined a total of 2399 scholarly papers that were published between the time frame of 2010 and 2020, as retrieved from the Web of Science database. The object of the study was to find whether the TAM is still viable or has become obsolete. According to them, approximately 1797 articles were published with 26220 citations using the TAM model. The most studied domains were electronic commerce, e-learning, social networks, mobile learning, Mobile commerce, Cloud computing, and argument reality. China leads the list of countries with the highest production and citation rates in TAM-related papers, followed by the United States, Taiwan, Malaysia, South Korea, Spain, England, Indonesia, Australia, and India. The journal with the most TAM publications is "Computers in Human Behavior," which has 80 research articles and 4213 citations. With 78 studies, the TPB is the most common theory integrated with TAM, followed by D&M, UTAUT, TRA, SCT, DOI, TTF, ECM, and SDT.

Based on the evidence shown above, TAM is not only widely accepted as a reliable model to assist in assessing technological deployments, but it is also a reliable method for qualitative research on a wide variety of topics. So, considering the literature review of chapter two and sufficient evidence provided in summarized tables 2.1 and 2.3. A hypothetical model of an integrated framework is proposed in Figure 3.1 using TAM extended along with (IDT, D&M, and UTAUT) by selecting their constructs and variables, i.e. (Perceived Cost, System Quality, Application Complexity, Social Influence, Facilitating Condition, Student learning motivation, Covid-19, PEOU, and PU) to find the behaviour intention for the adoption of e-learning during covid-19.

The suggested study model determines e-learning adoption behaviour concerning defined system quality, application complexity, cost, social impact, student learning motivation, and enabling factors. These external factors are integrated with PU and PEOU

to find the actual use, and some prior research also used this sort of integration scheme (Mailizar & Damon Burg, 2021; Sarosa, S., 2021; Alkhawaja et al., 2021; Al-Marroof et al., 2021; Al-Rahmi et al., 2019; Prasetyo et al., 2021; Sukendro et al. 2020). Among the external factors, student learning motivation, System Quality, and cost were intended to influence behavioural intention directly, while application complexity was intended to influence behavioural intention indirectly. The remaining external factors, social influence, COVID-19, and facilitating conditions were also discussed, directly and indirectly, impacting behavioural intention for adopting e-learning during COVID-19. Moreover, Individuals' beliefs about the antecedent are mediated by PU and PEOU beliefs.

3.3 DEVELOPMENT OF HYPOTHESES

Developing hypotheses involves producing brief and verifiable statements or informed inferences about the relationships between variables or processes a researcher wishes to investigate. The subsequent section provided the proposed hypothesis for this study.

3.3.1 Behaviour Intention Dependent variable (BI)

In various IS/IT adoption theories and models, behaviour intention is the most important aspect; it is the user's probability of adapting to the system and has a very close relationship with actual system use (Kiraz & Ozdemir, 2006); For example, in theories such as TRA and TPB and technology adoption models UTAUT and TAM, it is used as the central factor that shows the readiness and performance of the user to use the system Ajzen, I. (1991), According to Davis (1989) for any technology the behaviour intention can be predicted using two most essential factors which are PU and PEOU. It is an originator of action that grows stronger as people become more motivated to participate in the behaviour Ajzen, I. (1991). Several past studies suggest that it is a powerful interpreter for the actual use of the system (Venkatesh et al., 2003; Taylor & Todd, 1995; Davis et al., 1989). Therefore, behavioural intention is a dependent variable for this work in finding the probability of adopting e-learning technology throughout COVID-19 in Pakistan.

3.3.2 Perceived Usefulness Mediating variable (PU)

It is the amount a user trusts to use the system that can improve his/her career production. It is the most significant factor influencing e-learning adoption throughout COVID-19. It motivates the user to adopt the system rapidly (Utami, et al. 2022). According to (Keržič & Umek, 2019), perceived usefulness is a good factor for predicting the e-learning system effectively; it can help and support the student's behaviour-intention to use the system. In another study by Mailizar (2021), Perceived usefulness is a robust interpreter for finding teachers' intention to use e-learning in Saudi Arabia. It has a quality that reproduces the ease of use in HCI (Amsal et al. 2021). In this framework, perceived usefulness has been taken for predicting the usefulness of e-learning systems, and it is hypothesized that.

***H1.** Perceived Usefulness will have an encouraging positive effect on Behavioral Intention to adopt e-learning throughout COVID-19.*

3.3.3 Perceived Ease of Use Mediating variable (PEOU)

It is a degree to which a person believes that there will be fewer efforts required to use the specific system or technology (Davis, 1989). Another study by Shah (2014) found it is the most promising factor in inducing the implementation of technology-based systems. There are two essential factors in the TAM model: Perceive-usefulness and Perceived ease of use; these factors are responsible for finding the user's intentions regarding how and when they will use the system (Davis et al., 1989). According to Wei (2009), perceived ease of use directly or indirectly affects behavioural intention; several other studies related to online learning have proven that PEOU and PU positively affect attitude (Hsieh, et al., 2021). For example, as per Utami, (2022), in his study, Teacher's willingness to use the cloud-based learning system if the user finds innovation in any system, they are more interested in using it, and this reason specifies an optimistic association between e-learning and its adoption by the user. Therefore, it is theorized as under:

***H2a.** Perceived-ease of use will have a positive encouraging effect on Behavioral Intention to adopt e-learning.*

H2b. *Perceived-ease of use will have an encouraging effect on PU to adopt e-learning throughout Covid-19.*

3.3.4 Perceived Cost external variable (PC)

In the context of e-learning, the term cost refers to the expenses required by the user for procuring IT-related hardware (PC, Laptop Tablets, and mobile, etc.), Internet packages cost, software licensing cost, and electricity cost needed to conduct the e-learning during COVID-19 Sarosa, S. (2021). During COVID-19, the cost factor was studied by server researchers concerning their culture and context; for example, in Indonesia, an education gap was created during COVID-19 due to the inadequate ability to procure internet packages, electricity, and other related supporting facilities by the student as their cost were high. So, the impact of the internet and other related costs were transferred to the students (Asvial et al. 2021). A similar study by Sarosa, S. (2021) in the same country states that, typically, a student uses up to 4 gigabytes per week to attend the online session conducted by his institution. It was an additional financial burden for the students besides their standard fees during the COVID era and negatively influenced them. Moreover, a Chinese scholar Twum (2021), found that perceived financial cost significantly affects the intention of students to adopt e-learning during COVID-19. In Pakistan, a study conducted by (ABBAS, et al., 2022) suggests that apart from an internet connection, communication structure, and well-trained staff, the cost is the most critical issue faced by medical students, and it directly influences e-learning in Pakistan. So, based on the above facts provided by the researchers, the cost factor has been chosen for this study to empirically demonstrate its influence on the higher education population of Pakistan for the adoption of e-learning. Following is the hypothesis of this factor.

H3. *Perceived Cost will have a negative, discouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19.*

3.3.5 System Quality external variable (SQ)

According to Delone & Mclean, the definition of system quality is the level at which the system requires minimum effort for its utilization; they point out the primary five traits of system quality: (availability, usability, adaptability, and response time). Another study by (Calisir, et al. 2015) states that SQ is an important issue in an e-learning system from which students can benefit effectively. Researchers found that quick access to the system will positively impact students and their behavioural intention to adopt it (Jaber et al., 2016). For the system's success, the system quality is the primary factor and directly influences perceived usefulness from the student's perspective (Alkhawaja, et al., 2022). Another study suggests that a system with technical problems may negatively influence users' willingness to accept it. (Ghazal et al., 2017). SQ is essential in finding the usage, subject to the function and features offered by the system (Costa et al. 2016), Considering the above literature review, it is justifiable that system quality problems are significant, and they need to be comprehensively examined by the researcher from the learner's point of view. In this study, the system quality has been taken concerning the availability and response time; so, the hypothesis for System quality is:

H4. System Quality, in terms of availability and response time, will have a positive encouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19

3.3.6 Complexity external variable (CO)

It is the level of difficulty to understand and accept the system (Lee et al., 2011). Complexity determines user intention to use the system, in particular by how complicated it is to learn and apply (Rogers, 1995; Davis et al., 1989), so we can say that less complex systems have more chances to be accepted by individuals than individuals in a more complex system. Several experiential studies proved that complexity has a significant opposing effect on the willingness to use the system (Shih et al., 2007) & (Hardgrave, et al., 2003). Another researcher found adverse effects between complexity and PEOU. Similarly, another study found that more complex e-learning systems have lower user

willingness to use them (Lee. et al., 2011). In the present study, the researcher proposed the idea that the level of application complexity has significant effects on individuals' behavioural intention (BI), which diverges from the above research findings. It was conceptualized that the development of less complex applications would have a substantial impact on the field of technology. Prior research has analysed the significant favourable correlation between application complexity and perceived ease of use (PEOU) based on empirical evidence (Idoga et al., 2022; Chin et al., 2016; Aypay et al., 2012). These studies have evaluated the adaptability of new information systems (IS). On the basis of the above literature, the hypothesis for complexity is as follows:

H5a. Application Complexity will have a positive encouraging effect on Perceived-ease of use.

H5b. Application Complexity will have a positive encouraging effect on Perceived Usefulness.

3.3.7 Social Influence external variable (SI)

People are influenced in many ways by social institutions, close friends, colleagues, and family members who believe that individuals should accept or adopt the new system (Viswanath et al., 2003). Social influence was included in the UTAUT model to guess the users' willingness to use the system, which is an essential factor (Jokar, et al., 2013). UTAUT combines constructs from previous models and theories, such as subject norms, Social Issues, and Images. The mix-up of all these previous works is called a social influence (Rutherford, 2010). The social support component can vary according to the environment due to its multidimensional nature (Huang et al., 2010). According to (Cheng et al., 2004) there are three aspects of social support: Family, Friends, and others; these aspects are reflected as complex. As for e-learning, especially during COVID-19, teachers, and family members can provide social support to students to create their behaviour and intention to accept the system. Several studies specify the benefits for online learners when teachers support their students by interacting with them online (Cheng, et al., 2004). So, in the reflection of the above literature review for this study, the social-influence construct has

been taken in expressions of family, friends, and teacher support to the students throughout COVID-19 for the adaptation of e-learning, so it is hypothesized as:

H6a. *Social Influence will have an encouraging positive effect on Perceived usefulness to adopt e-learning throughout COVID-19.*

H6b. *Social Influence will have an encouraging positive effect on the Behavioral Intention to adopt e-learning throughout COVID-19.*

3.3.8 Facilitating conditions external variable (FC)

It can be defined when the user studies that the presence of power, internet, and related facilities are adequate to create the user's interest in accepting the system (Viswanath V. et al., 2003). So, we can say that it is the point to which e-learning users trust that technical infrastructure is fair enough to support the technology. It is the direct factor of behavioural intention (Viswanath V. et al., 2003). In this work, facilitating conditions are raised for internet and power infrastructure availability in the country. For the smooth operations of e-learning, the availability of broadband internet and power is mandatory; it will influence the behavioural intention of the user to accept e-learning. Facilitating conditions will determine students' understanding and how the required tools, services, and technical support will increase the ease of use for e-learning (Jameel, et al., 2020). The availability of infrastructure and services will increase the chances of easy access to e-learning resources. Facilitating conditions has an optimistic and vital effect on behavioural intention (Gunasinghe, et al., 2019). So, by having all the above literature facts in this study, facilitating conditions have been taken to find the adoption of e-learning in Pakistan. So, the hypothesis is as follows:

H7a. *Facilitating Conditions will have a positive encouraging effect on Perceived-ease of use to adopt e-learning throughout COVID-19.*

H7b. *Facilitating Conditions will have a positive encouraging effect on the Behavioral Intention to adopt e-learning throughout COVID-19.*

3.3.9 Covid-19 external variable external variable (CVD)

This study has selected COVID-19 as a variable to examine the effect of the epidemic on the growth of online education. Based on current scholarly understanding, this particular construct has yet to be previously selected to investigate its impact on e-learning, particularly within the specific context of Pakistan. The study proposed one direct association in-between the COVID-19 construct and behavioral intention (BI), as well as two indirect relationships between COVID-19, perceived usefulness (PU), and perceived ease of use (PEOU) on BI.

The primary objective of choosing this construct was to analyze the environmental impact resulting from the pandemic, particularly concerning the implementation of e-learning, which has been influenced by causes such as lockdown measures, fear, and stress. One of the studies provided evidence that psychological distress and anxiety negatively affect the adaptation of e-learning under COVID-19 lockdown pressure (Roman et al., 2021). In another study, the students at Indian West Bengal universities faced several challenges during lockdowns: stress, depression, slow internet, uncomfortable environment, and anxiety. Students from remote areas were the most effective during the lockdown situation (Kapasias et al., 2020). Another study conducted by a Zambian scholar found that underprivileged students, concerning resources, faced several problems related to learning throughout the COVID-19 lockdown (Kombe, et al., 2021).

Based on the previously mentioned research, the primary objective of this study is to investigate the effects of the COVID-19 epidemic on behavioral intention, Perceived-usefulness (PU), and Perceived-ease of use (PEOU). Therefore, it is hypothesized in the following manner:

H8a. COVID-19 (lockdown, Fear, and stress) will have a negative, discouraging effect on Behavioral Intention to adopt e-learning.

H8b. COVID-19 (lockdown, Fear, and stress) will have a negative discouraging effect on Perceived-ease of use.

H8c. COVID-19 (lockdown, Fear, and stress) will have a negative discouraging effect on Perceived Usefulness.

3.3.10 Student Learning Motivation external variable (SLM)

Motivation is an essential factor in learning which may decide failure or success (Mao, 2011). For the adaptation of e-learning, especially in a situation like COVID-19, the student must be motivated to face the challenges produced by pandemics (Kakepotoa et al., 2021). There are two types of motivation intrinsic and extrinsic. Intrinsic motivation is produced within the self, and it further leads to interest, wishes, and strong feelings. Extrinsic motivation is produced by external forces that lead to a desire for learning (Kong, 2009). Four objects of motivation are goal, effort, conduct, attitude, and desire for learning (Pintrich & Schunk, 2002). Students securing higher grades are more motivated than those securing low grades (Dörnyei et al., 2010). Keeping the above background in mind, in this study student motivation factor has been taken to find its impact on Behavior Intention to use e-learning.

H9. Student Motivation will have an encouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19.

3.4 CHAPTER SUMMARY

This chapter aims to conceptualize and outline the hypothetical model for this study, as shown in Figure 3.1, as well as the interrelationships of the constructs chosen for the proposed model. It was developed using well-known models and theories (TAM, TRA, TPB, IDT, and UTAUT), previously discussed in chapter two. A total of ten constructs are chosen for an appropriate understanding of the e-learning adoption during COVID-19, including the cost from TRA, system quality from the M&D model, social influence and facilitating condition from UTAUT, and complexity from IDT. TAM3 was used to select student learning motivation and two mediating variables, PU and PEOU. Considering the study's focus on COVID-19, it is imperative to investigate the visible and hidden impacts

of COVID-19 in conjunction with lockdown measures, fear, and stress to achieve optimal research outcomes.



CHAPTER FOUR

RESEARCH METHODOLOGY

4.1 INTRODUCTION

Chapter four of this study provides a philosophical background to justify and explain the proper research methodology in order to reach the study's primary objective. Moreover, considering the methodological foundations, critical study paradigms and philosophies concerned with information systems research will also be described in detail. Similarly, the data collection method, instrument design, and data analysis techniques will also be clarified. This research aims to observe and outspread the information in comprehension and identify the most critical aspects affecting user adoption of e-learning throughout COVID-19 in developing countries, i.e., Pakistan; Prior to this, in Chapter Three, a research model is proposed along with its hypothesis to find the aims and objective of this research. This study uses the positivist (quantitative) method to attain its goals and objectives. The questionnaires for the quantitative survey were created based on previously validated instruments and scales. Respondents were requested to answer several questions related to different variables of the proposed research model. SPSS software version 26.0 and SmartPLS 4 software version 4.0.9.2 are employed to analyze data in this study.

Mooving on section 4.2 of this work begins with a discussion of research paradigms and describes the relationship between them and their corresponding philosophical expectations: Ontology, Epistemology, and Methodology. Section 4.3 differentiates positivist and interpretive research approaches. Section 4.4 highlights the most used research methods in the IS domain. Section 4.5 shows and defends the choice of the positivist approach against the interpretive methodology adopted for this study. Section 4.6 discusses survey validity and research strategy justifications. Section 4.7 describes the research design, including the study object, investigation type, setting, analysis unit, and horizon time. Section 4.8 explains and justifies the population and sampling strategy chosen

for this study. The data collection procedure used by the researcher in this study is highlighted in Section 4.9. Section 4.10 defines survey questionnaire/instrument development, which includes questionnaire wording, response formatting, and scale development. Section 4.11 goes over the pre-testing process and the results of the pilot study analysis. Section 4.12 describes the data analysis tools and techniques researchers use to achieve their research goals. Section 4.13 describes the ethical considerations that were considered during the data collection stage of this research work. Lastly, in section 4.14, there is an outline of this chapter.

4.2 RESEARCH PARADIGMS

The term paradigms can be defined as the “broad view that directs the researcher regarding the boundaries and limitations in which researcher expects to conduct research” (Guba & Lincoln, 1994). As per Hussey and Collis (2013), the definition of paradigm is “a scientific process that drives the human assumption and philosophies related to knowledge of nature and the world”. In 2011 researcher Saunder described that philosophy would be determined by how their views on knowledge growth affect the studies they design and carry out. Furthermore, he comments that predicting which paradigm is better is tough, and selecting the research paradigm depends on the research question. So, finally, the research paradigm suggests a framework in which research can be conducted.

According to some past research by Yin (2013), Collis and Hussey (2013), and Bryman (2015), there are several factors on which the selection of paradigm influenced such as research question type, nature of the study, and control limits required for a survey related to context over behavioral events and the scholar's philosophical attitude. Furthermore, Kuhn (2012) believed that a paradigm is the center of scientific progress because it provides methods, theories, and techniques for defining data. In the same way, Morgan (1979) categorized the uncertainty of paradigms and gave three ways to look at paradigms in academic research: from a social, philosophical, and technical point of view. Easterby-Smith et al. (2012) and Guba and Lincoln (1994) found and categorized three parts of a research paradigm. These parts, ontology, epistemology, and methodology are

three ways to think about research philosophy. Ontology studies what exists in the world and how the universe functions. The study of how one comes to know the world around them is called epistemology. Alternatively, the methodology concerns research issues and procedures, particularly in collecting and verifying empirical evidence. A researcher Guba & Lincoln (2000) also categorized these three paradigms into four denominations. These denominations are positivism, post-positivism, critical theory, and constructivism. Their details are as under.

4.2.1 Positivism

As per Bryman and Bell (2015), positivism promotes worth-free (objective) and natural science methods to study social reality, it is considered a one-way mirror of inquiry, presuming that both the researched object and the researcher are independent entities that do not influence one another.

4.2.2 Post-positivism

According to this school of thought, a researcher will not be 'positive' about the demanded experience in research on human behaviour and actions. (Creswell, 2013; Bryman and Bell, 2015) said that this approach is based on the philosophy of objectivism, which states that public phenomena are independent of the people who are involved in them. This is the same as positivism, but there is a contradiction in the methods of inquiry, which are used not only to challenge theoretical assumptions or hypotheses but also to prove the cause-and-effect relationship.

4.2.3 Critical Theory

This approach argues that the researcher's research objective(s), which are complexly linked with one another, significantly impact how people understand the results of the researcher's work (Guba & Lincoln, 1994). Another study states that it is founded on the theory of realism/subjectivism, in which a social actor's consideration affects the social trend and

how they know about the truth Bryman and Bell (2015). A critical theory approach examines a problem (i.e., realism) based on theoretical concepts to present a testable hypothesis through an interview and observation process (Bryman & Bell, 2015; Guba & Lincoln, 1994).

4.2.4 Constructivism

According to this approach, social actors continually produce social phenomena and their meanings (Bryman & Bell, 2015). In constructivism (also known as 'postmodernism'), hermeneutics and interviews are primarily used to examine the objective(s) (Klein & Myers, 1999). Like critical theory, the main principle of constructivism is subjectivism, with its one most important exemption: experiences are created by public communication frequently categorized or communicated by several people. Sometimes Positivism and upright Positivism are called 'scientific deductive schemes' for conducting empirical and quantitative research (Creswell, 2013). These approaches are opposite to each other concerning constructivism or interpretivism (Denzin, 2011).

In positivism and post-positivism, the deterministic-reductionist approach is reflected in which thoughts are distributed into small-scale variables along with their outcomes and effects. In this regard, Creswell (2013) states that hypotheses are designed by variables numerically calculated by conducting positivist and post-positivist experiments. However, social constructivism and social critical theory are founded on subjectivism and interpretivism. (Mertens, 1998). These 'naturalistic inductive methods' of study are ways that people try to know the world by making subjective values of their experiences towards objects. These values are derived from the person's interactions with those objects. Crotty (1998) added that in contrast to objectivism, interpretivism employs a style of inquiry known as "qualitative." According to this method, concepts are not broken down into distinct portions of variables but are developed further into theories with a particular context.

4.3 POSITIVIST AND INTERPRETIVISM RESEARCH APPROACH

Both positivist and interpretive research methodologies are reflected in the primary research paradigms in methodological research paradigms (Collis, 2013). The positivist method is famous for being quantitative and is a scientific approach. On the other hand, the interpretive process is qualitative in its very essence. According to Bryman (2015), both positivist and interpretive approaches have, in one way or another, both positive and negative impacts on various contexts of research, even though the primary concern remains the same. Orlikowski (1991, page 2) wrote, "Positivist studies are premised on the existence of a priori fixed relationships within phenomena which are typically investigated with structured instrumentation". This contrasts the statement that "realist studies are premised on the existence of a priori variable relationships within phenomena". In addition, Chua (1986) assumed that positivist research evaluates fundamental relationships, which then serve as the foundation for generalized knowledge.

Moreover, he argued that positivist research attempts to consider actual statistics, statistical assessment, and mathematical assessment to explain causal relationships and would be the most appropriate for answering the investigation questions if the positivist study were used. Therefore, positivist research is utilized to test hypotheses and generalize phenomena based on hypotheses that have been successfully tested (Chen, 2007). Orlikowski (1991) summarized interpretive research, stating that it investigates and identifies public practices in a general unit. This method determines how members' beliefs, meanings, and goals constitute their social actions. On the other hand, Carson et al. (2001) provided a more in-depth definition of both the positivist and interpretive paradigms and a summary of the differences between the two. The first distinction, as they see it, is that the positivist paradigm is not dependent on the researchers or the instruments that they use. It also assumes that reality is objective. On the other hand, an interpretive paradigm tries to recognize and comprehend phenomena based on the meaning that individuals ascribe to those phenomena without distinguishing between dependent and independent variables. Second, in contrast to interpretive research, the positivist research paradigm necessitates many participants in the study. Third, in positivist research, the researcher typically tests an

existing theory. In contrast, in the interpretive research paradigm, the emphasis is placed on developing a new theory.

To change pre-defined variables, positivist researchers must employ quantitative, mathematical methodologies and the logic of science, as stated by Collis and Hussey (2013). Orlikowski's (1991) results confirm that quantitative research can expose the association between organizational, technological, and individual characteristics. This is verified by the findings of Orlikowski (1991). The informative paradigm results from studies on social phenomena and the opinion held by many researchers that the world should be understood via subjective explanations of human experiences and behaviour rather than exclusively through objective assessments of human activity. This resulted in the creation of the interpretive paradigm (Bryman, 2012).

4.4 RESEARCH METHODS FOR INFORMATION SYSTEMS

Prior sections highlighted and examined the advantages, limitations, and individualities of employing positivist and interpretive research paradigms. Researchers need a clear understanding of the conclusions of their study experience and must act in methods that reproduce information. Although both philosophies propose a deeper view addicted to the phenomena of interest in IS research, researchers need to work in ways that imitate that knowledge. While both perspectives suggest a deeper view addicted to the phenomena of interest in IS research, researchers need to act in ways that imitate that knowledge.

Information Systems is an emerging area that has quickly amassed significant academic attention in a short time. Checkland and Holwell (1998) stated that information systems (IS) are a blend of the study of computer science and business management. Similarly, Information Systems research was referred to as multidisciplinary research by Lee (1999) and Land (1993). On the other hand, Lyytinen and King (2004) mentioned that research in information systems is a new concept of a marketplace of thoughts.' According to them, IS studies must concentrate on distributing information built on system management and design while considering the relevant technologies deployed in the

systems. Due to technological advancements and developments, research concerning the acceptability and adoption of information systems and information technology has received much attention over the past two decades. Example (Davis et al., 1989; Lyytinen, 2002) According to a review of previous research, a significant number of researchers have gravitated toward the positivist research paradigm in IS (Mailizar & Damon Burg, 2021; Sarosa, S., 2021; Alkhawaja et al., 2021; Al-Marooof et al., 2021; Al-Rahmi et al., 2019; Prasetyo et al., 2021; Sukendro et al., 2020).

Considering the connection that exists between students, e-learning, and information technology, numerous IS studies have concentrated on assessing the influence and level of acceptability of IT from the point of view of an individual's level of satisfaction (Baroudi, 1985; Jureviciute, 2011; Nassar et al., 2014). At the same time, many earlier studies attempted to comprehend how introducing IT affects the general operations of businesses (Al-Somali, 2011; Franz & Robery, 1984; Osmani, 2015; Shemi, 2013). Similarly, much research has been conducted to find the effects of extensive information technology use on humanity (Kling, 1984; Somekh, 2008).

According to Carson et al. (2001), various investigation studies may need diverse epistemological, ontological, and methodological participation. Similarly, Galliers (1987) uses either a positivist or interpretive methodology. Methods like these include polls, trials, examinations, recreations, and case studies. Mingers (2003), who studied the many research paradigms used in the IS/IT field, said that positivist, interpretive, critical, and critical realist approaches were all present. Orlikowski (1991) made a similar claim, saying that the most popular quantitative methods in management information systems include surveys, experiments in a controlled environment, and numerical methods. Positivist research, according to many scholars (Araujo, 2003; Quaddus, 2005), offers a straightforward way to study and understand information systems phenomena. Creswell (2013) says that the three most common research approaches used in studying Information systems are quantitative, qualitative, and mixed.

4.5 DATA SOURCE

This section introduces and compares two distinct research methodologies, Quantitative and Qualitative, and offers reasons for selecting a quantitative technique for the present study. The subsequent parts will proceed to present and contrast primary and secondary data while offering a rationale for employing primary data in this study.

4.5.1 Quantitative Research Method

The main objective of this strategy lies in gathering statistical data, which is then analyzed to accept or reject research hypotheses (Bryman & Bell, 2015). According to Collis and Hussey (2013), a quantitative method is a systematic approach to quantifying data and utilizing statistical analytic techniques. This strategy involves collecting extensive data by researchers to perform statistical analysis. Subsequently, the researchers utilize the study's findings to propose a conclusive action plan. Furthermore, they extrapolate these findings from a population sample to make generalizations (Creswell, 2014). Fowler (2013) contends that this approach is suitable for evaluating human behaviors and quantifying attitudes.

This methodology utilizes a survey that incorporates closed-ended and open-ended specified methods for data collection. Subsequently, the collected data is analyzed and validated to support or enhance existing ideas (Creswell, 2014). According to Fowler (2013), this methodology uses statistical techniques to analyze the collected quantitative data. Using a quantitative technique has been shown to possess significant value and practicality in understanding human behavior through the analysis of extensive datasets (Creswell, 2014). Fowler (2013) argues that surveys are a more cost-effective and manageable research method than various qualitative studies and this approach allows the researcher to assess the dependability and accuracy of data through the utilization of statistical techniques. According to Zikmund et al. (2013), an important aspect of this strategy is separating data analysis from the data collection process.

4.5.2 Qualitative Research Method

Qualitative research is an investigative approach that prioritizes examining and comprehending complex issues pertaining to human conduct, events, opinions, and societal occurrences. This methodology involves collecting data on a limited scale without statistical data collection or analysis techniques. The purpose is to gain a qualitative knowledge of the factors that drive the development and reporting of early understanding (Zikmund et al., 2013; Creswell, 2014). Typically, this approach involves focus-group discussions and in-depth interviews, while large-scale surveys are employed within the framework of quantitative methodologies. Qualitative methodologies provide a lower degree of structure in comparison to extensive surveys.

One of the primary justifications for employing qualitative methodology is its ability to understand the issue under investigation systematically. This is achieved through an examination of the individual's emotions and perspectives. This technique focuses on identifying challenges within a particular context, and it should be noted that these findings may not reflect broader study endeavors (McDaniel et al., 2011). Nevertheless, this technique presents several challenges. For instance, it might be challenging for individuals working in the government sector to access private experiences. Additionally, the reliability of the data obtained from respondents may need to be investigated. Furthermore, imposing an explanatory framework can prove to be a complex undertaking.

4.5.3 Choice of Research Method

The information system field is vital in research; it provides standards and strength (Lyytinen, 2004). Burrell (1979) states that the unique evidence of appropriate research depends upon its aims and questions. The goal of this research is to determine what factors of e-learning context are most influential throughout the COVID-19 time frame. Reflecting the nature of this study, a proposed model for e-learning adoption was developed by drawing on established theories and models for IS adoption. According to Leedy & Ormrod

(2005), adopting and investigating this type of research relationship can be measured as a progression study that identifies the variable and tests the hypothesis.

In light of the extensive literature review provided in Chapter 2, on technology adoption, this study has a critical theoretical purpose of positivism. Several similar studies have been conducted in which researchers formulate a framework for the testing relationship among chosen constructs and verify the proposed hypothesis. Furthermore, models and theories such as UTAUT, TAM, IDT, and M&D used in this study are typically tested in positivist science. As per the researcher Creswell (2013), business and social studies demand quantitative methods that can be understood and verified statistically. Having read the extensive literature in the IS field and based on the most common research method related to the topic, the methodology selected for this study is quantitative, with a positivist approach. There are many reasons for this type of approach for this study; some are discussed as follows.

Reason one is that this approach provides the most robust and established conduct for studying any human interaction related to technology. This method is primarily applied in the domains of both natural and social science. It is beneficial for creating reliability and validity of earlier studied hypothetical and theoretical suggestions most dependent on measurement and research methods (Abbasi, 2011; Blumberg et al., 2014; Patton, 1990). Similarly, Straub (2005) states that the quantitative and positivist approach is appropriate for research questions related to human behaviour for adopting technology.

Reason two is that the positivist modes are more appropriate for those studies under research and are not entirely explored; the quantitative research approach is very suitable for finding the critical association in-between the variables in the suggested model via collecting data related to human behaviour using structured instruments. This study collects data through ethical propositions, proves the significance of individualities from the higher education population, and measures calculable variables.

Reason three is according to (Malhotra, 2003), theories and hypotheses manage the basic philosophical expectations of positivist research. So, this study also examines whether the adoption theories and models selected, such as UTAUT TAM, IDT, and M&D for this study, are applicable or not for e-learning adoption during COVID-19.

Finally, as stated by Chua (1986) positivist paradigm is a situational and societal procedure for technological novelty adoption. This is very close to the objective of this research and motivates the quantitative research methodology. So, we conclude that for this study positivist and scientific approach is most suitable.

4.6 SELECTION OF SURVEY AS THE RESEARCH STRATEGY

Selecting a proper research plan is a significant challenge that must be addressed to avoid any unacceptable results that could be argued. In the context of technological and social research, several research plans are recommended by several scholars (Chen & Hirsch Heim, 2004; Creswell, 2013; Crotty, 1998; Myers, 1997). These plans include research on laboratory experiments, survey methods, action research, case studies, grounded theory, phenomenology, ethnography, mathematical modelling, and so on. Numerous studies have been carried out for the review and to categorize the applicability of the correct research approach for the information system field, particularly in technology implementation (Choudrie, 2005).

According to Pinsonneault and Kraemer (1993), apart from others, the survey provides a comprehensive and clear explanation regarding variables and their correlation based on selecting a framework or a model. In another study, Yin (2013) and Zikmund (2012) state that survey approaches directly deal with the sentiments, views, and thoughts of respondents, mainly when data collection is essential about the beliefs and attitudes of individuals. Another study was carried out by Zikmund (2012) & McDaniel (2006); according to them, a survey study is beneficial for identifying the characteristics of a research problem. This means that the researcher can determine what is going on (for example, a decrease in the consumption of a particular product), what is happening

procedure (for example, a pre-action process like decision-making, period, etc.), what are the reasons for it happening (for example, some idea about why people do (e.g., the individuals, groups, characteristics, organizations, etc.)).

Literature focusing on meta-analyses offers an excellent summary of survey research in information systems. Mingers (2001, 2003) evaluated articles published between 1993 and 1998 to determine the prevalent methods utilized in IS adoption research. They discovered that surveys, interviews, experiments, and case studies had been used most of the time. In addition, Choudrie and Dwivedi (2005) looked at 633 articles published in IS journals and concluded that roughly 74% of research utilized a survey approach to analyze the technology adoption, while only 26% used a case study approach. After thoroughly investigating recent meta-analyses published on the topic of IS/IT adoption and acceptance, it has become abundantly clear that the survey methodology has been the most widely recognized method. On the other hand, different methods, such as case studies and experimental procedures, have been employed as second and third choices.

The survey research method is ideal for this investigation, considering that earlier research studies opted to accomplish the same research aims and meta-analysis evidence. For this research study, a survey approach was chosen for several reasons. Number one, it is the one best suited to and has the most bearing on the context of this research study. Second, this methodology has been used in many earlier research investigations that have been done in ways analogous to these studies. In addition, Pinsonneault and Kraemer (1993) state that three primary criteria must be met to use the survey research approach. Number one, if a piece of study uses a quantitative method of investigation and provides standardized information (for example, the link between variables and hypotheses) regarding its topic, then it is said to be accurate (i.e., projects, organizations, or communities, applications, systems, individuals, groups, etc.). Second, suppose a study wants to generalize information about an entire community's features, behaviour, or attitude based on a sample of individuals and groups. In that case, it must use a representative sample. Third, this is essential if a research project requires collecting data using a pre-defined structured instrument or a questionnaire. It can be understood from the criteria set

by Pinsonneault and Kraemers (1993) that the study's aim and objectives are grounded in a positivist paradigm using a quantitative study technique. This is the conclusion that can be drawn from the criteria. In addition, this investigation made explicit definitions of hypotheses and links between constructs (i.e., dependent, independent) by providing a clear justification based on well-cited earlier research works (see Chapter 3).

One more vital point to remember is that the current research focuses on persons as the unit of analysis. This is a crucial point because it is the subject of the investigation. Hence, according to the thinking of Gilbert (2001) and Hussey (1997), the survey method is suitable for this study since it allows the researcher to contact many people quickly, cost-effectively, and easily. Besides the relevant literature, survey research is a fast, economical, accurate, and efficient way to examine target population information. (Zikmund et al., 2013)

4.7 RESEARCH DESIGN

One definition of a research design is "a plan for conducting research on a particular topic". Designing a research study must be carried out in stages, each successive stage depending upon the results of preceding one. In accordance with Sekaran (2016) it is a series of procedures for making decisions that includes the typical means of expressing problems or asking questions, data collection techniques, data interpretation and analysis, and investigative reporting methods. Furthermore, Hussey and Hussey (1997) state that the only factor in determining whether the research will be accomplished is the researcher's selection of research techniques and steps in the research design. It can be described from another angle; the research design is the methodical procedure that should be tracked to obtain and investigate the responses to research questions (Cooper & Schindler, 2001). According to another suggestion, the overall research design typically formulates research problems. It explains the position taken for data compilation, moral constraints, data gathering, evaluation methods, and research's part around the information collection procedure. This is a fundamental assumption but not the only one (Creswell, 2013).

Typically, the determination of an appropriate research approach in most research investigations depends upon several factors, including the nature of the research problem, the research questions at hand, the suggested research model, and the hypotheses being tested (Creswell, 2013). This study focuses on studying the factors impacting the adoption of e-learning and the relationship between these aspects. Therefore, based on the suggestion by Leedy (2005), the assessment for this kind of relationship can be known as an assessment study due to its changing nature to examine the assumptions contributing to classifying constructs of a theoretical framework. Although Cooper and Schindler (2001) provided a more in-depth explanation, generally, academics have identified three distinct types of research strategies: the "exploratory," "descriptive," and "explanatory" techniques. This research utilized all these research design stages. Figure 4.1 depicts the flowchart of critical steps involved in the research design of this study.

According to the flowchart, first, exploratory research was used to develop the background information about the research problem. Once the research problem is identified, the next step is the formulation of research hypotheses in the light of the most appropriate published literature, as suggested by (Churchill, 1995). In addition, a systematic analysis of the existing research and the results of earlier empirical testing preceded the identification of variables, followed by the formulation of study hypotheses (presented as the proposed research model in Chapter 3. Moreover, the research topic was clarified, and research objectives were homed in on locating the significant aspects affecting the adaptability of e-learning through the testing of an integrated research model. The second step is a descriptive study approach which was utilized to describe the respondents' characteristics and ascertain the standard deviation, percentages, frequencies, and mean of the constructs utilized in the proposed model. Because descriptive research could not adequately explain the link between the variables (Zikmund et al., 2013), the researchers turned to explanatory research to sufficiently describe the correlation and relationship between the model's variables.

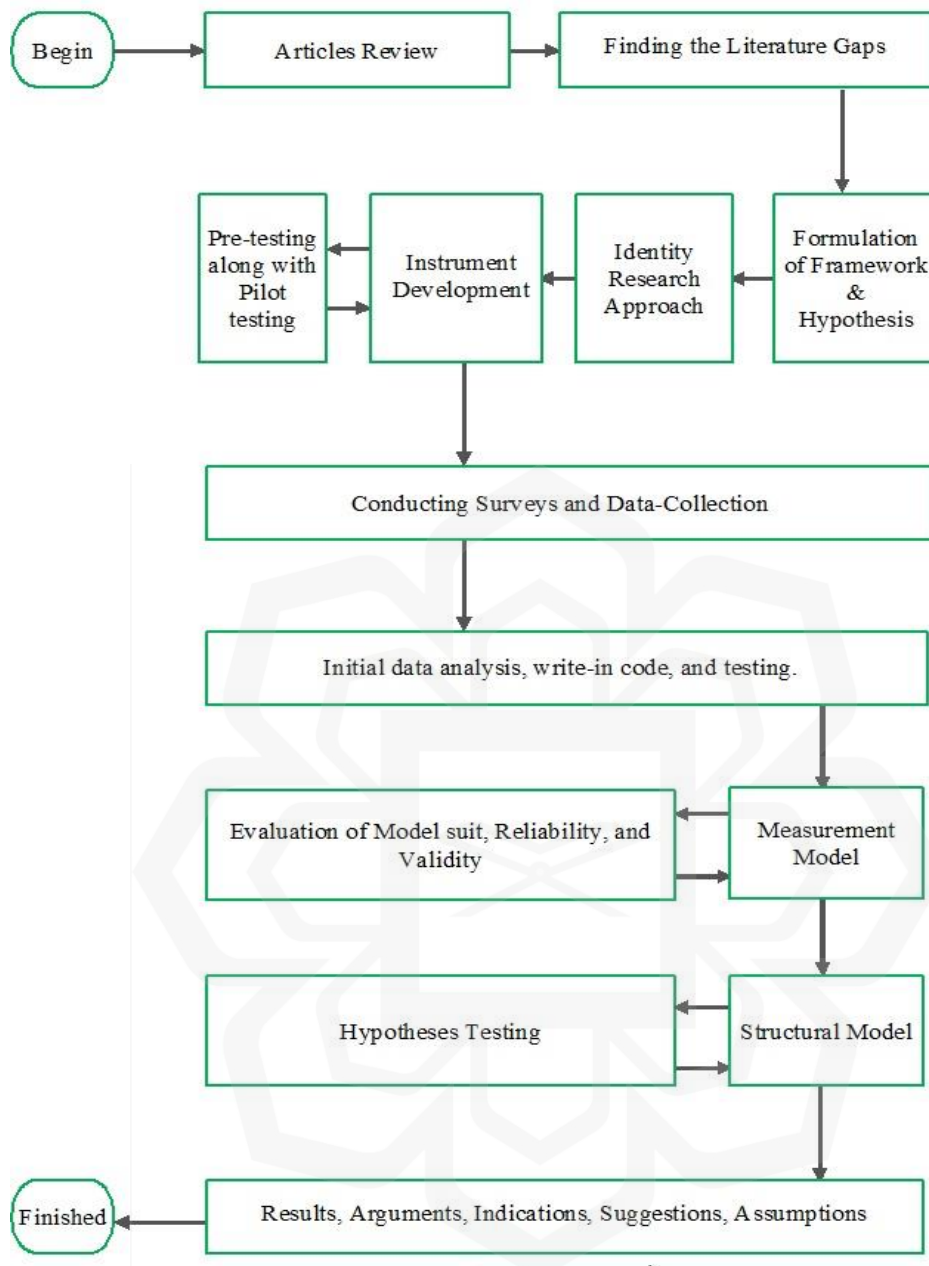


Figure 4.1 Significant steps required for research design.

Besides these steps required for the research design, it is also essential to complete the various processes and phases involved in successful completion of the study's objectives. The researcher followed Sekaran's (2006) suggestions to determine the study's intention, analysis type, research situations, analyzing unit, and planning horizon.

4.7.1 Purpose of the Study: Hypotheses Testing

As per the researcher, Sekaran (2016), the type of research that can be classified based on its needs is exploratory, descriptive, and testing hypothesis. Descriptive research is recommended when there is a need to explore new characteristics in the study. Similarly, exploratory research can be chosen if a new dimension is required. Hypothesis testing is suitable when it is already described and explored as per the type of problem. So, researchers suggest that hypothesis testing is the appropriate approach to accomplish the goals and purposes of the research study. Furthermore, considering the nature of this study survey method is chosen along with the positivist approach for data collection, its analysis, and finding the relationship among the selected dependable or intendable constructs and variables.

4.7.2 Type of Investigation: Correlational Study

According to (Sekaran, 2016). There are two major groups such as causal and correlational, for studies with a hypothetical relationship. Casual investigation studies of most appropriate when there is a need to find the direct and indirect effect on variables, whereas studies such as correlational investigation are most suitable when we have to find the relations among the constructs related to the specific issues of a specific domain. (Bordens & Abbott, 2007; Sekaran, 2016). As this study aims to find the essential relations among the constructs selected in the proposed model, as detailed in Chapter 3, for finding the behaviour intention for adopting e-learning during COVID-19, the correlation investigation is more appropriate than the causal type of investigation.

4.7.3 Study Settings: Non-contrived

Research studies that use a correlational method of investigation (also known as field studies) are typically carried out in environments that have not been artificially manipulated. On the other hand, studies that investigate causes, such as laboratory experiments, are considered to be conducted in artificial environments (Sekaran, 2016). So

as mentioned in earlier sections of this study, the correlational investigation method is selected and considered a non-contrived study.

4.7.4 Unit of Analysis: Individuals

According to Creswell (2013), when creating the Problem statement or expressing the research question, careful consideration must be given to the unit selection because it plays a vital role and must be given due consideration. While the current research aims to investigate the factors influencing the higher education institutions (HEI) population's willingness to engage in e-learning during COVID-19, the HEI population will be the unit of analysis for the research questions.

4.7.5 Time Horizon: Cross-sectional

Based on the time horizon, there are two types of studies: cross-sectional, in which data is collected once within weeks or months, and longitudinal studies, in which data is collected repeatedly after a fixed time interval to note the changes in variables. Considering the aims and objectives of this study, cross-sectional research is selected because this study investigates the significant factors for adopting e-learning during COVID-19 using a multivariable analysis methodology. According to (Bordens & Abbott, 2007), the cross-sectional approach is very appropriate for this type of study in which a large data sample is required within a minimum period by making fewer efforts.

4.8 POPULATION AND SAMPLING

In research, "population" and "sampling" refer to subsets drawn from a greater entirety for investigation. The subsequent subsection provides an in-depth discussion of the concepts pertaining to population and sampling.

4.8.1 Population

According to Bryman (2015), the population concerning research can be described as “everyone in the sample from which results will be drawn”. The entire population guides researchers in making the best choice of analysis unit in any given situation. As the COVID-19 breakout, all the educational institutions were forced to shift their education from face-to-face to online as social distancing was mandatory. The most affected people in the education sector were students and instructors during the pandemic. So, it is essential to find the problems they faced during COVID-19, especially in developing countries like Pakistan. Hence the target population of this study is students and academic staff of higher education institutions involved in using e-learning during the COVID-19 period.

4.8.2 Sampling

In the field of research, the term sample refers to a part of the population selected very carefully for predicting the generalized results representing the entire target population chosen for the study (Bryman, 2015; Sekaran, 2016). According to Airasian (2000), a random sample is a strategy by which information related to the whole population can be collected. Moreover, Saunders (2003) states that sampling allows the researcher to collect data from sub-groups that look sensible to represent the entire population. Within the disciplines of social science and IT management, under certain situations, it is challenging to get data from the entire population for analysis due to several limitations like cost, time, and accessibility (Airasian, 2000). Considering these limitations, it is recommended to reduce the number of participants to a suitable unit called a sample used to achieve the required results from a focus on the population that was used to make the sample. The sampling method is beneficial for research studies like marketing, where the population is enormous, and the researcher must take opinions in the form of a sample depicting the target population.

4.8.3 Sampling Method for this Research

In light of the objectives and answers for the research question, cluster sampling has been identified for approaching the targeted population selected for this study. As discussed in an earlier section the population for this study is the students and academic staff of universities around the country that is Pakistan. Pakistan is geographically divided into four populated provinces, so, using the clustered sampling technique, data has been collected from (Four clusters) Sindh, Khyber Pakhtunkhwa, Punjab, and Baluchistan Public sector Universities. For the adaptation of the sampling technique, there are several reasons behind it. Number one, this strategy is very appropriate where there are limitations to the researcher, such as cost, time, security, and accessibility.

According to Teddlie and Yu (2007), if the population is widely spread in a vast area and the researcher needs to collect the data representing the whole population, the small groups called clusters representing the entire population should be selected for data collection considering the limitations. Secondly, e-learning during COVID-19 was unexpected, and the sudden shift of education from face-to-face to online was a new challenge to students and instructors in every country. Hence, collecting data from each student is impossible. The third reason is the presence of universities in almost every major city, even their campuses in rural areas which show a significant population network. So, considering the limitations and geographic reasons cluster sampling strategy is selected for this study to achieve the desired results.

4.8.3.1 Sample Size

From the statistical analysis view, selecting a suitable sampling strategy and identifying the sample size is complicated, essential, and challenging. Some suggestions related to proper sample size led to having the best possible results considering the limitations such as cost and time. As per Hair et al. (2006) and Comrey (1992), suppose the sample size is less than expected; the probability of reduced parameter accuracy will be high along with failure convergence and incorrect outcomes. On the other hand, there are difficulties, such as waste

of money, and time, and the process of obtaining responses if the sample size is more prominent than required (Bryman & Bell, 2015; Hair et al., 2006; Zikmund et al., 2013). Furthermore, determining the proper sample size is critical to obtaining credible, reliable data representing the commonly targeted population.

This study's sample size selection is based on the data analysis approach called structure equational modelling (SEM). SEM is one of the most appropriate tools to investigate complicated models statistically (Hair et al., 2006). Furthermore, SEM also provides the execution of multivariate statistical methods (β) such as variance and multiple regression analysis, causal modelling using latent variables, and structural path analysis (Alavifar et al., 2012). Several general thumb rules related to data analysis are available to accomplish reliable and vigorous outcomes employing SEM, some of which are discussed as follows.

According to Harris and Schaubroeck's (1990) suggestion for a robust SEM analysis, the minimum sample size requirement is 200 respondents. On the other hand, Gorsuch (1983) said that to get satisfactory results, the minimum number of respondents per construct should be five and, overall, not less than 100 to analyse the data. Another study by Kline (2011) recommended that dealing with the model has a complicated path; the minimum requirement for sample size should be 200 or above. As per Stevens (1996), if there is a need to conduct the test like a least square multiple regression analysis, at least 15 cases per construct are enough. In the same way, Bentler (1987), a sample having a minimum of five points for each parameter can be considered valid for ideally normalized and distributed data with no missing or outlying points. Also, Loehlin (1992) found that a sample size of a minimum, and Lee (1992) rated various sample sizes. They concluded that 50 respondents are an inadequate sample size, a sample size more than or equal to 100 is inferior, a sample size more than or similar to 200 is fair, a sample size more than or identical to 300 is good, a sample size more than or similar to 500 is perfect, and a sample size more than, or similar to 1,000 is excellent. Alternatively, Fidell (2007) proposed a general rule of thumb, which states that if the factor loading value is more than 0.80, a sample size of 150 respondents is enough; else, the minimum desirable cases are 300 for

the best results of factor analysis. Finally, according to Hair et al. (2006), the sample size should not be less than 200 and above 400 to get the best possible results from the study. He also said that if the sample size is more than 400 to 500, the results of SEM analysis can be very complex in measuring the Goodness-Of-Fit (GOF) indices and display indices that have a poor match.

Therefore, by considering the ideas and suggestions previously discussed by the researchers, a general thumb rule is adopted for this study and adhered to the standards presented by Hair (2006) and Tabachnick (2007). Considering the suggestions, the researchers sought to collect between 300 and 400 legitimate responses (after accounting for ignoring data) to analyze the trials given in the study framework with reasonable estimations.

4.9 DATA COLLECTION PROCEDURE: QUANTITATIVE

One of the most critical aspects of research design is data collection from the relevant population, which includes correct information and respondent feelings regarding the research question or research topic (Zikmund, 2013; Churchill, 1987; Sekaran, 2016). For data collection, several techniques have been identified by the researcher in the literature review chapter two, such as interviews (face-to-face or through telephonic conversations or video conferences) and survey questionnaires using Google Forms (shared via WhatsApp, email, or any other electronic sources).To select the appropriate methods for data collection, the researchers need to know the type of research question they are asking, the size of the sample they need, the expenditure required for collecting the answers, research relevant contents, and overall time to conduct the survey Fowler (2013).

In this study, the researchers gathered primary data using an online questionnaire survey form after content validation using the pre-testing method. The form link was distributed through WhatsApp and email. The study focused on a population consisting of students. studying in higher education institutions (public sector universities) of major cities such as Karachi, Lahore, Peshawar, Quetta, and Faisalabad of the country. A cover

page the information related to e-learning, its definition, and the study's aims and objectives is also included on the first page of the questionnaire used for the survey on the Google form. Furthermore, a statement related to privacy was also included on the cover page to remove the reservations of respondents as their data is safe and completely confidential. The respondents were free to stop responding to the survey at any stage of the form as their participation was entirely on a volunteer basis. Moreover, in case of any query related to the study, the complete contact detail was also provided to the respondents so they could make contact if needed.

The questionnaire was designed to inspect the factors responsible for the sadoption of e-learning during COVID time, and it was divided into two sections. The first section includes the questions related to the respondent, called demographic questions, and the second section contains the questions related to each construct selected for the study. A cumulative sum of 567 replies was obtained across the country. Some respondents were biased from the received responses, and their responses were removed by calculating the standard deviation recommendation that any response with a less than 0.25 score should be eliminated. Therefore, 461 valid answers were finalized for data analysis. The following tables depict the received response distribution.

Table 4.1 Received response distribution.

Name of City	Response received
Sindh Province City Karachi	230
Punjab Province Universities Cites Lahore and Faisalabad	169
KPK Province Universities City Peshawar.	96
Baluchistan Province Universities City Quetta	72

The variation among the responses can be observed in the above table for some reasons. In the province of Sindh, there is a metropolitan city called Karachi which is the largest city

in Pakistan concerning population along with a high literacy rate as there are eight public universities in the city; the city is also the country's financial hub. The second highest response was received from the province of Punjab due to highly populated cities like Lahore and Faisalabad having excellent literacy rates and sufficient universities. The third highest response was received from Khyber Pakhtunkhwa because Peshawar city has a reasonable number of public sector universities. Last, the minimum response rate was obtained from the universities of Baluchistan provinces due to low literacy rates and lack of modern communication facilities such as broadband internet in most parts of the region. This province is very large and has rough terrain. Most areas are hilly and have poor law-and-order situations, so accessibility is more challenging in the region than in others.

4.10 INSTRUMENTS/QUESTIONNAIRE DEVELOPMENT

For data collection, the questionnaire is the most appropriate technique comprising a set of questions to know the respondents' feelings about the study (Malhotra & Birks, 2003). The design of a proper survey instrument is essential to obtain the exact and most relevant results (Zikmund, 2013). As per Saunders (2003), If a researcher is constrained by limited time to gather a large amount of data from a considerable population economically, the survey questionnaire method will be the best fit for him compared to others. Similarly, according to (Bell, 1999; Oppenheim, 2000), Formulating an appropriate questionnaire is a complex job even though it is commonly used for data collection. The questionnaire formulation is creative skills gained through experience (Malhotra, 1999). Considering the research goals and objectives, the survey instrument was formulated by dividing it into several steps per the suggestion of the research (Aaker, 1998; Sekaran, 2016; & Zikmund, 2013).

4.10.1 Questionnaire Wording

As mentioned in the previous study part, the quantitative positivist methodology was chosen to collect empirical data through a questionnaire survey strategy. The primary objective of data gathering for this study was to ascertain students' behaviour intentions

towards e-learning during a specific period, for which research questions were designed in the best possible way to elicit the likely response from respondents. To seek the maximum participation of respondents, 's questionnaire's items were made easy, to the point, and clear so the user may respond quickly (Cooper, 2001; Frazer, 2000; Zikmund, 2013). Items for questioners were adapted from previously well-known studies and adapted to suit this study's context, namely the adoption of e-learning during COVID-19. Table 4.2 includes the survey instrument and the reference form for which items were adopted.



Table 4.2 Survey Questionnaire associated with variables.

Construct	Code	Item	Hypotheses	Source
Behavior Intention	BI1	I intend to use e-learning as often as needed during COVID-19.	Dependent Variable	(Davis, 1989; Davis 1993; Moon and Kim 2001; Venkatesh and Davis, 2000)
	BI2	I intend to continue using e-learning in any COVID-19 type situation.		
	BI3	Assuming I have access to e-learning, I intend to use it.		
	BI4	Given that I may have e-learning access, I predict I will use it.		
	BI5	I will strongly recommend others to use e-learning in the type COVID-19 situation.		
Perceived Usefulness	PU1	In COVID-19, using e-learning enabled me to accomplish my academic tasks more quickly.	H1	(Davis, 1989; Moon and Kim, 2001. Venkatesh, 2003).
	PU2	Using e-learning increased my academic productivity and performance during COVID-19.		
	PU3	Using e-learning enhanced my effectiveness during COVID-19.		
	PU4	Using e-learning make it easier for me to engage in online educational activities during COVID-19.		
	PU5	Using e-learning enabled me to access much information during COVID-19.		
	PU6	Overall, I found it practical learning. In COVID-19		
Perceived Ease of Use	PEOU1	Through e-learning, I found that what I wanted via e-learning was easy during COVID-19.	H2a, H2b	Davis, 1989; Moon and Kim, 2001. Venkatesh, 2003).
	PEOU2	My interaction with e-learning was clear and understandable during COVID-19.		
	PEOU3	I found e-learning to be flexible in interacting during COVID-19.		
	PEOU4	It was easy to remember how to use e-learning during COVID-19.		
	PEOU5	Overall, I found e-learning easy to use.		
Cost	CS1	The equipment cost was expensive for using e-learning during COVID-19.	H3	(Sun et al., 2010; Wu and Wang 2005)
	CS2	The access cost was expensive using e-learning during COVID-19.		
	CS3	The internet package cost was expensive for using e-learning during COVID-19.		
	CS4	There were financial barriers to my use of e-learning during COVID-19.		
System Quality	SQ1	The e-learning system I used for online classes was always available when and where needed.	H4	(Calisir. et al. 2015; Jaber et al., 2016; Ghazal et al., 2017; Vijai, J. P. 2018).
	SQ2	The e-learning system I used for online classes responds quickly during the busiest hours of the day.		
	SQ3	The response time of the e-learning system I was using for online classes was consistent.		
	SQ4	The e-learning system I was using for online classes was reliable.		
	SQ5	The e-learning system I was using for online classes makes Information easier to access		
	CO1	The software platform I was using for online classes was user-friendly	H5a, H5b	

App. Complexity	CO2	The software platform I was using for online classes was easy to navigate.		(Lee. et al., 2011; Shih et al., 2007; Hardgrave, et al., 2003)
	CO3	The software platform I was using for online classes was well structured.		
	CO4	The software platform used for e-learning operates with sufficient features.		
	CO5	The software platform used for e-learning functions is considered to be satisfactory.		
Social Influence	SI1	People who influenced my behavior think that I should use e-learning during COVID-19.	H6a, H6b	(Khalifa, 2008; Venkatesh, 2003; Wei et al., 2009)
	SI2	People who are important to me thought I should use e-learning in any COVID-19 type situation.		
	SI3	I will use e-learning if my colleagues/fellows use it.		
	SI4	I would use e-learning if people in my community widely use the service.		
	SI5	Mass media reports influenced me to try out e-learning during COVID-19.		
Facilitating Conditions	FC1	I had all the necessary resources available for e-learning during COVID-19	H7a, H7b	(Venkatesh et al., 2003)
	FC2	I experienced a power failure which turned to effect on my online classes during COVID-19.		
	FC3	The speed of the internet connection was sufficient to take online classes during COVID-19.		
	FC4	It was easy to get the knowledge necessary to use e-learning.		
	FC5	A specific Person (or group) was available for assistance during COVID-19.		
COVID-19 affected variable	CVD1	During COVID-19, the lockdown affected my financial assets, which involved using online education.	H8a, b, c	(Al-Marroof, et al., 202; Raza et al., 2021; Roman et al., 2021; Kapasia. et al., 2020)
	CVD2	During COVID-19, the lockdown affected required facilities for conducting or taking online classes, which involved my use of online education.		
	CVD3	During COVID-19, the lockdown affected my online education's ease of use.		
	CVD4	I believe that during COVID-19, the lockdown put stress and anxiety on me and my colleagues/fellows, which turned into an effect on the use of online education.		
	CVD5	During the COVID-19 lockdown, online learning could have been more helpful to me.		
Student learning Motivation	SLM1	Attending online classes through e-learning saves travel time, money, and energy for students.	H9	(Pintrich & Schunk, 2002; Dornyei et al., 2010)
	SLM2	Through e-learning, students can achieve better grades exceptional in COVID-19 type situations.		
	SLM3	Online classes were convenient and flexible during COVID-19.		
	SLM4	Through online classes, students can improve their real-time skills.		

4.10.2 Response Formatting

To measure the respondent's behaviour intention related to using e-learning during COVID-19 time, two methods, Likert and nominal scale, were executed in questionnaire development. Given the nature of this investigation's exploratory nature, the researcher included controlled or close-ended questions. This approach is more efficient and needs less time for the respondent to respond to the questions. (Hair et al., 2006) Similarly, another researcher, Alreck & Settle (1995), states that there are negligible chances of biases in the closed-ended questionnaire approach; this approach also motivates the respondent to participate. With a closed-ended system, researchers are more flexible in tabulating and coding the quantitative analysis responses of respondents (Sekaran, 2016; Zikmund, 2013). Meanwhile, using the seven-point Likert scale tool, the researcher can measure the respondent's degree of acceptance or rejection of using the technology through a selected variable (Alreck & Settle, 1995). Moreover, the questions in the questionnaire were employed as per scope, logical order, and relevance to the subject matter (Frazer, 2000; Churchill, 1995).

4.10.3 Scale Development For this study

For this study, a seven-point Likert scale was adopted, which was proposed by Rensis Likert in 1932 for measuring the variables items used in a research framework. The range of this Likert scale starts from option 1, "strongly disagree," to option 7, "strongly agree," for finding the behaviour intention of the user regarding every item of the construct. The reason behind selecting the seven-point Likert scale is its familiarity and ease of data collection from respondents using a quantitative research survey approach (Sekaran, 2016; Viswanathan, 2004). Several studies in the past adopted a seven-point Likert or five-point Likert scale to know the behaviour intention of the user in the field of IS/IT (Mailizar & Damon Burg, 2021; Sarosa, S., 2021; Alkhawaja et al., 2021; Al-Marooof et al., 2021; Al-Rahmi et al., 2019; Prasetyo et al., 2021; Sukendro et al. 2020; Venkatesh & Bala, 2008; Venkatesh et al., 2003; Venkatesh & Morris, 2000; Venkatesh & Davis, 2000; Taylor & Todd, 1995). Considering the recommendation of these previous studies, the seven-point

Likert will significantly help to determine individual adoption behaviour for a given statement. Furthermore, the demographic variables were included as a nominal scale to get the respondents' background information. These variables contain respondent information such as Age, gender, occupation, education, information related to e-learning usage, and IT hardware like PC, laptop, and mobile phone.

4.11 PRE-TESTING AND PILOT STUDY

Before execution of the survey, the two most important activities (i.e., pre-testing and pilot study) are mandatory for finding the desired results. The researcher conducts these activities to check that the instrument is valid, error-free, ambiguity-free and has no biased items (Sekaran, 2016; Zikmund, 2013). These activities are beneficial to identify misunderstandings and confusion of the respondent related to the instrument so that he may participate in the survey without any difficulty.

4.11.1 Pre-testing

The primary purpose of pre-testing is to find whether a survey instrument is up to the standard using a well-controlled sample. As per the researcher (Zikmund, 2013) & Sekaran (2016), it is the initial evaluation of the survey instrument by receiving the responses from selective people to find the problems in the questionnaire like content, wording, and layout issues; along with these issues, problems like ambiguity and biasedness of questions will also be checked so the respondent may fill the form smoothly.

Before the execution of pilot testing, 55 responses were collected from graduate and postgraduate students studying at different universities in Karachi. For any improvement in the questionnaire, a request was made to students to provide suggestions related to survey items like their length, wording, or any other general observation that may improve the survey questionnaire.

The survey questionnaire was also verified and critically examined by the two professors at the universities of Pakistan. Some suggestions were received, like wording

correction and removing questions making the same perception or less relevant with constructs. All the provided suggestions and recommendations given through feedback were absorbed by re-writing the items, modifying, simplifying, or removing the uncertainties.

4.11.2 Pilot Study

For the development of a reliable instrument, a pilot study is one of the crucial processes to achieve the goals and purposes of the study. A pilot study can test the scale of questions and instructions, the reliability and content validity level, and ensure that the respondent fully understands the questions in the survey instrument (Sekaran, 2016). As per the researcher Ticehurst (2005), A pilot study is the best way to test and clean up the words, structure, order, similarity, response rate, time to complete the questionnaire, and how the instrument is analysed. Moreover, Van and Hundley (2002) list the nine reasons a pilot test should be done before the primary survey.

1. To make research tools and see how well they work.
2. To figure out if a full-scale study or survey is possible.
3. To discover what problems might arise when proposed methods are used.
4. To determine how different the results are so that the sample size can be set.
5. To find out if the sampling frame and method are reasonable.
6. To evaluate the proposed data analysis methods to find possible problems.
7. To develop a research question and a research plan.
8. A planned study must determine what resources (money, people).
9. To teach the researcher as much as possible about all the research process steps.

Many hypotheses were proposed by the researchers as potential options for study's sample size in the pilot phase to achieve an appropriate level of reliability. For example (Sim, 2012; Julious, 2005) recommended that a sample with 24 to 50 responses is adequate for a pilot test to get reliable results. According to another suggestion, the small response of respondents between 10 to 30 is good enough to represent the sample size (Luck & Rubin, 1987). According to (Diamantopoulos & Siguaw, 2000), the number of responses for a

sample size should be 100. After considering the recommendations as suggested in the pre-testing phase, a pilot study for this research was conducted in November 2022 based on a sample size of 55 respondents to check the reliability and validity of the questionnaire.

4.11.3 Reliability Test

Reliability test is a way to keep track of how well the study's construct fits together. A construct is consistent if its Alpha (α) value is more significant than 70 (Hair, 2017). Consider reliability was measured using Cronbach's Alpha. The result shows that the Behavior intention scale with five items ($\alpha = .923$), Perceived Usefulness with six items ($\alpha = .864$), Perceived Ease of Use with six items ($\alpha = .886$), Cost Use with five items ($\alpha = .886$), System Quality Use with five items ($\alpha = .909$), Application Complexity Use with five items ($\alpha = .899$), Social influence with five items ($\alpha = .860$), Facilitating Conditions with five items ($\alpha = .799$), COVID-19 effect with five items ($\alpha = .838$), and Student learning motivation with four items ($\alpha = .725$). Reliability findings are summarized in Table. 4.3

Table 4.3 Reliability Statistic.

Constructs	No. of Items	Alpha (α)
Behavior intention	5	.923
Perceived Usefulness	6	.864
Perceived Ease of Use	5	.886
Cost	4	.886
System Quality	5	.909
Application Complexity	5	.899
Social Influence	5	.860
Facilitating Conditions	5	.799
COVID-19 affect	5	.838
Student Learning Motivation	4	.725

The above table is comprised of three columns. The first column is Constructs: This column lists the different constructs or variables that were measured in the study. Each construct represents a specific aspect or factor being analyzed. The No. of Items: This column shows the number of items or questions used to measure each construct. More items generally

indicate a more comprehensive assessment of the construct. The third column is Alpha (α): This column provides the alpha coefficient, which is a measure of internal consistency or reliability of the items within each construct. The alpha coefficient ranges from 0 to 1, where higher values indicate greater consistency among the items. Typically, a value above 0.7 is considered acceptable for research purposes, although the threshold may vary depending on the context.

Based on received results constructs like "Behavior Intention," "System Quality," "Application Complexity," and "Social Influence" have high internal consistency, indicated by alpha coefficients ranging from .860 to .923. "Perceived Usefulness," "Perceived Ease of Use," and "Cost" also have acceptable levels of internal consistency, with alpha coefficients ranging from .864 to .886. "Facilitating Conditions" and "COVID-19 affect" have slightly lower but still acceptable levels of internal consistency, with alpha coefficients around .799 to .838. "Student Learning Motivation" appears to have the lowest internal consistency among the constructs, with an alpha coefficient of .725, which might suggest that the items measuring this construct may not be as reliably related to each other.

Overall, this table provides valuable insights into the reliability of the measures used in the study and helps researcher assess the quality of data.

4.11.4 Respondents Demographic Profile of Pilot Study

For the data analysis of the pilot study, the questionnaire's reliability was determined using SPSS. Table 4.4 demonstrates the analysis results of demographic variables.

Table 4.4 Demographic analysis for a pilot study with sample size=55

	Group	Frequency	Percentage
Gender	Male	44	80
	Female	11	20
Age	<20	2	4
	21–30	49	90
	31–40	2	4
	41–50	1	2

	51–60	0	0
	>60	0	0
Education	Undergraduate	44	80
	Graduate	11	20
	Postgraduate	0	0
Occupation	Student	53	96
	Faculty	2	4

The table presented above displays the demographic data gathered for the pilot study conducted in this research. The data presented offers insights into the demographic composition of participants, including variables such as age, gender, level of education, and occupational status. The specific information about each group is included in the following sections:

Gender: There are two categories: Male and Female. Among the respondents, 44 individuals (80%) identified as Male, while 11 individuals (20%) identified as Female.

Age: Age categories are presented in ranges. The majority of respondents, 49 individuals (90%), fall within the age range of 21 to 30. The other age categories (<20, 31–40, 41–50, 51–60, and >60) have very few or no respondents.

Education: Respondents are categorized into Undergraduate and Graduate. The majority of respondents, 44 individuals (80%), reported being Undergraduate students, while 11 individuals (20%) reported being Graduate students. There are no respondents in the Postgraduate category.

Occupation: Respondents are classified into Student and Faculty. The overwhelming majority of respondents, 53 individuals (96%), reported being Students, while only 2 individuals (4%) reported being Faculty members.

Overall, the table provides a snapshot of the demographic composition of the sample surveyed. It indicates a predominantly young population, with a majority of respondents being male, undergraduate students, and students in terms of occupation.

4.12 DATA ANALYSIS PROCEDURE

The main objective of the data analysis is to transform the information gathered via questionnaires into comprehensive reports and conclusions, which aid in presenting the study's findings (Zikmund et al., 2013). Choosing adequate statistical tools and methodologies is commonly acknowledged as a difficult research procedure (Malhotra, 2010). The primary objective of statistical approaches is to assist in the validation of the theoretical framework and assess the degree to which the different explanatory factors seem to influence the dependent variable. The main aim of this investigation is to examine and ascertain the determinants that affect the adoption of e-learning by students in the COVID-19 epidemic. Consequently, the process of data analysis was segmented into two distinct phases. During the initial stage, the researcher conducted preliminary data analysis using the statistics tools SPSS 26.0 as outlined in the subsequent subsections. During the subsequent data analysis stage, the software Smart-PLS 4.0.9.2 was employed to investigate the interdependencies among independent and dependent variables inside the hypothetical model under consideration.

To ascertain the importance of several factors influencing the adoption of e-learning during the COVID-19 pandemic, this study employed measurement and structural model analysis methodologies. The subsequent subsections comprehensively clarify each application tool, method, and statistical procedure employed for data analysis.

4.12.1 Initial Data Analysis

The SPSS software is widely regarded as a highly favored statistical analysis tool in several fields, such as sociological research, marketing strategies, information technology, and commerce (Griffith, 2009; Pallant, 2013). According to Zikmund et al. (2013), SPSS has demonstrated its efficacy and effectiveness as a statistical analysis tool across all disciplines. In addition, the researcher employed SPSS software to perform various statistical procedures, including data coding, descriptive analysis, testing for normality

using mean, kurtosis, and skewness tests, as well as identifying missing values and outliers, as recommended by Hair et al. (2010).

4.12.2 Missing Data

One of the primary challenges encountered in data analysis, particularly when working with an adequate sample size, is missing data (Tabachnick & Fidell, 2007). Furthermore, the researchers found that the problem of missing data extends beyond the lack of specific values. As per the findings of Hair et al. (2010), missing data can arise for a variety of reasons, such as respondents leaving items unreciprocated, mistakes in data entry, or faults in the data collection process, and this affects the entire data analysis and may lead to two major issues: No.1 sample size reduction and statistical significance; No.2 results may be biased. Furthermore, they classified missing data into two categories: ignorable missing data and non-ignorable missing data. According to their findings, the presence of ignorable missing data does not demand any interventions because software solutions frequently account for missing data as a routine component of data processing. Nonignorable missing data can arise from two primary sources: researcher errors during data entry and respondents' reluctance to answer specific questions in the survey instrument.

According to the research conducted by Hair et al. (2017), it was determined that the Smart PLS program employs three distinct methods for managing missing data. Like mean value substitution, case-wise removal, list-wise removal, and pair-wise deletion. Among the options available, one effective method for addressing missing values is determining the mean of the subset representing the identified variable.

Additionally, it was stressed that handling complicated models containing missing values must be handled before analysis with the Smart PLS program. Therefore, the researcher adhered to the recommendations of Hair et al. (2017) and employed the mean substitution method to address the issue of missing values. The method described in the literature is commonly employed to address a variable's missing values. It involves computing the mean based on the available and correct values of the variable in question (Hair et al., 2010).

4.12.2.1 Outliers

Outliers are defined as cases in a dataset that exhibit unique scores, either lower or higher, compared to other observations, as stated by Pallant (2013) and Hair et al. (2010). The presence of problematic outliers can have significant implications on the outcomes of statistical analysis, particularly disturbing variables, and model estimations. These outliers could introduce a negative variance, affecting the results' accuracy and reliability (Tabachnick & Fidell, 2007). There are two sorts of outliers: multivariate and univariate (Tabachnick & Fidell, 2007; Pallant, 2013). Univariate outliers are cases exhibiting an exceptionally high or low value on a single variable. In contrast, multivariate outliers are cases that display a unique mix of values across two or more variables.

Although there is no categorization of extreme value outliers in the existing literature, a commonly accepted guideline proposes that any observation exceeding three standard deviations above or below the mean should be categorized as an outlier (Hair et al., 2010). The study used a Likert scale from 1 (strongly disagree) to 7 (strongly agree), and as a result, univariate outliers were not detected. In this study, responses that fell on the extreme ends of the rating scale were considered outliers and were removed from the dataset. The outliers were detected using the Mahalanobis distance (D2) method in SPSS version 26.0 (Griffith, 2009).

4.12.2.2 Normality

According to the definition provided by (Hair et al. 2010), normalcy refers to the distribution of data for various items in a linear combination, where each item exhibits a normal distribution. Data normality plays a crucial role in multivariate analysis, as highlighted by several scholars (Fidell & Tabachnick, 2007; Hair et al., 2010; Kline, 2011). Examining the assumption of normalcy can be divided into two levels: the univariate level, which focuses on the distribution of scores for individual items, and the multivariate level, which considers the mixture of more than one distribution of scores.

Furthermore, data normalcy can be assessed by examining measures of skewness and kurtosis, as Pallant (2013) suggested. Skewness is a statistical measure that quantifies the degree of symmetry in a distribution, while kurtosis is a measure that describes the extent of "flatness" or "peakedness" in the distribution. To display a significant skew distribution, the skewness and kurtosis scores should be zero and the skewness within the range of ± 1 (Hair et al., 2010). According to Kline (2011), skewness values of more than 3.0 are skewed, and 8.0 and 20.0 or higher may imply extreme kurtosis. As a result, the researcher estimated the most admissible range of observations to be 1 for skewness and 3 for kurtosis.

4.13 STRUCTURAL EQUATION MODELING

Identifying an adequate and relevant statistical method is crucial in investigating the hypothetical association presented in a research model. Regression analysis and structural equation modeling are two common methods. Regression analysis is an appropriate statistical method for dealing with models involving a single dependent variable. This is because regression investigation allows the direct examination of the impact of exogenous variables on the endogenous variable (Alavifar et al., 2012). SEM is a statistical method utilized for analyzing interactions in-between many independent and dependent variables. Furthermore, it allows for assessing and verifying various connections within extensive theories and models (Hair et al., 2010).

According to Tabachnick and Fidell (2007, p. 676), SEM is a collection of statistical procedures used to study correlations between discrete or continuous independent variables and discrete or continuous dependent variables. Given the complex structure of the research model suggested in this investigation, Structural Equation Modelling (SEM) emerged as the most appropriate methodology for examining the postulated association between exogenous and endogenous variables. The SEM method is widely employed across diverse domains, including information technology and information systems (IT/IS). For instance, it has been applied in the context of e-learning (Siron et al., 2020; Aloulou et al.; R., 2022), online banking (Alalwan & Williams, 2014), and online shopping (Pascual-Miguel et al., 2015). Moreover, it is worth noting that there exist two widely recognized SEM methods,

namely (PLS) partial least squares SEM covariance-based SEM (CB-SEM) and (PLS-SEM) (Hair et al., 2017). Hence, the investigator employed the PLS-SEM method to test and evaluate the measurement and structural models, accomplishing the study's aims. The subsequent subsection elaborates extensively on the justification for employing PLS-SEM.

4.13.1 Selection Reasons for PLS-SEM

A thorough understanding of statistical approaches' fundamental principles can help researchers decide which statistical techniques to use. The decision between PLS-SEM and CB-SEM is influenced by several aspects, including model evaluation, measurement model design, data characteristics, research aims, and structural model modeling. Henseler and Ringle (2009) claim that PLS-SEM facilitates the assessment of both formative and reflective constructs. On the contrary, CB-SEM is limited to research models exclusively using reflective variables. While certain researchers incorporated formative characteristics into the structural model, it typically resulted in challenges related to identification. Using formative measures in the context of CB-SEM would make it unfeasible to explain the covariance of indicators (Chin, 1998). Furthermore, it should be noted that PLS-SEM can measure a research model that incorporates reflective and formative measurements (Hair et al., 2017; Hair et al., 2011; Chin, 1998).

Analyzing reflective and formative constructs inside a study model using the CB-SEM technique is a complex process, as highlighted by Urbach and Ahlemann (2010). When choosing in-between PLS-SEM and CB-SEM methodologies, it is the responsibility of the investigator to choose the research objective. PLS-SEM is a suitable method in cases where the primary aim is to construct and predict theories, also called soft modeling. This technique places significant emphasis on identifying the optimal prediction of variable associations and maximizing the covariance among latent variables to enhance the model's explanation (Hair et al., 2011; Sosik et al., 2009).

In contrast, CB-SEM is a viable approach for hypothesis testing or validation. Testing a theory aims to assess its ability to absorb observable facts and demonstrate its

robustness effectively. Furthermore, CB-SEM offers a framework for addressing the challenges associated with modeling the covariance matrix, as discussed by Barclay et al. (1995). The utilization of PLS-SEM is a more flexible and appropriate methodology that does not obligate the assumption of normal distribution for the data. This is due to the implementation of measurement mechanisms within PLS-SEM, which transform non-normally distributed data into a dataset that adheres to the principles of the central limit theorem (Barclay et al., 1995; Hair et al., 2017).

The CB-SEM requires certain expectations to be fulfilled before conducting additional data analysis. These assumptions include observer independence, data multivariate normalcy, and variable measurement similarity (Sosik et al., 2009). Unlike PLS-SEM, CB-SEM requires an adequate sample size and data with a consistent distribution (Hair et al., 2017). Concerning the assessment of structural models, the primary aim of Partial Least Squares (PLS) is to forecast and assess a model formulated based on existing literature rather than determining which alternative model is the most suitable for the data. There is an association between the latent variables and the residuals on the visible variables in PLS-SEM, allowing PLS to assess the model effectively. As a result of the preceding explanation, this study has chosen PLS-SEM as the statistical method to evaluate the conceptual research framework, as justified by the following justifications.

First, the main objective of this study is not to measure the model's invariance. This study seeks to determine what factors influence student adoption of online learning during the COVID-19 epidemic. Hence, evaluating the significance of the correlations between latent variables is crucial by considering the resulting scores of said variables.

Second, this study incorporates many latent factors and a complex research model. The PLS approach suits a research model with numerous latent factors (Henseler & Ringle, 2009). The primary aim of the research is to examine the hypothesized correlations among variables by theoretical propositions. The appropriateness of the PLS-SEM approach is supported by its capacity to assess the relationship between residuals and their impact on the theoretical model (Urbach & Ahlemann, 2010; Henseler & Ringle, 2009).

4.13.2 Partial Least Square (PLS)

The Partial Least Squares (PLS) technique was first proposed by Herman Wold in 1966, as documented by Chin (1998). According to Henseler and Ringle (2009), the term PLS is a collection of alternating least squares methods or prescriptions that expand upon the concepts of principal components and systematic correlation analysis. According to Hair et al. (2017), the PLS route models are often characterized by two components: the measurement model, also referred to as the outer model, and the structural model, also known as the inner model. Prior research studies in numerous fields have commonly used PLS due to its effective component-based approach, Henseler and Ringle (2009).

The importance of using Partial Least Squares (PLS) for theory validation cannot be overstated. PLS enables the detection of potential correlations between latent variables and the determination of whether these relationships exist. Furthermore, PLS supports alternative test hypotheses (Chin, 1998). Although Partial Least Squares (PLS) can evaluate both the inner and outer models quickly, the assumption of multivariate normal data distribution is not required. Furthermore, earlier research has shown that PLS does not require a larger sample size (Hair et al., 2017).

4.13.3 Measurement Model

One of the significant methodologies employed in SEM is Confirmatory-factor Analysis (CFA), as described by Kline (2011). This methodology proves to be efficacious when prior familiarity exists with the essential measurement items and variables, as stated by Pallant (2013). According to Henseler et al. (2009), the connection between latent variables and their indicators can be conceptualized as a measurement model, also called an outer model. The evaluation of the measurement model involves the examination of reliability statistics for both items and constructs, as well as the validation process, which includes assessing discriminant and convergent validity (Hair et al., 2017).

Reliability test is important when derived variables are utilized for subsequent predictive analysis. In the context of a survey questionnaire, the internal consistency of items or the average correlation is determined using Cronbach's alpha standards (Santos, 1999). Moreover, this concept is linked to evaluating the consistency of outcomes generated by a measuring tool, particularly when many individuals assess the items using a comparable methodology (Zikmund et al., 2013; Sekaran & Bougie, 2010). In contrast, multi-item constructs exhibit distinct characteristics compared to single items. To effectively quantify a single item, researchers are advised to employ alternates or other approaches for evaluating validity (Hair et al., 2017, p. 99). Furthermore, as per Nunnally (1994), values of Cronbach's α that are equal to or greater than 0.7 are deemed satisfactory.

Convergent Validity pertains to the degree of association between concepts (Zikmund et al., 2013). Construct validity measures how well a construct variable correlates with other construct indicators. (Hair et al., 2017). Furthermore, it elucidates the correlation among responses acquired through different methodologies for evaluating the identical construct (Peter, 1981). Specifically, it indicates that a collection of indicators signifies the identical main construct, which can be ascertained through their compatible measures (Henseler et al., 2009). This study assessed convergent validity using "Average Variance Extracted (AVE)" (Henseler, 2009; Hair et al., 2017; Chin, 2010).

The purpose of AVE is to quantify the degree of variation that a construct exhibits about its related measurements while accounting for the influence of measurement errors (Fornell & Larcker, 1981). Hence, following the suggestion put forward by Hair et al. (2017), the researcher should employ a measurement model using outer loadings, composite reliability (CR), and average variance extracted (AVE). The measurement model was evaluated using certain minimal criteria proposed by (Fornell and Larcker 1981; Henseler et al. 2009; Hair et al. 2017). These criteria included factor loadings greater than 0.7, composite reliability exceeding 0.6, average variance extracted beyond 0.5, and construct reliability higher than 0.6. In the context of a single-item construct, using average variance extracted (AVE) as a measurement tool may not be appropriate due to the fixed loadings of 1,000 (Hair et al., 2017, p.104).

Discriminant Validity is a concept that establishes the genuine differentiation between constructs based on empirical criteria (Hair et al., 2017). Furthermore, Fornell and Larcker (1981) proposed that the standards for assessing discriminant validity include ensuring that the square root of the average variance extracted (AVE) values derived from the components surpass the variance for all inter-component correlations. The idea of discriminant validity is characterized by its complementary nature, wherein it is necessary for there to be a substantial distinction between two distinct concepts (Henseler et al., 2009, p.299).

4.13.4 Structural Model (SM)

Partial Least Squares Structural Equation Modelling (PLS-SEM) encompasses two primary stages: the measurement and structural models. The above methods are commonly employed to assess the validity, reliability, and unidimensional nature of latent variables, as well as to identify causal associations among latent variables inside the model (Tabachnick & Fidell, 2007; Kline, 2011; Hair et al., 2010, 2017). Furthermore, it is necessary to employ a structural equation modeling (SEM) approach in any research attempt to construct a path diagram, also known as a path model, which visually represents the interrelationships among variables and hypotheses to be examined. The path diagram comprises two parts. The structural model and measurement model are two fundamental components of academic research. The structural model is the theoretical framework that outlines the association in-between constructs and variables in a study. It provides a conceptual understanding of how different factors interact and influence each other.

The primary objective of the structural model is to elucidate the interconnections among latent constructs. In contrast, the measurement model explicates the associations between latent variables (LVs) and their corresponding indicators, also known as measures (Hair et al., 2017). The structural and measuring models are essential elements in academic research. The structural model is the conceptual framework that explains the associations among constructs and variables in a study. It gives a conceptual perception of how various

things interact and influence one another. The structural model's major goal is to explain the relationships between latent constructs. In contrast, the measurement model explains the association among latent constructs (LVs) and their related indicators, referred to as measures (Hair et al., 2017).

4.14 ETHICAL CONSIDERATION

Ethical considerations are essential for any research study that investigates human behaviour. Ethical standards must be followed at every step of the research process, such as gathering data, analysing data, writing a report, and sharing information online. If ethical rules are broken during or before a survey, respondents might not be as interested in the study, which could change the results (Sekaran, 2016; Zikmund et al., 2012). As per Blumberg et al. (2008), ethics is the study of executing research study ethically and sensibly. Sekaran (2016) suggested that researchers take the following ethical measures to prevent violating human rights.

- Declaring individuals that no one will ask for their personal information.
- Declaring to individuals that their information will not be shared with anyone else.
- Declaring individuals that their information will be used correctly.
- Making sure that the respondents have high self-esteem and respect for themselves.
- Getting clear on the study's purpose and goals.
- Asking for consent before data gathering and avoiding pressure.

Ticehurst and Veal (2000) suggested some general research ethics rules along with these recommendations. Number one, ensure subjects' free participation; number two, no harm should come to the research participants; and Number three, Participants should give their prior informed consent before participating.

In this study, the researcher considered all aspects of ethical responsibility to assure the authenticity of the research. In addition, the researcher complied with the recommended and advised guidelines with the questionnaire survey to improve participants' confidence. The cover letter includes the research title, the researcher's contact information in case

respondents have concerns, the purpose of the study, and an assurance that respondents' confidentiality and privacy will be a top priority and that their identities will be protected. Furthermore, respondents were told that their answers would only serve this research study, that their participation was voluntary, and that they could stop whenever they felt worried.

4.15 CHAPTER SUMMARY

This chapter aimed to review the various research patterns, designs, data collection methods, Statistical methods, pilot study, pre-tests, and validity & reliability of the survey questionnaire applied to gain the aims and objectives of the research.

First, the two primary schools of thought in the field of research, the positivist and the interpretive schools were explored in great detail. It was established that the positivist school of thought is scientific and typically utilized in quantitative research domains. In contrast, the interpretive school of thought is most at home in qualitative research domains. It was also argued that adopting a positivist (quantitative) method had been widely employed in IS. This approach is suitable for the current research project, which uses a quantitative survey tool for data collection. In addition, it demonstrated that the positivist approach is the reasonable solution for this investigation since it makes it easier for researchers to offer a theoretical research framework following a thorough investigation of the relevant literature.

The study focused on the student population enrolled at institutes of higher education who used e-learning during the COVID-19 time in Pakistan, as it was impossible to take the opinions of every Pakistani student due to several reasons such as time, cost, and accessibility clustered sampling proved best for data collection from the universities of selected cities that is Karachi, Lahore, Peshawar, and Quetta were selected as a cluster to sample the population. Furthermore, a quantitative cross-sectional survey was used because the research objective was to directly get respondents' feelings, attitudes, judgments, views,

and feelings to provide the scholar with the ability to more efficiently, economically, and quickly generalize population-targeted study findings.

Furthermore, the survey questionnaire for this study was created by modifying question items from previous relevant studies; all of the essential measures were taken into account, including the rewording of items, the validation of items, and the relevance of both content and operational items. Moreover, to engage respondents, the researcher optimized question items and response categories and simplified items as much as feasible. Before the main survey, pre-test and pilot studies are done. Several efforts were made to simplify the survey instrument to eliminate confusion, misinterpretation, inaccuracy, and ambiguity. Once pilot research measuring item reliability tests were successful, the final survey was completed. In addition, data investigation instruments and methods used in this study are addressed in detail. SPSS and SmartPLS4 version 4.0.9.2 were appropriate by widespread academic research acceptance. SPSS was used to code, screen, process missing data, identify outliers, and assess data normality. SPSS also calculated percentages, frequencies, mean values, and standard deviations. In SEM one-dimensionality, the measurement model looked at the validity and reliability of latent constructs.

In the same way, hypotheses about the association in-between latent constructs are evaluated in the structural equation model. Last, we talked about how ethically we collected the data. The subsequent chapter provides an analysis of the data collected in the research investigation.

CHAPTER FIVE

DATA ANALYSIS

5.1 INTRODUCTION

This study aims to investigate the factors that influence the e-learning level of adoption during COVID-19. Chapter three focuses on developing and discussing a hypothetical model proposed to accomplish the study objective and answer the research questions. In Chapter 4, the researcher discussed the research idea, data gathering, design instrument, tools used for investigation, and procedures used for this research. The current chapter evaluates and examines the suggested study framework by applying collected data from respondents using a survey method. Figure 5.1 depicts the data analysis techniques in detail.

The initial step summarizes the final poll's response rate and the aggregate number of valid responses gathered after invalid responses have been eliminated. The second step was data screening, which included the detection and treatment of missing values as well as the examination of outliers. In the third step, the demographic data results were investigated.

Furthermore, descriptive statistics were done on all constructs in the fourth stage. During the fifth stage, a psychometric evaluation was performed to assess the measures' reliability and validity. This involved an assessment of both internal consistency and whole procedures, utilizing Cronbach's coefficient α . Moreover, in phase six, the multivariate statistical method known as SEM was used with the Smartpls4 version 4.0.9.2 software package to assess the measurement and structural model. After that, the hypothesized correlations between latent components were tested and path coefficients were calculated. Finally, the proposed framework was modified to produce a simple model that successfully accounts for the available data.

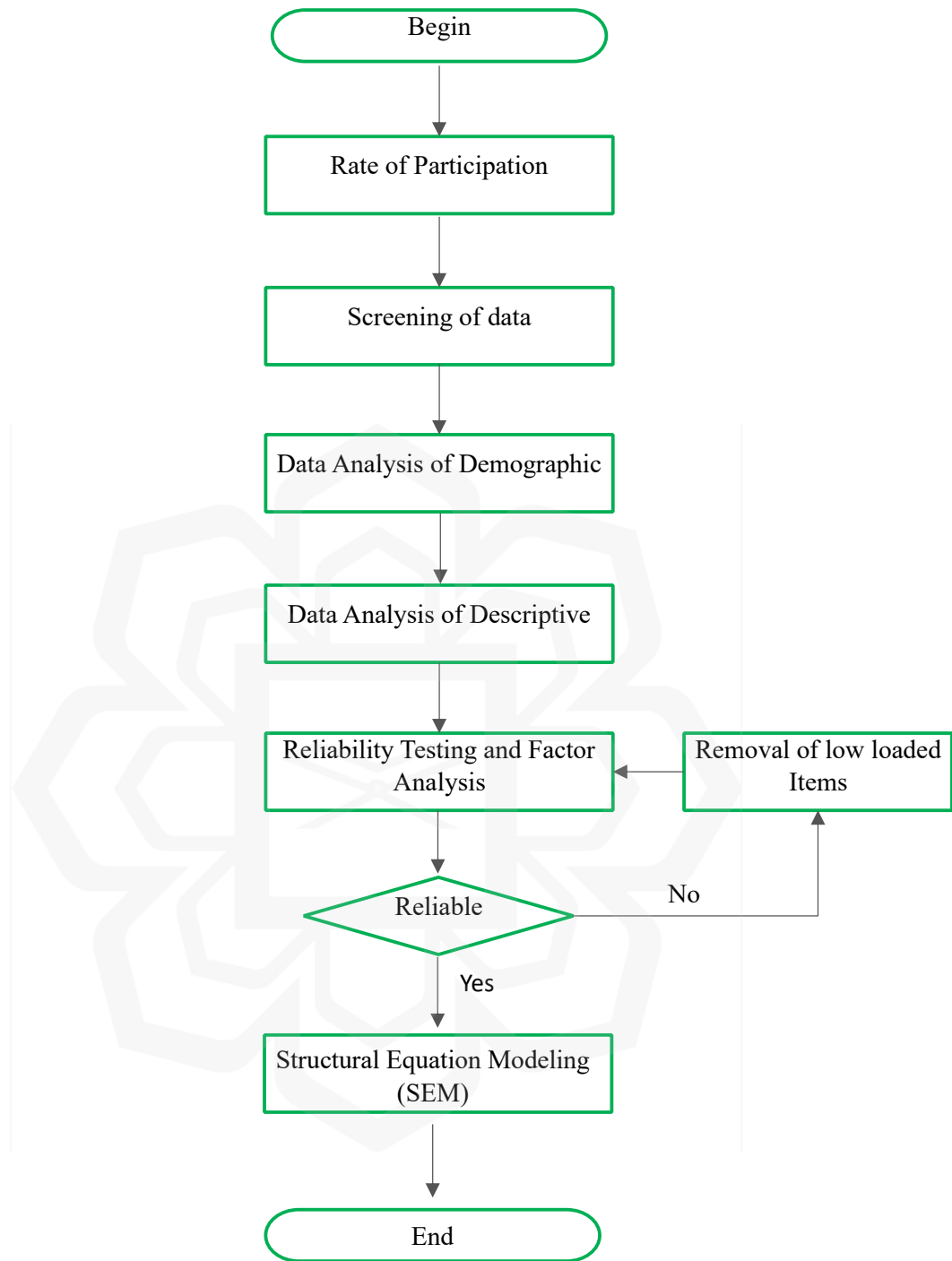


Figure 5.1 Flow Chart for the Data Analysis

5.2 RATE OF PARTICIPATION

During the survey, the total number of responses received from the respondents was 567. Out of these 567 responses, some respondents did not fill out certain questions about their demographics, education, employment history, etc. Some respondents were biased from the received responses, and their responses were removed by calculating the standard deviation recommendation that any response with a less than 0.25 score should be eliminated, Collier, J. E. (2020). As a result, 461 replies were finalized for further data analysis using SPSS version 26 and SmartPLS4 version 4.0.9.2.

5.3 DATA SCREENING

A preliminary data screening was performed to detect and address any missing values or outliers discovered. The researcher proceeded through the following stages to carry out the data screening.

5.3.1 Identification and Handling of Missing Data

As per Zikumnd (2013), Missing information is often a problem in survey-based studies. Because of the possibility of serious issues throughout the data analysis process, finding and treating missing data is an important pre-analysis step. It was possible to assess the breadth and pattern of the missing data that could not be ignored at the item and construct/variable levels (Hair et al., 2010). The researcher collected data via an online survey approach, and to deal with missing values, the Google form was designed accordingly to encourage the user to fill in the missing information before moving to the next step.

5.3.2 Outliers Examination

The presence of outliers in the obtained data from the respondents might lead to a deviation from the normal distribution, resulting in skewed statistical findings (Tabachnick, 2007;

Hair, et al., 2010; Kline, 2011). The data was subjected to univariate and multivariate oddity analysis to identify any anomalies. The observed data's Z-score distribution frequency was calculated to identify univariate outliers (Kline, 2011). Given that a 7-point Likert scale was employed in this analysis, having a choice range from One to Seven, there was no single outlier in the data. Because of this, Mahalanobis distance (D2) was used to find multivariate outliers. Hair et al. (2010). Therefore, Mahalanobis distance (D2) was used for multivariate outlier detection. The Mahalanobis distance (D2), according to Hair et al. (2010), delivers a single value by determining how far apart each observation is relative to the average or center of all observations in a multidimensional space.

The study employed a rigorous statistical significance test ($p < 0.001$) with the Mahalanobis distance measure. This approach indicates that cases with higher D2 values are more likely to be considered outliers as the corresponding probability value decreases. This methodology has been previously discussed in the literature (Tabachnick, 2007; Hair et al., 2010). From the results, approx. In 18 items, the outliers were observed using the Mahalanobis distance (D2) test. Hair et al. (2006) claimed that removing outliers helps multivariate analysis but that doing so carries the risk of reducing generalizability. Furthermore, Tabachnick (2007) recommended that outliers can be accounted for that don't significantly affect the outcomes. Researchers considered this advice and kept certain multivariate outliers for later investigation.

5.4 DEMOGRAPHICAL DATA ANALYSIS

The demographic questions inquired about the respondents' genders, ages, educational ability levels, occupations, and geographic locations. Table 5.1 shows the variables' frequencies, percentages, and cumulative values. The group functions as an additional subset for data collecting. Frequency is a quantitative measure of how frequently an event or observation occurs.

The percentage represents a numerical value or proportion that is symbolized by a portion of 100. Finally, the cumulative refers to the sum of frequencies allocated across various class intervals. Table 5.1 indicates the demographic information about the sample.

Table 5.1 Respondents' Demographic Details

Survey data n=567				
Variables	Group	Frequency	Percentage	Cumulative
Gender	Male	403	71.1	71.1
	Female	164	28.9	100.0
Age	<20	140	24.7	24.7
	21–30	390	68.8	93.5
	31–40	25	4.4	97.9
	41–50	12	1.9	99.8
	51–60	0	0	0
	>60	0	0	0
Education	Undergraduate	444	78.3	78.3
	Graduate	99	17.5	95.8
	Postgraduate	24	4.2	100.0
Occupation	Student	538	94.9	94.9
	Faculty	29	5.1	100.0
City-wise University responses	Karachi	230	40.56	40.56
	Lahore and Faisalabad	169	29.80	70.36
	Peshawar	96	16.93	87.29
	Quetta	72	12.71	100.0
Internet usage experience on handheld devices	Less than one year	21	3.7	3.7
	1-2 years	50	8.8	12.5
	2-3 years	86	15.2	27.7
	More than 4 years	69	12.2	39.9
	More than 5 years	341	60.1	100.0
e-learning use Before COVID-19	Yes	248	43.7	43.7
	No	319	56.3	100.0
e-learning Usage Frequency	Daily	289	51.0	51.0
	Weekly	278	49.0	100.0

According to the statistics, the male population constitutes 71.1%, and the female population accounts for only 28.9%. The statistics also indicated that individuals aged 21 to 30 and those under 20 showed the highest level of interest in the survey, with response rates of 68.8% and 27.4%, respectively. Furthermore, the involvement of undergraduate students was recorded at a peak rate of 78.3%, followed by graduate students at 17.5%, and post-graduate students at 4.2%.

Moving on to the respondents' occupations, the percentage of students is maximum at 94.9%, followed by faculty members with 5.1 %. The target population for this study was students and faculty members of universities around the major cities of the country. So, the city-wise responses received from universities are as high as the Universities of

Karachi city at 40.56%, followed by the Universities of Lahore and Faisalabad at 29.80%, Universities of Peshawar city at 16.93%, and the last Universities of Quetta city at 12.69%. The maximum response received from Karachi city as it is a highly populated city in the country. Moreover, in this digital era, 60.1% of respondents are familiar with the internet and handheld device usage for more than five years, while the remaining 49.9% are familiar with handheld devices used for less than five years.

The statistics indicate that efforts are still required to improve digital literacy in the country. Even before COVID-19, 56.3% of respondents did not know e-learning usage, while 43.7 % were familiar with e-learning, which indicates the adoption of e-learning in the country. The e-learning usage frequency of respondents during COVID-19 was 51% daily and 49 % weekly, from the usage frequency it can be observed that in any pandemic situation where social distancing is mandatory, e-learning will be the only option to continue education uninterruptedly, for which it is necessary to find the factors involved in adoption of e-learning during COVID-19 which is the object of this study. As a result, responses were only requested from students and staff members who employed e-learning during COVID-19 to meet the study's goals and objectives.

5.5 DESCRIPTIVE ANALYSIS

Descriptive analysis is a statistical method used in research and data analysis to summarize and explain a dataset's main characteristics, features, and patterns. The primary objective of descriptive analysis is to give an overview of the data and learn more about it, not to make assumptions or draw conclusions about a bigger population.

5.8.1 Behavioral Intention Construct (BI)

All respondents were given a seven-point Likert scale to rate how likely they were to engage in e-learning-related behavioural changes, from 7 (strongly agree) to 1 (strongly disagree). Five survey items were aimed at obtaining responses from respondents regarding this concept. Descriptive statistics, as well as measures of data normality (skewness and

kurtosis), can be seen in Table 5.2 for all items used to assess this construct. The data normality values were determined to be within the permissible range of skewness of less than five, and kurtosis of less than 2 and results also indicated that the average rating of the elements comprising this construct was between 4.90 (1.910) & 5.00 (1.810).

Table 5.2 BI Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
BI1	4.90	1.910	3.648	-.781	-.576
BI2	4.95	1.879	3.530	-.807	-.546
BI3	4.98	1.912	3.655	-.781	-.593
BI4	4.90	1.866	3.482	-.788	-.504
BI5	5.00	1.810	3.277	-.810	-.391

5.8.2 Perceived Usefulness Construct (PU)

Respondents rated six elements related to PU on a Likert scale providing seven choices strongly- disagree to strongly- agree. Table 5.3 displays the statistical descriptors and data normality scores (skewness and kurtosis) for all items that were utilized to evaluate this attribute. Skewness was found to be less than five, and kurtosis was found to be less than two. Therefore, the data is generally disseminated. The data also reveals that the average rating of the questions used to gauge this concept was 4.83 (1.841) and 4.98 (1.881).

Table 5.3 PU Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
PU1	4.98	1.881	3.538	-.880	-.350
PU2	4.83	1.841	3.390	-.634	-.740
PU3	4.85	1.825	3.332	-.782	-.468
PU4	4.89	1.813	3.287	-.690	-.587
PU5	4.96	1.848	3.415	-.825	-.429
PU6	4.88	1.964	3.855	-.734	-.745

5.8.3 Perceived-Ease of Use Construct (PEOU)

The researcher asked respondents to rate their agreement with seven statements about the PEOU of e-learning using a 1 to 7 scale this study ranges from strongly disagree to highly agree. Table 5.4 presents the findings of statistical analysis and tests for data normality, skewness, and kurtosis. The findings show that users are familiar with e-learning's 'ease of use,' with the average score for each part of this construct separating 4.91 (1.744) and 4.97 (1.678). Furthermore, the data had a skewness of less than five and a kurtosis of less than two, with normalcy levels within the permitted range.

Table 5.4 PEOU Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
PEOU1	4.92	1.767	3.122	-.740	-.461
PEOU2	4.91	1.744	3.042	-.696	-.536
PEOU3	4.91	1.748	3.055	-.701	-.547
PEOU4	4.92	1.686	2.842	-.601	-.577
PEOU5	4.97	1.678	2.816	-.746	-.379

5.8.4 System Quality Construct (SQ)

Respondents were asked to rate how much they agreed with seven narratives about system quality using a scale of 1-7 points to rate users' experiences of the quality of e-learning software during COVID-19. Table 5.5 displays the average ratings given to each component making up the system quality construct, with the highest ratings of 3.28(1.901) and the lowest rating of 2.93(1.652), respondents' low self-esteem was reflected in a mean score below the neutral threshold (i.e., 4). The degrees of normalcy are also appropriate, with a skewness of less than five and a kurtosis of less than two.

Table 5.5 SQ Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
SQ1	3.25	1.900	3.608	.619	-.825
SQ2	2.93	1.652	2.729	.892	-.010
SQ3	3.03	1.656	2.742	.738	-.388
SQ4	3.03	1.731	2.997	.835	-.271
SQ5	3.28	1.901	3.614	.616	-.837

5.8.5 Cost Construct (CS)

To find whether or not respondents felt the price of using e-learning in COVID-19 was expensive, four questions were asked on a 1–7 Likert scale (completely disagree to agree) about the cost element. The average ratings given to the different parts of the system quality construct are shown in Table 5.6, with the highest ratings at 2.83(1.721) and the lowest ratings at 2.64(1.509). Respondents' low self-esteem reflected in a mean score below the neutral threshold (i.e., 4). Skewness is less than five, and kurtosis is less than two.

Table 5.6 Cost Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
CS1	2.83	1.721	2.963	1.000	.093
CS2	2.81	1.735	3.011	.926	-.141
CS3	2.78	1.598	2.553	1.052	.233
CS4	2.64	1.509	2.278	.968	.236

5.8.6 Application Complexity Construct (CO)

To know the difficulty level faced by e-learning users while using e-learning software during covid time. Five items were asked from users using on a 1–7 Likert scale (completely disagree to completely agree) related complexity constructs. The results provided in Table 5.7 with the mean value from highest 4.97(1.587) to lowest 4.79(1.611), along with Skewness which is less than five, and kurtosis, which is less than two.

Table 5.7 CO Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
CO1	4.95	1.749	3.058	-.704	-.656
CO2	4.98	1.595	2.544	-.787	-.243
CO3	4.92	1.577	2.488	-.710	-.283
CO4	4.79	1.611	2.597	-.734	-.371
CO5	4.97	1.587	2.518	-.857	.032

5.8.7 COVID-19 Construct (CVD)

To measure users' experiences using the e-learning in COVID-19 pandemic situation, this survey asked participants to rate their agreement with seven statements concerning the COVID-19 effect on a 1–7 Likert scale (completely disagree to completely agree). Descriptive statistics related to this construct by asking five questions from respondents are provided in Table 5.8, showing 3.23(1.781) is the highest and 2.64(1.509) is the lowest mean value with Skewness, which is less than five, and kurtosis, which is less than two. Respondents' low self-esteem was reflected in a mean score below the neutral threshold (i.e., 4).

Table 5.8 COVID-19 (CVD) Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
CVD1	2.64	1.509	2.278	.968	.236
CVD2	3.16	1.920	3.685	.738	-.674
CVD3	3.08	1.772	3.141	.784	-.400
CVD4	3.23	1.781	3.174	.636	-.677
CVD5	3.22	1.850	3.423	.692	-.656

5.8.8 Social Influence (SI)

The descriptive statistics of respondents' opinions on the effect of social influence on e-learning adoption over the COVID-19 period are shown in Table 5.9. The response was sought on a 1–7 Likert scale (completely disagree to completely agree). There were five

items used to assess this factor. Descriptive statistics results indicate that the upper and lower mean ratings for all five items of this construct were between 4.90 (1.674) and 4.51 (1.844) and above the middle ground (i.e., 4), reflecting that participants were agreeable to all items. Moreover, the results of Skewness are less than five, and kurtosis, which is less than two.

Table 5.9 SI Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
SI1	4.77	1.745	3.046	-.509	-.888
SI2	4.90	1.674	2.804	-.531	-.755
SI3	4.66	1.737	3.018	-.500	-.725
SI4	4.81	1.758	3.092	-.590	-.708
SI5	4.51	1.844	3.401	-.319	-1.147

5.8.9 Facilitating Conditions (FC)

The five-item survey employed a 1–7 Likert scale (completely disagree to completely agree) to measure this concept. The summary statistics for all items that measure this construct are presented in Table 5.10, including averages, standard deviations, variances, and normalcy (skewness and kurtosis) values. Descriptive statistics results indicate that the upper and lower mean ratings for all five items of this construct were between 4.76 (1.727) and 4.59 (1.813) and above the middle ground (i.e., 4), reflecting that participants were agreeable to all items.

Table 5.10 FC Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
FC1	4.59	1.813	3.289	-.560	-.840
FC2	4.76	1.727	2.984	-.610	-.692
FC3	4.59	1.864	3.475	-.523	-.895
FC4	4.68	1.822	3.320	-.572	-.845
FC5	4.68	1.831	3.351	-.510	-.904

5.8.10 Student Learning Motivation (SLM)

To measure whether students were motivated or not by the usage of e-learning during covid time, respondents were asked four questions to measure their intention. The seven-point Likert scale was adopted to receive the responses, and the statistics results for all items that measure this construct are presented in Table 5.11, including averages, standard deviations, variances, and normalcy (skewness and kurtosis) values.

Table 5.11 SLM Descriptive Analysis

	Mean	Std. Deviation	Variance	Skewness	Kurtosis
SLM1	4.88	1.707	2.913	-.744	-.431
SLM2	4.88	1.612	2.598	-.689	-.340
SLM3	4.75	1.645	2.708	-.720	-.418
SLM4	5.04	1.560	2.432	-.927	.250

Finally, results show that respondents generally agree on the measurement variables, with mean rating values of all items in the constructs falling between 4.75 (1.645) and 5.04 (1.560), which is higher than the middle ground (i.e., 4). The Skewness and kurtosis of the data were likewise within a reasonable range. Skewness is less than five, and kurtosis is less than two.

5.6 NORMALITY OF DATA FOR LATENT FACTORS

Normality tests are typically carried out to determine whether the distribution of scores within the data is linear and regularly distributed. Shapiro-Wilk and Kolmogorov-Smirnov were the tests that the researcher used to determine whether the latent components exhibited univariate normality. The statistical results of both exams are in Table 5.12. The findings show no problem with the normality of the data, and each value is significant (P equal to or less than 0.05).

Table 5.12 Data normality Test

	Kolmogorov-Smirnova			ShapiroWilk		
	Census	Df.	Sig.	Census	Df.	Sig.
BI	.198	460	.000	.862	460	.000
PU	.180	460	.000	.891	460	.000
PEOU	.159	460	.000	.916	460	.000
SQ	.158	460	.000	.897	460	.000
CS	.149	460	.000	.898	460	.000
CVD	.172	460	.000	.906	460	.000
SI	.124	460	.000	.961	460	.000
FC	.152	460	.000	.908	460	.000
SLM	.144	460	.000	.922	460	.000
CO	.143	460	.000	.917	460	.000

Skewness and kurtosis distribution provide yet another method for determining whether data is normally distributed (Pallant, 2013). According to the findings of descriptive stats of latent constructs, which can be Seen in Table 5.13, all variables are under the standard limit of skewness and kurtosis, less than ± 2.58 (Hair et al., 2006). As a result, the hypothesis that the data followed a normal distribution was double-checked.

Table 5.13 Constructs Descriptive Analysis

	Lowest	Highest	Mean	S. deviation	Variation	Skewness		Kurtosis	
	Census	Census	Census	Census	Census	Census	St. Literal	Census	St. Literal
BI	5.00	35.00	24.7413	8.19376	67.138	-.895	.114	-.531	.227
PU	5.00	35.00	24.5109	8.03762	64.603	-.829	.114	-.494	.227
PEOU	5.00	35.00	24.6304	7.55592	57.092	-.749	.114	-.494	.227
SQ	5.00	34.00	15.5217	6.48289	42.028	.932	.114	-.130	.227
CS	4.00	28.00	11.0565	5.54139	30.707	1.001	.114	.205	.227
CVD	6.00	33.00	15.3413	6.37182	40.600	.789	.114	-.483	.227
SI	5.00	35.00	23.6370	6.30599	39.766	-.523	.114	-.492	.227
FC	5.00	35.00	23.3022	7.60676	57.863	-.611	.114	-.915	.227
SLM	4.00	28.00	19.5435	5.45014	29.704	-.913	.114	.186	.227
CO	5.00	35.00	24.6174	6.37442	40.633	-.975	.114	.326	.227

5.7 MEASUREMENT MODEL

A measurement model is a mathematical model that describes how a set of variables/constructs are related. It is used to measure the relationships between variables or constructs and to predict the values of one or more variables/constructs depending on other variables/constructs. The significance of each construct in the research is judged by how well the measuring model is evaluated. Factor loading is the first step in evaluating quality standards. After that, the researcher evaluated the concept of reliability and validity.

5.8.11 Factor Loading

Factor loading is a statistical technique employed to determine the degree of association in-between a variable and a factor. In the context of factor analysis, a statistical measure is employed to assess the extent to which a certain variable has a relation to a specific factor. The factor loading of each item reflects the strength of its association with the specified factor in a correlation matrix. According to Pett et al. (2003), a greater absolute value signifies a more robust correlation concerning the principal factor (p. 299). The values of factor loadings range from -1.0 to +1.0. Based on the findings of Hair et al. (2017), it is recommended that a factor loading value of 0.5 or more is considered to be the acceptable threshold. Table 5.14 presents the findings of the factor loading analysis conducted in this study. Only one item, specifically CVD1 of the COVID-19 construct, exhibits a factor loading value of 0.081, which falls below the recommended range. Consequently, this particular item is excluded from further analysis. On the contrary, all other items demonstrate factor loading values within the intended range.

Table 5.14 Factor loadings results

	BI	CO	COST	CVD	FC	PEOU	PU	SI	SLM	SQ
BI1	0.853									
BI2	0.880									
BI3	0.894									
BI4	0.868									
BI5	0.875									
CO1		0.742								
CO2		0.723								

CO3		0.827								
CO4		0.796								
CO5		0.839								
CS1			0.809							
CS2			0.868							
CS3			0.876							
CS4			0.818							
CVD1				0.081						
CVD2				0.830						
CVD3				0.845						
CVD4				0.823						
CVD5				0.837						
FC1					0.857					
FC2					0.824					
FC3					0.861					
FC4					0.803					
FC5					0.852					
PEOU1						0.877				
PEOU2						0.889				
PEOU3						0.906				
PEOU4						0.857				
PEOU5						0.850				
PU1							0.856			
PU2							0.858			
PU3							0.880			
PU4							0.858			
PU5							0.882			
PU6							0.865			
SI1								0.688		
SI2								0.729		
SI3								0.808		
SI4								0.816		
SI5								0.546		
SLM2									0.855	
SLM3									0.843	
SLM4									0.858	
SML1									0.785	
SQ1										0.584
SQ2										0.738
SQ3										0.746
SQ4										0.782
SQ5										0.746

5.8.12 Indicator Multicollinearity

Multicollinearity is a phenomenon characterized by strong associations among independent variables. Fornell and Bookstien (1982) utilize variance inflation factor (VIF) statistics to assess multicollinearity. According to the findings of Hair et al. (2017), the issue of

multicollinearity is considered to be of lesser concern when the Variance Inflation Factor (VIF) is below the threshold of 5.15. The variance inflation factor (VIF) results are presented in Table 2, and all values adhere to the specified threshold.

Table 5.15 Multicollinearity VIF results

ITEM	VIF	ITEM	VIF
BI1	2.571	PEOU5	2.472
BI2	2.869	PU1	2.774
BI3	3.267	PU2	2.761
BI4	2.908	PU3	3.155
BI5	2.819	PU4	2.744
CO1	1.464	PU5	3.224
CO2	1.595	PU6	2.801
CO3	2.097	SI1	1.358
CO4	2.008	SI2	1.469
CO5	2.276	SI3	1.678
CS1	1.888	SI4	1.731
CS2	2.573	SLM2	2.184
CS3	2.385	SLM3	2.008
CS4	1.824	SLM4	2.114
CVD2	1.922	SML1	1.746
CVD3	2.052	SQ1	1.379
CVD4	1.973	SQ2	1.934
CVD5	1.875	SQ3	1.925
FC1	2.522	SQ4	1.942
FC2	2.028	SQ5	1.192
FC3	2.66		
FC4	1.969		
FC5	2.376		
PEOU1	2.816		
PEOU2	3.128		
PEOU3	3.536		
PEOU4	2.602		

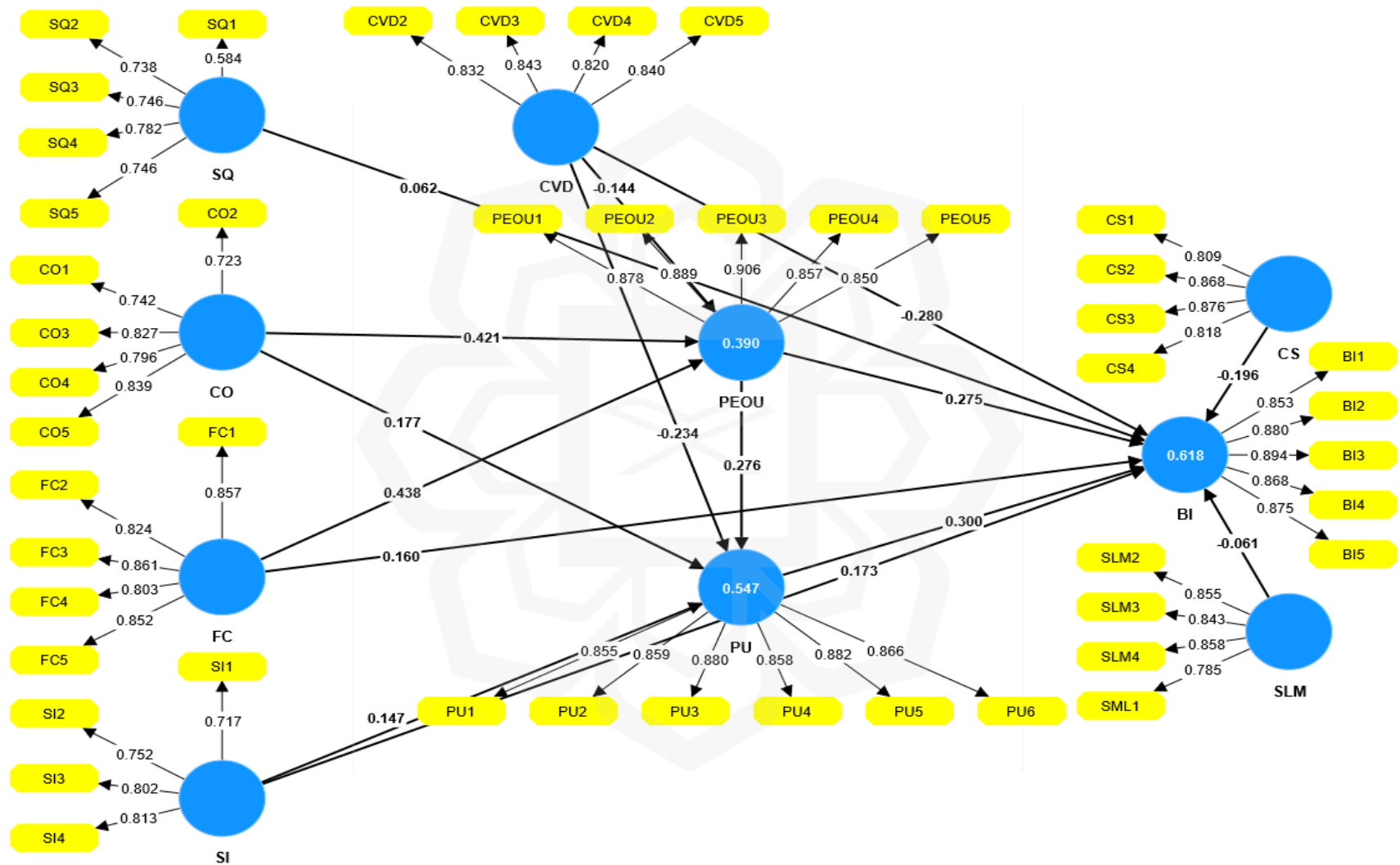


Figure 5.2 Model Reliability and Validity using PLS-SEM Algorithm.

5.8.13 Reliability Analysis

A researcher Mark (1996), states that reliability refers to the consistency of results obtained from a study. To ensure the authenticity and trustworthiness of their conclusions, researchers must ensure their data's reliability. Mark (1996), page 285, says that using an instrument repeatedly will always lead to an identical result. The two most common methods of calculating reliability are Cronbach's Alpha and Composite-reliability (CR). The current study sought to analyze the validity and reliability of the measurement model depicted in Figure 5.1. This objective was accomplished by employing the SmartPLS algorithm. Table 5.16 displays the outcomes for both approaches. Cronbach Alpha from a low of 0.750 to 0.934, and statistics for composite dependability varied between 0.844 to 0.943. (Hair et al., 2011) Both measures for reliability have reliability statistics that are higher than the needed threshold of 0.70. However, SQ1 of the system quality construct has a value of 0.584, which is less than 0.70 (see Table 5.14 factor loading and Figure 5.2 Model reliability). As a result, the item was eliminated; the rest of the items are within the threshold range, indicating that the reliability of the study was reached.

Table 5.16 Composite-Reliability & Cronbach's-Alpha results

Constructs	Alpha	Composite-Reliability
BI	0.923	0.942
CO	0.846	0.890
CVD	0.865	0.908
Cost	0.750	0.841
FC	0.895	0.923
PEOU	0.924	0.943
PU	0.934	0.948
SI	0.769	0.844
SLM	0.856	0.903
SQ	0.792	0.844

5.8.14 Construct Validity

The statistical verification of construct validity can be achieved through the utilization of Partial Least Squares Structural Equation Modelling (PLS-SEM) when both convergent and discriminant validity are established.

5.8.15 Convergent Validity

Convergent validity refers to the phenomenon wherein various measurement approaches consistently yield similar results when assessing the same construct. Bagozzi et al. (1991) conducted research indicating that reliable measurements of a given concept should exhibit a strong association, even when repeated observations of the same phenomena are made. When the mean score of items exceeds 0.50, it signifies the presence of convergent validity, as explained by Fornell and Larcker in 1981. The present investigation reveals that, according to the mean scores, all the measures fall within the allowed range, indicating the establishment of convergent validity. Table 5.17 presents the mean validity scores for each measurement.

Table 5.17 Convergent construct validity AVG

Constructs	Obtained AV
BI	0.764
CO	0.619
CVD	0.711
Cost	0.557
FC	0.705
PEOU	0.768
PU	0.751
SI	0.525
SLM	0.699
SQ	0.522

5.8.16 Discriminant validity

The term "discriminant validity" sometimes denotes how much a measure can distinguish between distinct concepts. When many ideas are considered different, the factors used to compare them must have little or no overlap: Bagozzi and others, 1991, p.425.

5.8.17 Fornell and Larcker Criterion

Fornell and Larcker (1981) proved that discriminant validity exists when the association of a construct is greater than the square root of the average variance extracted (AVE) Henseler et al. (2015). The study discovered that the associations with the average square root of an item's AVE were much stronger when compared to the relationship among the construct/variables and other items. The evidence needed to show discriminant validity can be found in Table 5.18.

Table 5.18 Discriminant validity F & L

	BI	CO	CVD	Cost	FC	PEOU	PU	SI	SLM	SQ
BI	0.874									
CO	0.590	0.787								
CVD	-0.473	-0.439	0.843							
Cost	-0.523	-0.412	0.163	0.834						
FC	0.567	0.580	-0.340	-0.479	0.840					
PEOU	0.625	0.583	-0.469	-0.401	0.490	0.876				
PU	0.671	0.636	-0.348	-0.499	0.553	0.612	0.867			
SI	0.532	0.497	-0.311	-0.421	0.518	0.477	0.526	0.724		
SLM	0.505	0.582	-0.422	-0.398	0.512	0.581	0.597	0.471	0.836	
SQ	0.095	0.049	-0.012	-0.001	0.101	0.052	0.025	-0.002	0.022	0.756

Note: Bold and Italic represent AVG's square root.

5.8.18 Cross loading

Cross-loading is a statistical technique employed to ascertain the extent to which an item is associated with a particular construct. This technique examines the item's loading on its parent construct compared to other constructs within the research framework. Table 5.19 shows that all items' factor loadings are much higher on foundational constructs than the alternative construct under examination. According to the cross-loading study, discriminant validity is confirmed.

Table 5.19 Factor Cross Loading

	BI	CO	CS	CVD	FC	PEOU	PU	SI	SLM	SQ
BI1	0.853	0.532	-0.424	-0.440	0.531	0.540	0.521	0.457	0.472	0.061
BI2	0.880	0.515	-0.409	-0.513	0.494	0.566	0.585	0.460	0.444	0.098
BI3	0.894	0.500	-0.438	-0.475	0.480	0.571	0.625	0.486	0.423	0.109
BI4	0.868	0.493	-0.381	-0.429	0.467	0.509	0.604	0.485	0.411	0.034
BI5	0.875	0.540	-0.416	-0.430	0.508	0.544	0.595	0.486	0.457	0.104
CO1	0.570	0.742	-0.300	-0.394	0.579	0.488	0.609	0.429	0.523	0.044
CO2	0.440	0.723	-0.332	-0.253	0.364	0.386	0.382	0.268	0.678	0.055
CO3	0.425	0.827	-0.371	-0.308	0.439	0.490	0.494	0.426	0.780	0.020
CO4	0.415	0.796	-0.335	-0.297	0.415	0.418	0.457	0.371	0.766	0.082
CO5	0.448	0.839	-0.388	-0.341	0.446	0.486	0.517	0.428	0.797	-0.005
CS1	-0.367	-0.333	0.809	0.121	-0.285	-0.367	-0.265	-0.254	-0.350	-0.004
CS2	-0.358	-0.342	0.868	0.098	-0.259	-0.417	-0.263	-0.242	-0.347	-0.026
CS3	-0.459	-0.421	0.876	0.155	-0.286	-0.473	-0.347	-0.302	-0.400	-0.002
CS4	-0.398	-0.372	0.818	0.169	-0.315	-0.314	-0.285	-0.245	-0.322	-0.021
CVD2	-0.438	-0.358	0.153	0.832	-0.444	-0.362	-0.404	-0.384	-0.335	-0.008
CVD3	-0.439	-0.348	0.103	0.843	-0.391	-0.326	-0.409	-0.338	-0.310	0.004
CVD4	-0.382	-0.302	0.130	0.820	-0.366	-0.263	-0.363	-0.338	-0.330	0.025
CVD5	-0.477	-0.358	0.156	0.840	-0.392	-0.374	-0.476	-0.339	-0.352	-0.012
FC1	0.478	0.477	-0.251	-0.431	0.857	0.432	0.453	0.466	0.434	0.062
FC2	0.495	0.495	-0.338	-0.374	0.824	0.435	0.461	0.439	0.367	0.089
FC3	0.453	0.463	-0.234	-0.391	0.861	0.404	0.464	0.426	0.431	0.067
FC4	0.462	0.511	-0.298	-0.414	0.803	0.361	0.420	0.411	0.474	0.097
FC5	0.490	0.489	-0.302	-0.402	0.852	0.420	0.520	0.439	0.448	0.101
PEOU1	0.577	0.510	-0.415	-0.382	0.429	0.878	0.594	0.431	0.530	0.018
PEOU2	0.542	0.503	-0.417	-0.374	0.474	0.889	0.539	0.441	0.525	0.079
PEOU3	0.588	0.546	-0.420	-0.377	0.433	0.906	0.562	0.472	0.534	0.020
PEOU4	0.504	0.509	-0.412	-0.316	0.436	0.857	0.484	0.393	0.490	0.053
PEOU5	0.522	0.482	-0.388	-0.303	0.371	0.850	0.493	0.353	0.460	0.066
PU1	0.597	0.535	-0.299	-0.372	0.478	0.517	0.855	0.487	0.488	0.050
PU2	0.565	0.532	-0.303	-0.451	0.493	0.530	0.859	0.461	0.518	0.006
PU3	0.582	0.565	-0.316	-0.439	0.517	0.564	0.880	0.471	0.534	-0.002
PU4	0.575	0.543	-0.262	-0.437	0.454	0.523	0.858	0.410	0.516	0.038

PU5	0.586	0.533	-0.307	-0.420	0.456	0.520	0.882	0.423	0.483	0.076
PU6	0.585	0.596	-0.319	-0.477	0.477	0.527	0.866	0.453	0.564	0.006
SI1	0.436	0.321	-0.231	-0.291	0.356	0.354	0.343	0.717	0.274	0.038
SI2	0.393	0.364	-0.208	-0.327	0.373	0.382	0.375	0.752	0.363	0.046
SI3	0.417	0.428	-0.264	-0.379	0.479	0.387	0.451	0.802	0.438	-0.073
SI4	0.431	0.415	-0.255	-0.295	0.392	0.357	0.431	0.813	0.378	-0.019
SLM2	0.417	0.773	-0.358	-0.358	0.465	0.547	0.540	0.446	0.855	0.017
SLM3	0.429	0.738	-0.323	-0.345	0.421	0.449	0.466	0.362	0.843	0.070
SLM4	0.466	0.788	-0.398	-0.309	0.432	0.520	0.545	0.431	0.858	-0.016
SML1	0.366	0.689	-0.329	-0.325	0.392	0.419	0.438	0.334	0.785	-0.013
SQ1	0.043	0.018	-0.022	0.009	0.042	0.027	0.052	-0.011	-0.010	0.584
SQ2	0.039	0.002	-0.017	0.073	-0.002	-0.026	-0.033	-0.036	-0.012	0.738
SQ3	0.037	0.033	0.006	-0.006	0.081	0.043	0.005	-0.007	0.041	0.746
SQ4	0.066	0.058	-0.024	0.017	0.073	0.044	0.037	-0.021	0.038	0.782
SQ5	0.103	0.040	-0.001	-0.039	0.109	0.062	0.033	0.022	0.005	0.746

5.8.19 Heterotrait-Monotrait Ratio (HTMT)

The HTTM technique relies on estimating the relationship among components, serving as a foundation for assessing the discriminant validity of a test. However, previous studies (Henseler et al., 2015) have extensively examined the appropriate threshold for HTMT and put up a recommended threshold of 0.95 or below. The HTMT data obtained are displayed in Table 5.20, indicating that the ratio of HTMT to HTMT is below the minimum threshold of 0.90. The HTMT data obtained have been displayed in Table 5.20, indicating that the ratio of HTMT to HTMT is below the minimal criterion of 90.

Table 5.20 Discriminant validity HTMT

	BI	CO	CS	CVD	FC	PEOU	PU	SI	SLM	SQ
BI										
CO	0.662									
CS	0.525	0.509								
CVD	0.585	0.474	0.186							
FC	0.624	0.656	0.385	0.546						
PEOU	0.675	0.652	0.521	0.445	0.537					
PU	0.723	0.703	0.383	0.554	0.604	0.657				
SI	0.644	0.603	0.377	0.515	0.623	0.566	0.61			
SLM	0.565	0.468	0.487	0.467	0.586	0.649	0.665	0.576		
SQ	0.094	0.069	0.037	0.054	0.103	0.07	0.061	0.085	0.063	

5.8 STRUCTURAL MODEL ASSESSMENT

The Structural model's evaluation includes examining t-values, predictive significance (P values), and effect sizes (Beta Coefficient). Researchers (Ringle et al., 2020; Hair et al., 2017) suggest that the bootstrapping approach, utilizing 5000 subsamples, is advisable for evaluating t-values. For this study, following a comprehensive evaluation of the Measurement Model the structural path is evaluated to determine the significance of the structure path coefficient (the association in-between the research constructs). In order to obtain t-values for hypothesis testing, the bootstrapping method was adopted, and the findings are shown in Figure 5.3 and Table 5.21. Moreover Table 5.21. indicates the Hypothesis number, relationship between constructs, beta coefficient values, standard deviation, T-stats, p-values, and results.

The beta coefficient, also called nomological validity or the examination of hypothetical links, was conducted to assess the importance of path relations within the structural model, also known as the inner model (Hair et al., 2017; Chin, 1998). The path coefficient (β) was employed to analyze the path relationships outlined in the research model proposed in this work. The significance of the path coefficient is determined by the t-value, which was calculated using PLS Bootstrapping with 5,000 resamples.

Standard deviation is a statistic that compares an estimate's precision to the hypothesized distribution for a large sample of similar estimates. It simply refers to the distance between the sample's mean and the population's mean. The lower the value, the more favorable the outcome.

The t-value measures how much your data deviates from the assumption of no correlation between variables. The path is statistically significant if the value exceeds 1.96 (two-tailed).

The P value represents the probability. This statistical method is useful for testing the significance of any possible relation in-between two constructs. According to (Hair et al., 2017) P value significance criteria is based on T values such as if $t=2.57$ then $p<0.01$, if $t=1.96$ then $p<0.05$, and if $t=1.65$ then $p<0.10$. As a result, a researcher can accept the hypothesis and reject the alternative (null) hypothesis. According to the results of this study, the suggested hypotheses (1, 2a, 2b, 4, 5a, 5b, 6a, 6b, 7a, 7b) are positively accepted, and

hypotheses (3, 8a, 8b, 8c) are negatively accepted only two hypotheses **H7b**, and **H9** were rejected based on its predictive significance and effect size. A thorough analysis of each hypothesis is presented in the following section representing the degree to which each independent variable was affected by each predictor variable i.e., (The greater the value, the bigger the predictor's influence of the dependent variable).

Table 5.21 Construct Relationship and Hypothesis Testing.

No.	Hypothesis Relation	β Coefficient	Std-deviation	T-Statistics	P-Values	Results
H1	PU -> BI	0.302	0.061	4.974	0.000	Accepted
H2a	PEOU -> BI	0.192	0.055	3.466	0.001	Accepted
H2b	PEOU -> PU	0.276	0.060	4.575	0.000	Accepted
H3	CS -> BI	-0.197	0.042	4.732	0.000	Accepted
H4	SQ -> BI	0.066	0.031	2.101	0.036	Accepted
H5a	CO -> PEOU	0.421	0.061	6.843	0.000	Accepted
H5b	CO -> PU	0.322	0.052	6.253	0.000	Accepted
H6a	SI -> PU	0.147	0.048	3.057	0.002	Accepted
H6b	SI -> BI	0.129	0.042	3.045	0.002	Accepted
H7a	FC -> PEOU	0.177	0.066	2.693	0.007	Accepted
H7b	FC -> BI	0.110	0.057	1.916	0.055	Rejected
H8a	CVD -> BI	-0.182	0.049	3.714	0.000	Accepted
H8b	CVD -> PEOU	-0.144	0.051	2.840	0.005	Accepted
H8c	CVD -> PU	-0.195	0.046	4.256	0.000	Accepted
H9	SLM -> BI	-0.061	0.052	1.191	0.234	Rejected

Note: PU= Perceived usefulness, FC Facilitating Conditions CS= Cost, CO= Application complexity, BI= Behavioral Intention CVD= COVID-19, SLM= Student Learning Motivation, H= Hypothesis, PEOU= Perceived ease of use, SI= Social Influence,

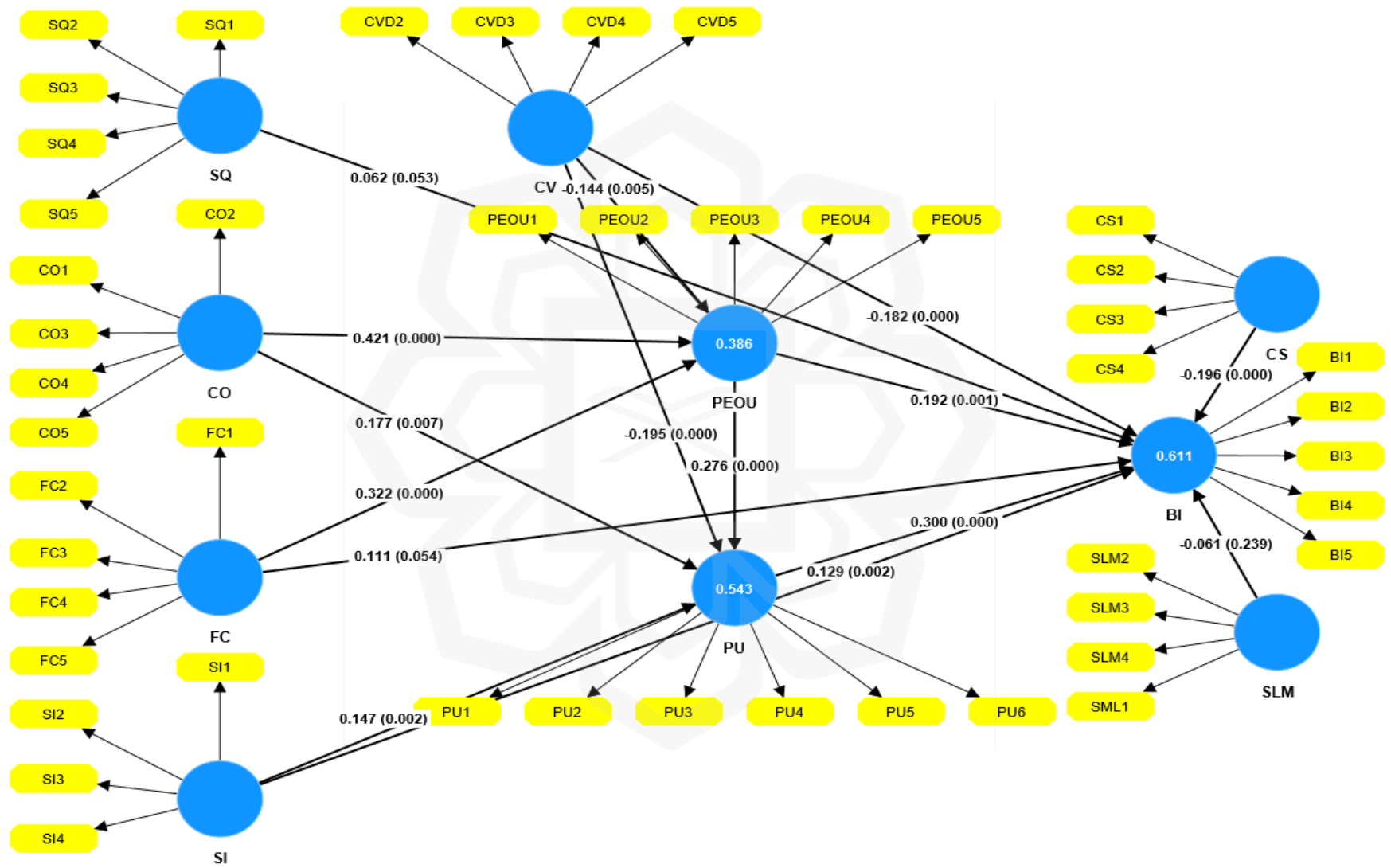


Figure 5.3 Structural Model. 1st Bootstrap through SmartPLS4

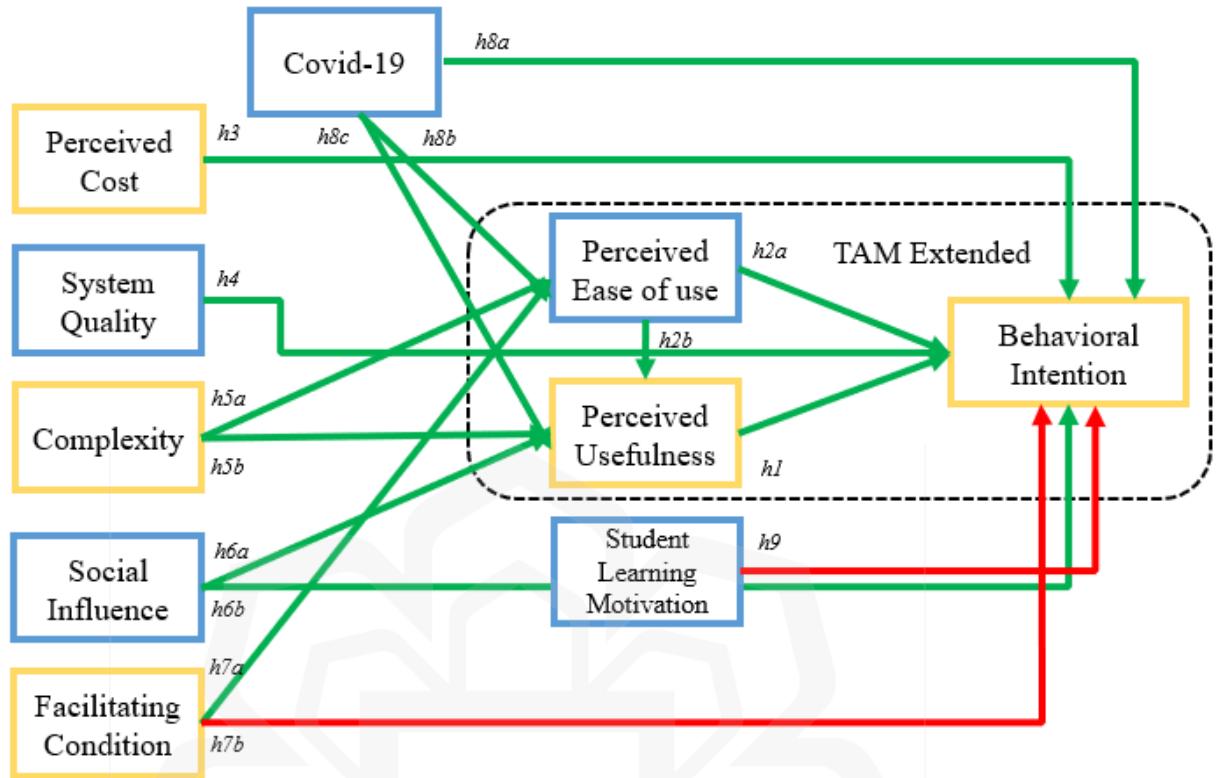


Figure 5.4 Structural Model

H1. *Perceived Usefulness will have an encouraging positive effect on Behavioral Intention to adopt e-learning throughout COVID-19.*

The above hypothesis examines the correlation in-between Perceived Usefulness and the Behavioral Intention to adopt e-learning, specifically exploring whether perceived usefulness positively encourages individuals to engage in e-learning activities. Research has indicated a positive association in-between Perceived Usefulness and Behavioral Intention ($\beta = 0.302$, $t = 4.974$, $p = 0.000$). Consequently, hypothesis H1 was accepted, and the corresponding findings are presented in Table 5.21.

H2a. *Perceived-ease of use will have a positive encouraging effect on Behavioral Intention to adopt e-learning.*

This hypothesis examines whether the relationship among these constructs is statistically significant, and the results show a positive correlation between constructs signifying how people think about e-learning and their intention to use it during COVID-19 time. ($\beta =$

0.192, $t = 3.466$, $p = 0.001$). Consequently, hypothesis H2a was accepted, and the corresponding findings are presented in Table 5.21.

H2b. *Perceived-ease of use will have an encouraging effect on PU to adopt e-learning throughout COVID-19.*

Based on the available data, a significant correlation exists between Perceived Ease of Use and Perceived Usefulness. ($\beta = 0.276$, $t = 4.575$, $p = 0.000$). A positive encouraging correlation between constructs was determined. As a result, hypothesis H2b was accepted, and the corresponding findings are presented in Table 5.21.

H3. *Perceived Cost will have a negative, discouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19.*

The statistical significance between Cost and Behavioral Intention is tested by testing the above hypothesis, the results (See Table 5.21.) exhibit a negative connection. ($\beta = -0.197$, $t = 4.732$, $p = 0.000$). The findings suggest that users' actions are influenced negatively by the cost of employing e-learning. The cost is inversely proportional to their intention of using e-learning, particularly in the COVID-19 context. In summary, it is possible to conclude that cost is a major factor that directly hinders the adoption of e-learning and H3 was accepted.

H4. *System Quality, in terms of availability and response time, will have a positive encouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19.*

The above hypothesis examines whether System Quality is favorable and supports the Behavioral Intention to use e-learning. As per the results (See Table 5.21) ($\beta = 0.066$, $t = 2.101$, $p = 0.036$), The data imply a favorable association between System Quality and Behavioral Intentions to use e-learning during the COVID-19 study. As a result, researchers accept H4.

H5a. *Application Complexity will have a positive encouraging effect on Perceived-ease of use.*

The less complex application can be used easily by the users. This hypothesis investigates the association between application complexity with Perceived-ease of use. ($\beta = 0.421$, $t = 6.843$, $p = 0.000$). The results (See Table 5.21) revealed a strong positive association between Application Complexity and Perceived-Ease of use. Therefore, H5a was accepted.

H5a. *Application Complexity will have a positive encouraging effect on Perceived Usefulness.*

More user-friendly applications can enhance the skills of users easily. The researcher develops the hypothesis to determine the relation between Application complexity and Perceived usefulness. ($\beta = 0.322$, $t = 6.253$, $p = 0.000$). The findings (See Table 5.21) demonstrate the statistical significance of this hypothesis (H5a), and it is accepted.

H6a. *Social Influence will have an encouraging positive effect on Perceived usefulness to adopt e-learning throughout COVID-19.*

The above hypothesis tests the association between Social Influence and Perceived-usefulness, results show a strong positive relationship between these constructs ($\beta = 0.147$, $t = 3.057$, $p = 0.002$). Similarly, these investigations suggest that social influence has a considerable, favorable impact on the perceived usefulness of e-learning adoption. As a result, people will find e-learning more helpful as their social standing improves. In conclusion, the benefit of e-learning is a major determinant in the user's intention to adopt it; hence the hypothesis is accepted.

H6b. *Social Influence will have an encouraging positive effect on the Behavioral Intention to adopt e-learning throughout COVID-19.*

The above-said hypothesis investigates whether Social Influence is beneficial and supports the behavioral intention to use e-learning. ($\beta = 0.129$, $t = 3.045$, $p = 0.002$). These findings suggest that the path among these constructs found statistical significance; as a result, the presented hypothesis is accepted. In addition, it can be concluded from these findings that social influence directly impacts the adoption of e-learning.

H7a. *Facilitating Conditions will have a positive encouraging effect on Perceived-ease of use to adopt e-learning throughout COVID-19.*

The researcher proposes this hypothesis to examine the significant association in-between Facilitating Conditions and Perceived-ease of use. ($\beta = 0.177$, $t = 2.693$, $p < 0.007$). The results show the presence of a positive statical relationship among these constructs. So, the proposed hypothesis is accepted. Hence, facilitating conditions have an important and meaningful influence on e-learning's Perceived Ease of Use (PEOU). Additionally, the adoption of e-learning is probably rises when users have Faith it is a user-friendly alternative.

H7b. *Facilitating Conditions will have a positive encouraging effect on the Behavioral Intention to adopt e-learning throughout COVID-19.*

This hypothesis aims to investigate the strong correlation between Facilitating Conditions and behavioral intent, as proposed by the researcher. ($\beta = 0.110$, $t = 1.916$, $p = 0.055$). The findings point to a statically insignificant link between these constructs. Therefore, the hypothesis is rejected.

H8a. *COVID-19 (lockdown Fear & Stress) will have a negative, discouraging effect on Behavioral Intention to adopt e-learning.*

This hypothesis tests the direct effect of COVID-19 with respect to (lockdown Fear & Stress) and behavioral intention. Results revealed a negative effect of COVID-19 on Behavioral Intention was observed. ($\beta = -0.182$, $t = 3.714$, $p = 0.000$). Therefore, the hypothesis is accepted.

H8b. *COVID-19 (lockdown Fear & Stress) will have a negative discouraging effect on Perceived-ease of use.*

This hypothesis examines the direct influence of COVID-19 proposed by the researcher on said constructs ($\beta = -0.144$, $t = 2.840$, $p = 0.005$) and results revealed a negative effect of COVID-19 concerning (lockdown Fear & Stress) on Perceived-ease of use, consequently hypothesis is accepted.

H8c. *COVID-19 (lockdown Fear & Stress) will have a negative discouraging effect on Perceived Usefulness.*

As the results revealed ($\beta = -0.195$, $t = 4.256$, $p = 0.000$). The COVID-19 pandemic has been observed to have a result of a direct and negative impact on PU with respect to (lockdown Fear & Stress). Hence the hypothesis is accepted.

H9. *Student Motivation will have an encouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19.*

The statistical significance between student learning motivation and Behavioral Intention is tested by testing the above hypothesis, and the results demonstrate no association. ($\beta = -0.06$, $t = 1.191$, $p = 0.234$) between the constructs therefore the hypothesis is rejected.

5.8.1 Mediation Analysis

In the present study, the Perceived-ease of use (PEOU) & Perceived Usefulness (PU) mediate the relationships in-between independent and dependent variables. Therefore, analyzing these constructs to determine their potential mediating effect is essential. Mediation effectiveness was measured using a technique developed by Preacher and Hayes (2008). According to research by Rungtusanatham et al. (2014) and Baron & Kenny (1986), the bootstrapping procedure with subsamples of 5000 is considered the most optimal approach for assessing mediation. So, for this study, the bootstrapping two-tailed approach was applied using SmartPLS version 4.0.9.2 software, and the results (See Table 5.22) revealed the paths in which PEOU & PU acted as mediating roles. Moreover, Table 5.22 comprises the constructs' Total, direct, and indirect effects; these effects are measured through t-values, predictive significance (P values), effect sizes (Beta Coefficient), and percentile confidence, which show no zero between. In summary, the construct's Perceived-ease of use and Perceived Usefulness serve as a partial mediator in the association between Application Complexity and Behavioral Intention.

The association in-between Social Influence and Behavioral Intention is also partially mediated by Perceived-Usefulness. However, concerning the association between COVID-19 and Behavioral-Intentions Perceived-Usefulness acts as a partial mediator, and Perceived-ease of use does not mediate within constructs. Moreover, Perceived-ease of use entirely mediates the association in-between Facilitating Conditions and Behavioral Intentions. The idea of facilitating conditions refers to the circumstances that make it possible for a given activity to occur or provide support for its execution. These factors can include resources, skills, knowledge, and environmental conditions that make it easier for individuals. The subsequent section provides a more detailed analysis and discussion of the above findings as presented in Table 5.22.

Table 5.22 Mediation Analysis for PU and PEOU

Paths	(β) Beta	T- values	P- values	Paths	(β) Beta	T- value s	P- values	Paths	(β) Beta	Std.	T- value s	P- values	Ci 2.5%	Ci 97.5%	Meditatio n Results
CO -> BI	0.213	5.462	0.000	CO -> BI	0.323	2.604	0.009	CO -> PEOU - > BI	0.081	0.02 6	3.094	0.002	0.032	0.134	Partial
CO -> BI	0.213	5.462	0.000	CO -> BI	0.323	2.604	0.009	CO -> PU -> BI	0.097	0.02 5	3.875	0.000	0.053	0.150	Partial
SI -> BI	0.173	3.909	0.000	SI -> BI	0.129	3.045	0.002	SI -> PU -> BI	0.044	0.01 6	2.723	0.006	0.016	0.079	Partial
FC -> BI	0.159	2.700	0.007	FC -> BI	0.110	1.916	0.055	FC -> PEOU - > BI	0.034	0.01 6	2.146	0.032	0.008	0.070	Full
CVD -> BI	-0.280	5.531	0.000	CVD -> BI	- 0.182	3.714	0.000	CVD -> PU -> BI	-0.059	0.02 1	2.736	0.006	-0.106	-0.023	Partial
CVD -> BI	-0.280	5.531	0.000	CVD -> BI	- 0.182	3.714	0.000	CVD->PEOU - > BI	-0.028	0.01 4	1.932	0.053	-0.062	-0.006	No Mediatio n

Perceived-ease of use (PEOU) mediates the association within Application Complexity & Behavioral Intention

A mediation investigation was conducted to find out the role of Perceived-ease of use as a mediator in the association between Application Complexity and Behavioral Intention. The findings (see Table 5.22) demonstrated that Application Complexity had significant indirect impacts on Behavioral Intention ($\beta = 0.081$, $t = 3.094$, $p = 0.002$). The total effect of Application Complexity on Behavioral Intention was also significant ($\beta = 0.213$, $t = 5.462$, $p = 0.000$), upon addition of a mediator the direct impact of Application Complexity on Behavioral Intention was still significant ($\beta = 0.323$, $t = 2.604$, $p = 0.009$). This demonstrates that Perceived-ease of use here plays a complementary partial mediating impact between Application Complexity and Behavioral Intention.

Perceived usefulness mediates the association in-between Application complexity (CO) and Behavioral Intention (BI)

As per the results presented in Table 5.22, indicate a statistically significant indirect impact of Application Complexity on Behavioral Intention. ($\beta = 0.097$, $t = 3.875$, $p = 0.000$) The overall impact of Application Complexity on Behavioral Intention was significant according to the statistics ($\beta = 0.323$, $t = 2.604$, $p = 0.009$). However, even after considering the mediator, the effect of Application Complexity on Behavioral Intention remained statistically significant ($\beta = 0.213$, $t = 5.462$, $p = 0.000$). This shows that perceived usefulness provides a complementary partial mediation impact on the association in-between application complexity and behavioral intention.

Perceived usefulness mediates the association in-between Social Influence (SI) & Behavioral Intention (BI)

The data in Table 5.22 suggests that SI has a considerable indirect impact on Behavioral Intention (BI). ($\beta = 0.044$, $t = 2.723$, $p = 0.006$) Overall, Social Influences had a statistically significant effect on Behavioral Intention. ($\beta = 0.173$, $t = 3.909$, $p = 0.000$). Even after

accounting for the mediator, the Social Influence's impact on Behavioral Intention remained statistically significant ($\beta = 0.129$, $t = 3.045$, $p = 0.002$). Results suggest the significance of Perceived Usefulness as a mediator between Application Complexity and Behavioral Intention is a complementary partial mediator.

Perceived-ease of use (PEOU) mediates the association between Facilitating condition (FC) & Behavioral Intention (BI)

As presented in Table 5.22, the findings indicate a statistically significant indirect influence of Facilitating conditions on Behavioral Intention. ($\beta = 0.034$, $t = 2.146$, $p = 0.032$) The overall impact of Facilitating conditions on Behavioral Intention exhibited statistical significance ($\beta = 0.159$, $t = 2.700$, $p = 0.008$). nevertheless, even after considering the mediator, facilitating condition impact on Behavioral Intention remained statistically insignificant ($\beta = 0.110$, $t = 1.916$, $p = 0.055$). The results indicate that Perceived-ease of use entirely mediates the association between Facilitating Conditions and Behavioral Intention.

Perceived usefulness (PU) mediates the association in-between COVID-19 & Behavioral Intention (BI)

According to the findings presented in Table 5.22, evidence suggests that the presence of COVID-19 (CVD) has a significant indirect impact on BI. ($\beta = -0.059$, $t = 2.736$, $p = 0.006$) In general, it can be observed that COVID-19 exerted a statistically significant impact on BI. ($\beta = -0.280$, $t = 5.531$, $p = 0.000$). Despite controlling for the mediator, the effect of COVID-19 on Behavioral Intention remained statistically significant ($\beta = -0.182$, $t = 3.714$, $p = 0.000$). The findings of this study indicate that Perceived usefulness serves as a complementary partial mediator between COVID-19 & and BI.

Perceived-ease of use (PEOU) mediates the association between COVID-19 & Behavioral Intention (BI)

In the light of results presented in Table 5.22, the observed indirect effect within COVID-19 (CVD) and Behavioral Intention is deemed statistically insignificant ($\beta = -0.028$, $t = 1.932$, $p = 0.053$). Consequently, it can be established that perceived-ease of use has no impact on acting as a mediating factor in the association between COVID-19 and BI, despite the significance of total effect ($\beta = -0.280$, $t = 5.531$, $p = 0.000$) and direct effect ($\beta = -0.182$, $t = 3.714$, $p = 0.000$).

5.8.2 Explanatory Power

Explanatory power is a fundamental term in scientific research that is essential for assessing the quality and usability of a research model. It can be predicted by the following predictors.

5.8.1.1 Coefficient of Determination R Square

The R Square statistic shows how much of the difference between two independent factors can be explained by changes in the dependent variable (Shmueli & Koppius, 2011). The explanatory power of a model can be measured by its R Square value, which measures how much variation each endogenous construct can explain. It is also called "in-sample predictive power" (Rigdon, 2012). The R Square ranges from 0 to 1, with higher numbers showing more ability to explain. As per Cohen (1988), it is recommended to evaluate the R-Square values of related latent variables with the help of criteria: 0.02, 0.13, and 0.26 are the grades from weak moderate, and strong. The findings presented in Table 5.23 indicate for this study is that the R Square values for all the dependent constructs, such as Behavior Intention have a value (of 0.619), Perceived usefulness value (of 0.547) and Perceived-ease of use has a value (of 0.390) which exceeds 0.26, suggesting that the explanatory power of the model is significant (Choen, 1988).

5.8.1.2 F Square

The estimation accuracy of a model can be improved by adjusting the explanatory power of exogenous variables; the change in R Square is calculated by removing a specific exogenous construct from the model. This measure is commonly known as the effect size f^2 . The F Square is a way to calculate how much each independent variable affects the dependent variable. The PLS path model calculates the variance in squared correlations to determine whether removing an exogenous construct has a significant effect on the value of the endogenous construct.

According to Cohen (1988), at the structural level, the predictor variable has a significant impact when the f -squared value is 0.35. If the value of f -squared is 0.15, the impact is considered medium, and If the value of f -squared is 0.02, the impact is considered small. The impact size (f^2) of the model shows how an external latent variable affects the R^2 value of an endogenous latent variable. In simple terms, the effect size measures the intensity of the association between the latent variables. For this study, the value of impact size (f^2) ranges from 0.005 to 0.185 is presented in the table.5.23

5.8.1.3 Q Square

The Q-square statistic is utilized to evaluate the predictive significance of a model, indicating whether it possesses predictive relevance or not. A Q-square value greater than zero is considered favorable. Moreover, Q-square examines the predictive significance of endogenous constructs. Q-square values greater than zero indicate that the reconstructed values are accurate and that the model possesses predictive validity. A positive Q-square value indicates that the model possesses predictive significance. According to Hair et al. (2013), the degrees of predictive relevance for each effect are classified as strong (0.35), moderate (0.15), and weak (0.02). For this study results revealed (See Table 5.23) the Q-square value of BI =533, PEOU=0.390, and PU=0.547 are greater than 0 hence predictive relevance was established.

Table 5.23 Explanatory Power

Predictors	Dependent variable	R ²	f ²	Q ²
CS	BI	0.619	0.067	0.533
CVD			0.062	
FC			0.008	
PEOU			0.049	
PU			0.089	
SI			0.026	
SLM			0.005	
SQ			0.010	
CO	PEOU	0.390	0.185	0.375
CVD			0.025	
FC			0.030	
CO	PU	0.547	0.134	0.495
CVD			0.063	
PEOU			0.100	
SI			0.032	

In the above table, the Predictors (independent variables) are factors like CS(Cost), CVD(COVID-19) CO(Complexity), FC(Facilitating conditions), SI Social Influence, and Student Learning motivations, and the dependent variables are PEOU,(Percive ease of use) PU(Precives usefulness) and Behaviour intention. In terms of R² (R-squared), the 61.1% variance in behavioral intention is explained by its predictor variables. In order of importance, PU: (0.309) followed by COVID-19 (CVD: - 0.200), Cost (CS: - 0.198), perceived ease of use (PEOU: 0.189), Social influence (SI: 0.147), and System Quality (SQ: 0.075) are the most significant factors that influence the behavioral intention to adopt e-learning during COVID-19. 54.7% variance in PU is explained by its predictor variables, i.e., perceived ease of use (PEOU: 0.276), COVID-19 (CVD:-0.195), Application Complexity (CO: 0.179), and social influence (SI: 0.147) respectively and 39% variance in PEOU is explained by its predictor variables, i.e., Application Complexity (CO: 0.420), facilitating condition (FC: 0.322), and COVID-19 (CVD:-0.143), respectively (in a higher

to lower order). Referring to F square the CO(complexity has a large effect on PEOU with an f^2 of 0.185 and SLM (Student learning motivation has the minimum effect on BI(Behaviour intention) with an f^2 of 0.005. Moving on to Q^2 (Predictive Relevance) all the obtained values are within the desired range showing that the model has predictive relevance for the dependent variable

5.8.3 Changing the Structural Model by Removal Non-Significant Paths

Referring to results presented in Table 5.21, two hypotheses (H7b and H9) (See tabl.5.22) were rejected based on their predictive significance and effect size. To accomplish a qualified model that effectively aligns with the data, these two rejected paths were removed, and the bootstrapping approach, utilizing 5000 subsamples, was repeated. The repeated results of bootstrapping are demonstrated in Table 5.24. which shows that by removing the two rejected paths and re-executing the bootstrapping process, the beta coefficient, standard deviation, T-stats, and p-values are a bit changed but are still in the recommendation ranges. Hence, hypotheses (1, 2a, 2b, 4, 5a, 5b, 6a, 6b, 7a) are positively accepted, and hypotheses (3, 8a, 8b, 8c) are negatively accepted. The results of the revised structural model, as depicted in Table 5.24 and Figure 5.5, indicate that all hypotheses were determined to be statistically significant, with a significance level of $p \leq 0.050$. In brief, a qualifying model demonstrating high alignment with the dataset was obtained by removing insignificant paths (specifically, H9, and H7b). The study provides substantial evidence to support the strong alignment between its proposed model and the empirical data. The final version of the structural model is depicted in Figure 5.6.

Table 5.24 Revised Construct Relationship and Hypothesis Testing

No.	Hypothesis Relation	Beta Coefficient	Std. deviation	T-statistics	P-values	Results
H1	PU -> BI	0.309	0.054	5.729	0.000	Accepted
H2a	PEOU -> BI	0.189	0.054	3.462	0.001	Accepted
H2b	PEOU -> PU	0.276	0.060	4.575	0.000	Accepted
H3	CS -> BI	-0.198	0.040	4.902	0.000	Accepted
H4	SQ -> BI	0.075	0.032	2.319	0.020	Accepted
H5a	CO -> PEOU	0.420	0.061	6.845	0.000	Accepted
H5b	CO -> PU	0.322	0.052	6.253	0.000	Accepted
H6a	SI -> PU	0.147	0.048	3.057	0.002	Accepted
H6b	SI -> BI	0.147	0.043	3.447	0.001	Accepted
H7a	FC -> PEOU	0.179	0.066	2.723	0.006	Accepted
H8a	CVD -> BI	-0.200	0.046	4.390	0.000	Accepted
H8b	CVD -> PEOU	-0.143	0.051	2.834	0.005	Accepted
H8c	CVD -> PU	-0.195	0.046	4.256	0.000	Accepted

Note: PU= Perceived usefulness, FC Facilitating Conditions CS= Cost, CO= Application complexity, BI= Behavioral Intention CVD= COVID-19, SLM= Student Learning Motivation, H= Hypothesis, PEOU= Perceived ease of use, SI= Social Influence.

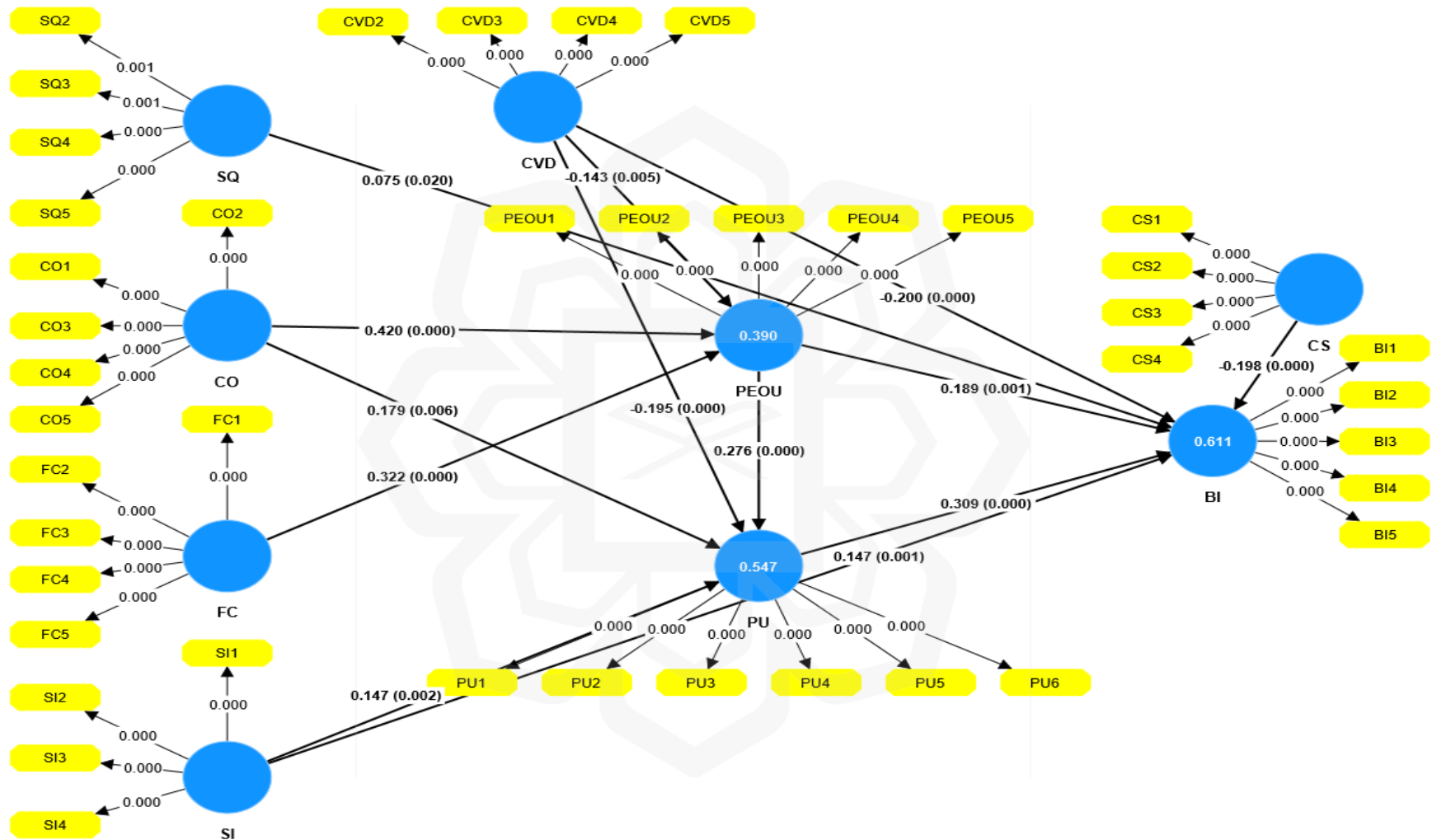


Figure 5.5 Revised Structural Model. 2nd Bootstrap through SmartPLS4

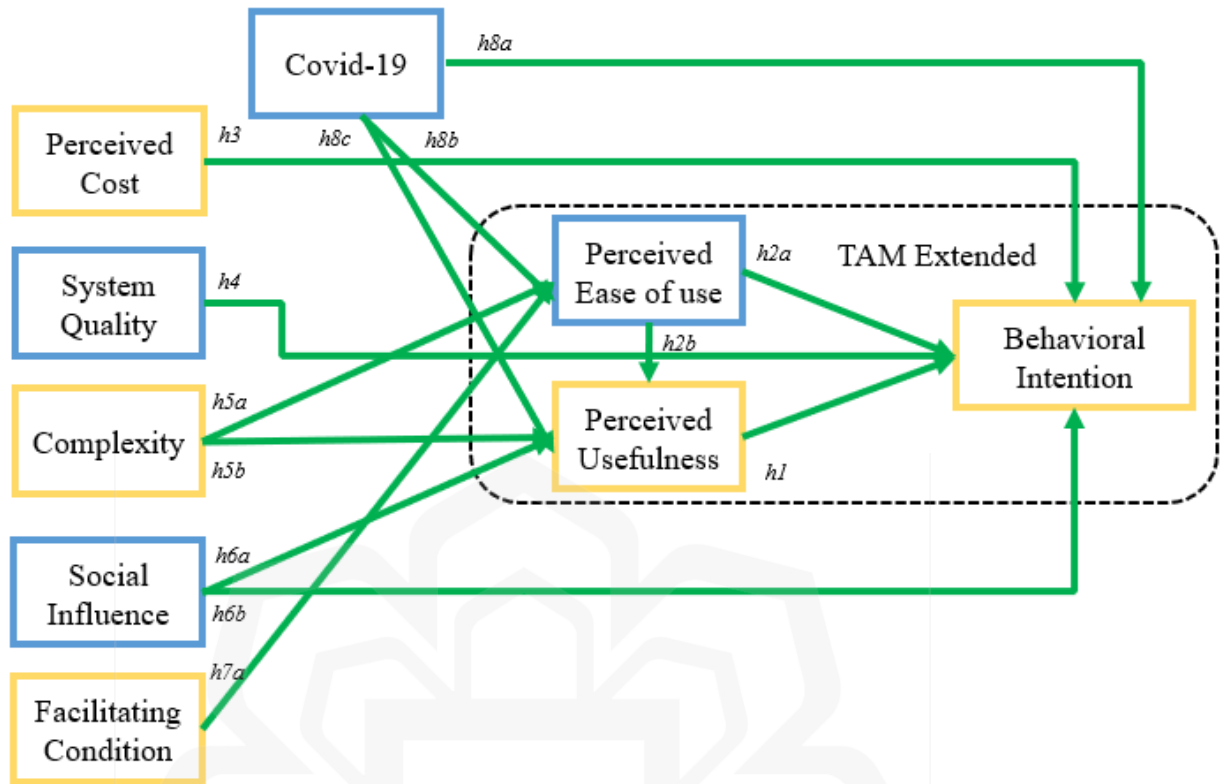


Figure 5.6 Final Structural Model

5.9 CHAPTER SUMMARY

This chapter aimed to analyse the collected data and evaluate the hypotheses presented in the research model stated in Chapter 3 to achieve the study objectives. The collected data was initially filtered to find missing values, outliers, and deviations from normality. This was accomplished by employing various statistical procedures within the SPSS software, notably version 26. 0. In addition, the outcomes of the skewness and kurtosis tests provided evidence that the data exhibited a normal distribution. Additionally, an analysis of the demographic data revealed that the proportion of male participants was 71.1%, while the proportion of female participants was 28.9%. Even before COVID-19, 56.3% of respondents did not know e-learning usage, while 43.7 % were familiar with e-learning, which indicates the adoption of e-learning in the country is lagging. The statistics indicate that efforts are still required to improve digital literacy in the country. The constructs' Mean,

Standard Deviation, and Variance were calculated using descriptive statistics, which quantify and define a data set's fundamental properties. The researcher examined the measurement and structural models utilizing SmartPLS 4 version 4.0.9.2 during the subsequent analysis phase. The initial stage in assessing the quality standards involves the determination of factor loading. Subsequently, the researcher proceeded to assess the concept of reliability and validity. The removal of items such as CVD1 and SQ1 was necessitated by their failure to meet the established reliability standards. Following the reliability and validity assessment, the researcher conducted a structural equation modelling (SEM) analysis to assess the hypothesized association within latent constructs. Additionally, an assessment of mediation analysis and explanatory power was employed to investigate the structural model further.

The study's findings indicate that two hypotheses were not supported, specifically **H7b** and **H9**. On the other hand, hypotheses 1, 2a, 2b, 4, 5a, 5b, 6a, 6b, and 7a were supported, suggesting a positive relationship. and hypotheses 3, 8a, 8b and 8c were also supported, indicating a negative relationship. Moreover, the PEOU and PU constructs partially mediate the association in-between Application Complexity and behavioral Intention. Perceived Usefulness also partially mediates the association in-between Social Influence and Behavioural Intention.

Regarding the relationship between COVID-19 and Behavioural Intentions, it has been observed that Perceived Usefulness acts as a partial mediator, while Perceived Ease of Use does not mediate between these constructs. The Explanatory Power analysis results reveal that the R Square values for all the dependent constructs, specifically Behavior Intention, PU and PEOU, are above the threshold of 0.26. This suggests that the model possesses significant explanatory power. Additionally, the Q-square values for Behavior Intention (0.533), PEOU (0.390), & PU (0.547) are above 0. This observation suggests that the model has successfully demonstrated its ability to make accurate predictions.

CHAPTER SIX

DISCUSSION

6.1 INTRODUCTION

In the preceding chapter, a thorough examination of data was conducted for this research endeavour, as it required to perform an empirical analysis using data obtained from participants via an online survey. This study also explores the potential predictors of e-learning adoption in Pakistan during COVID-19. Moreover, this chapter expands on the previous chapter's statistical data and discusses the importance and insignificance of the hypothetical relationships presented for this research approach. The chapter commences with an introductory section followed by a thorough review of data analysis results and hypothesis examination in order to answer the study's questions. Simply, this chapter emphasizes the study's findings and provides a relevant discussion that addresses the research questions and objectives.

6.2 RESULTS DISCUSSION

This section comprehensively reviews the key findings of this study's research analysis. Initially, there is a discussion on the respondent's rate of participation, demographical attributes, variables, and items. Furthermore, the hypothesis results are debated and justified.

6.2.1 Rate of Participation

There was a total of 567 replies collected. Following the implementation of data cleaning methods such as respondents' misconduct the 106 responses were removed as their standard deviation recommendation results were less than 0.25 Collier, J. E. (2020). Consequently, a total of 461 responses were selected for subsequent data analysis. The observed response

rate appears to be relatively low, yet it is comparatively higher than the rate of reply conveyed in other studies conducted within the same field. For example, several researchers have obtained a usable response rate, such as Asvial, et al. 2021 conducted a study with a sample size of 50, Mailizar & Damon Burg, 2021 have a sample size of 109, Altalbe, A. 2021 with a sample size of 160, Prasetyo, et al. 2021 have sample size 253, Almajali, et al. 2021 have a sample size of 300, Abbad, M. M. (2021) have sample size of 370 and Fauzi, et al. 2021 conducted study with a sample size of 388. Based on the statistical evidence presented by the researchers, the usable response rate for this research work is comparatively higher.

6.2.2 Demographical Characteristics of Respondents

The results of the demographics analysis for this study revealed that among participants, 71.1% were male students, and 28.9 % were female students. This number is not surprising when considering Pakistan's gender statistics and literacy figures. According to the Higher Education Commission of Pakistan's annual report HEDR (2021-22), the gender distribution of students in Pakistan is 51.35% male and 48.65% female. Based on the provided statistical data, it may be argued that the proportion of responses obtained from male respondents may be greater than that of female respondents. The demographic findings of the survey revealed that 68.8 percent of the participants were individuals under the age of 30. The findings indicate that the popularity of smartphones, tablet PCs, and the internet is increasing among younger generations.

The findings suggest that a majority of e-learning participants during the COVID-19 pandemic were undergraduate students who relied on Internet connectivity, smartphones, laptops, and personal computers to engage in online educational activities. Furthermore, the study revealed that a majority of the participants, specifically 94.9 percent, were enrolled as students, while a smaller proportion of 5.1 percent consisted of faculty members. The results of this work primarily focus on the population of students who engaged in e-learning during the COVID-19 pandemic. Moving forward for further demographic analysis, 60.1 percent of respondents used the internet and handheld devices

for the last five years. This shows that the country's growth rate for using smart devices such as smartphones, laptops, and personal computers is growing. The reason for this growth rate is the introduction of broadband services such as 3G and 4G by telecom operators and reinforcement policies by the Pakistan Telecommunication Authority (PTA Telecom indicators) to increase the subscribers of broadband services.

Further findings related to e-learning usage before COVID-19 revealed that only 43.7 percent of respondents knew about e-learning before COVID-19. This indicates that adopting e-learning technologies in the country was lagging even before COVID-19. After COVID-19, the importance of e-learning appeared necessary as social distancing was mandatory. Furthermore, throughout the COVID-19 pandemic, most students, specifically 51 percent, engaged in e-learning activities daily. Additionally, 49 percent of students utilized e-learning weekly, indicating a substantial frequency of e-learning usage. These indicators also highlight the necessity of addressing the e-learning issues pointed out by the researcher. Governmental bodies and higher education institutions must prioritize resolving issues encountered by users of e-learning platforms to facilitate a seamless adoption of online education mode within the country.

6.2.3 Constructs and Items

The purpose of this investigation was to identify the most important predictor influencing e-learning adoption in Pakistan during COVID-19 by employing a proposed research model that included various constructs and hypotheses. The subsequent sub-sections discuss the outcomes of constructs and their items.

6.2.3.1 Behavioural Intention (BI)

The concept of BI was evaluated by utilizing a collection of five Items. The study's findings indicate that the descriptive statistics for the mean and standard deviation of the items ranged from a minimum of 4.90 (with a standard deviation of 1.910) to a maximum of 5.00 (with a standard deviation of 1.810). These results suggest that the items on the scale tend

to be more positively oriented than neutral, as the neutral point on the scale is defined as 4. The BI factor items earned high values, indicating a strong preference for online learning mode in COVID-19 settings. The item "*Assuming I have access to e-learning*" and "*I intend to use it*" was found to carry greater significance when compared to the other four items of the BI. On the other hand, the item '*Given that I may have e-learning access, I predict I will use it*' obtained the lowest rating. The remaining three Items of BI achieved values ranging from 4.90 (1.910) to 5.00 (1.810), as indicated in Table 5.2. of Chapter Five. Similarly, Cronbach's coefficient (0.923) revealed that the measurement items about (BI) had a high internal consistency (see Table 5.16).

6.2.3.2 Perceived Usefulness (PU)

Six items were used to assess the perceived usefulness (PU) construct. The descriptive statistics for these items included mean values and standard deviations, with the lowest mean being 4.83 (with a standard deviation of 1.841) and the highest mean being 4.98 (with a standard deviation of 1.881) (see Table 5.3). Results exceed the neutral mark on the scale i.e. (4) and it appears that the participants recognized the importance of using e-learning, and strongly agreed with each item of the construct. Item number PU1: '*In COVID-19, using e-learning enabled me to accomplish my academic tasks more quickly.*' Obtained higher average evaluations (4.98) than other items. Statistics show that e-learning responders were very worried about how well their studies would work during the COVID-19 pandemic, which will allow them to get their work done more swiftly. On the other hand, item Number PU2 '*Using e-learning increased my academic productivity and performance during COVID-19*'. was given the lowest score (4.83) as compared to other items.

This finding suggests that students believe their performance participating in online educational activities via mobile devices would improve less than they hoped. However, based on the overall assessment of the construct mean score, the students agreed that e-learning is highly valuable for their online educational activities, especially in situations like the pandemic. The reliability of the construct is further demonstrated by Cronbach's coefficient, which is 0.934 (see Table 5.16).

6.2.3.3 Perceived Ease of Use (PEOU)

The participants' perceptions of this construct were assessed using a set of five items. The fifth item of the Perceived Ease of Use (PEOU5) scale, which states, "*Overall, I found e-learning easy to use*," received a high level of favourability from the participants, as seen by a mean score of 4.97. This finding indicates that there was an upward trend in the adoption of e-learning among students during the COVID-19 epidemic. In contrast, the second item of the Perceived Ease of Use (PEOU) construct, "*My interaction with e-learning was clear and understandable during COVID-19*", received a low mean rating of 4.91. The average rating of the remaining three items in this construct ranged from 4.91 (standard deviation = 1.744) to 4.97 (standard deviation = 1.678) (see Table 5.4) which demonstrates a positive incline towards the convenience of e-learning. These findings revealed that during the COVID-19 pandemic, students believed that e-learning was an easier-to-use option than other traditional learning methods. Moreover, Cronbach's coefficient for the PEOU is (0.924) (see Table 5.16) displaying a high degree of internal consistency and reliability of measuring items.

6.2.3.4 System Quality Construct (SQ)

The System quality construct was measured with the help of five Items. The descriptive statistic for this construct is presented in Table 5.5, with a mean value of 3.28 (Standard Deviation 1.901) for high ratings and 2.93 (Standard Deviation 1.652) for low ratings. These findings indicate that the mean score is less than the neutral threshold of 4. Furthermore, the mean value for the remaining three Items falls within the range of the above-mentioned rating, indicating respondents' poor self-esteem. Based on the research findings, it is evident that during the COVID-19 pandemic, the e-learning system was required to fulfill the respondents' requirements in terms of availability and response time. One expected reason for the revealed result could be a concurrent load on the system, as all educational institutions switched to online learning mode and poor internet connectivity due to weak infrastructure. Furthermore, Cronbach's coefficient for the system quality is

reported to be 0.792 (see Table 5.16), indicating satisfactory internal consistency and dependability of measuring items.

6.2.3.5 Cost Construct

The assessment of the cost construct was carried out using four Items. The average mean score for all items varied, with the highest being 2.83 (standard deviation = 1.721) and the lowest being 2.64 (standard deviation = 1.509), as indicated in Table 5.6 of the descriptive analysis. Considering the hypothesis that this construct negatively impacts the dependent variable, ratings with lower mean values further away from the neutral point (i.e., 4) were deemed more favourable. The results from the measuring items suggest that respondents expressed certain reservations regarding the cost associated with e-learning usage, particularly during the COVID-19 lockdown. However, these findings may not be surprising given that e-learning usage costs, such as Smart mobile devices, laptops, PCs, tablets, internet subscriptions, and software license costs, are some of the primary challenges in developing economies with low income. In addition to the cost construct's good mean rating score, Cronbach's α reliability value of 0.750 showed good internal consistency of assessment items (see Table 5.16).

6.2.3.6 Application Complexity Construct (CO)

The application complexity construct was assessed using a set of five items. Based on the descriptive analysis findings, as presented in Table 5.6, it was seen that the mean rating of all items within this construct varied between a higher value of 4.97 (with a standard deviation of 1.587) and a lower value of 4.79 (with a standard deviation of 1.611). The findings demonstrate that the outcomes exceeded a value of 4, commonly regarded as a neutral threshold. Item number CO4 “*The software platform used for e-learning functions is considered to be satisfactory*” received higher average ratings (4.97) than other items. The results indicate that selecting a suitable e-learning platform with a user-friendly interface for interaction is important. The less sophisticated e-learning software may increase the system's use behaviour. On the other side the Item Number. CO4 “*The*

software platform used for e-learning operates with sufficient features, was rated (4.79) low. Considering the construct's overall mean value, software application complexity for e-learning systems is the most important component in determining user behaviour intentions for e-learning adoption. Moreover, Cronbach's α reliability value of 0.846 showed a strong internal consistency among the construct and its items (see Table 5.16).

6.2.3.7 COVID-19 Construct (CVD)

The COVID-19 construct was employed to assess five distinct items, giving mean ratings that range from the highest score of 3.23 (standard deviation = 1.781) to the lowest score of 2.64 (standard deviation = 1.509) (see Table 5.7). Like the cost construct, this one was predicted to have a negative effect on the dependent variable, resulting in a lower mean rating and a greater distance from the neutral point, which indicates that 4 was deemed to be preferable. The findings revealed that participants had the highest level of anxiety regarding fear and stress associated with implementing lockdown measures during the COVID-19 pandemic. Implementing the lockdown measures had a significant impact on the financial assets of individuals, resulting in increased anxiety and stress. Furthermore, reliability statistics were verified using Cronbach's (0.865), showing that this construct's test items were consistent (see Table 5.16).

6.2.3.8 Social Influence (SI)

The feedback provided by the respondents regarding this construct was assessed using a set of five items. The average scores for the five items were seen higher than the neutral mark on the scale (i.e., 4) and ranged from the highest mean of 4.90 (standard deviation = 1.674) to the lowest mean of 4.51 (standard deviation = 1.844) (see Table 5.8), indicating that respondents generally agreed with all the items in this construct. Item number SI2 "*People who are important to me thought I should use e-learning in any COVID-19 type situation*" was rated high (4.90) which shows that respondents' social contacts have a strong favourable influence on their recommendation to adopt e-learning during COVID-19 pandemic. From the overall rating of the respondents for this construct, it can be predicted

that social influence plays a significant role in adopting online learning in Pakistan society, particularly in a situation where social distancing is required. Moreover, the analysis of the sample response reveals that societal factors and media influence significantly impact the wide use of e-learning in Pakistan. Additionally, Cronbach's coefficient for the SI is (0.769) displaying a good degree of internal consistency and reliability of measuring items (see Table 5.16).

6.2.3.9 Facilitating Conditions (FC)

The Facilitating Conditions construct was assessed using a set of five items. The average rating of all items under this construct varied, with the lowest average being 4.76 (standard deviation = 1.727) and the highest average being 4.59 (standard deviation = 1.813). These results suggest that the ratings were above 4, typically considered neutral (see Table 5.9). The findings of this study suggest that individuals who may potentially use e-learning consider the significance of various facilitating conditions. such as Licenced Software, Computing devices, hardware-software support, and other required resources for conducting online classes significantly impact their attitudes and intentions toward adopting e-learning. In addition to the given descriptive statistics, the reliability ratings obtained using Cronbach's α (precisely, 0.895) further demonstrate the satisfactory internal consistency of this construct (see Table 5.16).

6.2.3.10 Student Learning Motivation (SLM)

Four items were used to evaluate the feedback provided by respondents regarding this construct. The mean scores for the five items exhibited an average value greater than the neutral point of 4, (refer to Table 5.10), with a range spanning from a minimum of 4.75 (1.645) to a maximum of 5.04 (1.560), indicating that respondents generally agreed with all the items comprising this construct. Item number SML4 "*Through online classes, students can improve their real-time skills*" was rated high (5.04) which shows that due to the number of benefits provided by e-learning such as time efficiency and cost-effectiveness, students can enhance their skills accordingly. On the other side item Number

SLM “*Through e-learning, students can achieve better grades exceptional in COVID-19 type situations*” rated low (4.75). A possible cause for this result can be difficulties with student assessment in the setting of online programs. Furthermore, reliability statistics were verified using Cronbach's (0.856), showing that this construct's test items were consistent (see Table 5.16).

6.2.4 Relationships in-between Predictor Variables and the Outcome Variable

While evaluating adopting a new technology, service, or system in the field of IS/IT, actual use can be considered the most important dependent variable. Nevertheless, several researchers (Fauzi et al., 2021; Jie S. et al., 2021; Al-Rahmi et al., 2019; Younas et al., 2021) have argued that research studies examining predictors affecting users’ Behavioural intention to adopt new information systems or information technology service primarily employ "intention to use" as the endogenous variable relatively than actual usage. Since this study's primary goal was to determine what factors influence the adoption of online education during the COVID-19 epidemic, this research work used "Behavioural intention to use" as its endogenous variable instead of actual use. Similarly, many investigations have shown that the original TAM, PEOU, and PU constructions rely more on BI rather than on actual use (Alassafi et al., 2022; Fauzi et al., 2021; Jie S. et al., 2021; Al-Rahmi et al., 2019; Younas et al., 2021; Mailizar et al., 2021; Khan, S et al. 2020) empirically evaluated the adoption of IT/IS services and systems by utilizing BI as the endogenous variable.

In this study, the researcher examined a hypothesized research model to observe which factors (independent variables) are most predictive of behavioral intention to use (dependent variable). The results revealed that the dependent variable (BI) has a total variance of 61.1 which is justified by all its dependent variables. Concerning Figure 5.5 in Chapter 5 of this research work among direct constructs of BI, Perceived Usefulness explained the high variance PU (0.309) followed by Perceived-Ease of use PEOU (0.189), Social Influence SI (0.147), System Quality SQ (0.075), Cost CS (-0.198), and COVID-19 CVD (-0.200). Likewise, PEOU predictors explained 39% variance, i.e., Application Complexity CO (0.420), Facilitating Conditions FC (0.322), and COVID-19 CVD (-0.143).

Similarly, Perceived Usefulness predictors explained 54.7% variance, i.e., PEOU (0.276), Application Complexity CO (0.179), Social Influence SI (0.147), and COVID-19 CVD (-0.195) respectively. However, two direct hypotheses about BI and its determinants (Facilitating Conditions and Student Learning Motivation) were rejected.

6.2.5 Results of Hypotheses Testing

In order to identify the predictor influence on the adoption of e-learning during the COVID-19 time, fifteen hypotheses were employed. After carrying out a detailed analysis of the data, the outcomes of the hypothesis tests as presented in Table 5.24 from the preceding Chapter 5. The subsequent section provides a detailed discussion based on the outcomes of the hypothesis.

6.2.5.1 Examine the Impact of PU on BI

As per (Davis, et al., 1989) Perceived usefulness, PU can be defined as “user belief that a system, service, or technology will improve work performance”. Hypothesis H1 in this study is proposed as “*Perceived Usefulness will have an encouraging positive effect on Behavioral Intention to adopt e-learning throughout COVID-19*” was proposed. Based on the statistical results, the coefficient (β) was 0.302, alongside a corresponding t-value of 4.974 and a p-value of 0.000, indicating that the hypothesis is significantly positive and accepted. These findings provided empirical evidence for the claim that prospective students' perceptions of e-learning's usefulness influence their subsequent behavioral intentions during COVID-19.

The results also match the findings from the original TAM study, which showed that PU has a precise considerable impact on BI (Davis, 1989). Several experimental studies have been undertaken on the context information systems/technology adaptability (Alassafi et al., 2022; Fauzi et al., 2021; Jie S. et al., 2021; Al-Rahmi et al., 2019; Younas et al., 2021; Mailizar et al., 2021; Khan, S et al. 2020) revealed the same findings in which PU had a substantial effect on the intention to use. These experimental outcomes imply that users

were motivated to use e-learning during COVID-19 based on their opinions about its comparative benefits considering assessing its usefulness. Hence, it is expected that e-learning in Pakistan comprehends its value and its adoption rate increase during COVID-19. Finally, according to the findings of this study, the PU construct plays a crucial part in predicting the users' behavioural intention to adopt e-learning.

6.2.5.2 Examine the Impact of PEOU on PU and BI

PEOU refers to the “user's perception of the level of effort necessary to utilize new Information technology systems” (Davis et. al., 1989). This study's working hypothesis is that Perceived-ease of Use (PEOU) would employ positive in both direct and indirect influences on the Behavioural Intention (BI) to adopt e-learning, as proven by hypotheses H2a and H2b. According to the statistical analysis of this study, the coefficient (β) was 0.192, with a corresponding t-value of 3.466 and a p-value of 0.001, showing that the proposed association in-between PEOU and BI to use of e-learning in COVID-19 time revealed a positive significant results and hypothesis was accepted. The source of said hypothesis is the TAM model, according to the model, PEOU is a robust indicator of technological adoption (Davis et. al., 1989).

Several researchers such as (Alassafi et al., 2022; Fauzi et al., 2021; Jie S. et al., 2021; Al-Rahmi et al., 2019; Younas et al., 2021; Mailizar et al., 2021; Khan, S et al. 2020) discovered a substantial impact of PEOU on Behavioural Intention (BI). According to Abbasi et al. (2010), the experience of ease of use plays a significant role in influencing the intention of possible adopters to utilize a selected product or technology. So, by considering the previous studies, this research work was discovered by empirical data supporting the belief that the adoption of e-learning in the COVID-19 epidemic is substantially affected by its easiness observation. The outcomes are not unexpected; nevertheless, they align with numerous prior empirical investigations in similar contexts (Alassafi, M. O. 2022; Mailizar et. al., 2021; Fauzi et. al., 2021)

Hypothesis PEOU $\rightarrow$ PU (PEOU on PU), was suggested as “*Perceived-ease of use will have an encouraging effect on PU to adopt e-learning throughout COVID-19*”. According to obtained statistical results, the coefficient (β) was 0.276, with a corresponding t-value of 4.575 and a p-value of 0.000, implying sufficient evidence to support this hypothesis and declare it statistically significant. These findings show that the perceived utility of e-learning is significantly influenced by its ease of use, which may impact its adoption. The hypothesis is derived from the TAM, which proposes that the adoption of an information system (IS) is significantly impacted by its PU about ease of use (Davis et al., 1989). Previous research investigations in similar contexts demonstrated a favorable association between these constructs. (Davis et al., 1989; Alassafi et al., 2022; Fauzi et al., 2021; Jie S. et al., 2021; Al-Rahmi et al., 2019; Younas et al., 2021; Mailizar et al., 2021; Khan, S et al. 2020). As a result, in the context of e-learning adoption during the COVID-19 epidemic in Pakistan, favorable beliefs about its usefulness hold greater significance than the perceived ease of use. In general, PEOU and PU are very important when it comes to deciding whether or not to use e-learning.

6.2.5.3 Examine the Impact of Cost on BI

Cost refers to the potential expenditures associated with utilizing e-learning, involving equipment, internet connectivity, and software license costs Sarosa, S. (2021). In this research work the hypothesis proposed for cost is “*Perceived Cost will have a negative, discouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19*”. The statistical results indicate that the coefficient (β) was -0.197, with a corresponding t-value of 4.732 and a p-value of 0.000. The negative sign in the results implies a negative correlation between cost and intention to adopt e-learning during COVID-19. In other words, an escalation in the cost associated with its utilization would decrease its adoption. Previous research investigations in similar contexts demonstrated a negative association in-between these constructs (Sarosa, S. 2021; Asvial et al., 2021; Twum et al., 2021). Given this data and the outcomes of this research work, it is sensible to predict that, from the student's perspective, the cost is a major predictor of e-learning adoption determined and has a considerably direct adverse impact on Behavioural Intention to use. Furthermore,

these findings may come as a surprise because e-learning is more expensive due to factors such as internet connection costs, equipment costs, and software licence prices. In summary, the government and higher education institutions must place a specific emphasis on cost-effective pricing schemes to encourage e-learning throughout the country, especially in a pandemic situation like COVID-19.

6.2.5.4 Examine the Impact of System Quality on BI

Delone and Mclean (2003) argued that system quality can be measured in terms of how much of a system requires minimal effort for its usage. The authors identify five key attributes that contribute to system quality, namely availability, usability, flexibility, and response time. In the present study, the hypothesis put forwards pertains to the System quality “*System Quality, in terms of availability and response time, will have a positive encouraging effect on Behavioral Intention to adopt e-learning throughout COVID-19*”. According to obtained statistical results, the coefficient (β) was 0.066, with a corresponding t-value of 2.101 and a p-value of 0.036, indicating there is adequate data to conclude that this hypothesis is significant statistically.

The findings indicate that easy access to the system will benefit students' behavioral intentions to adopt it. The system's success depends on the quality of the system, which is mostly determined by the learner's perspective. Several previous research studies conducted in comparable situations have revealed a favourable correlation between these dimensions. (Alkhawaja et al., 2022; Altalbe, A. 2021; Costa et al., 2016).

Based on study findings, students' perceptions of the system's quality play an important part in predicting their intentions of adopting e-learning and have a considerable positive direct influence on their usage intention. Moreover, the findings also indicate that the student's intent to utilize e-learning systems in public institutions is directly impacted by the degree of system quality provided by the e-learning system. In summary, when choosing e-learning software to facilitate online classes, educational institutions should

prioritize factors such as prompt responsiveness, and high availability to enhance students' inclination to utilize the platform.

6.2.5.5 Examine the Impact of Application Complexity PEOU and PU

Complexity can be defined as the degree of hindrance involved in understanding and accepting a given system (Lee et al., 2011). It shows whether a user wants to utilize the system, especially based on how hard it is to understand and use. This research examined how complexity affected people's willingness to use e-learning during the COVID-19 epidemic, with the mediating factors of PEOU and PU. H5a was used to test the hypothesized association between complexity and PEOU worded as "*Application Complexity will have a positive encouraging effect on Perceived-ease of use*". Statistical results revealed a positive significant association in-between these constructs as the coefficient (β) were 0.421, with a corresponding t-value of 6.843 and a p-value of 0.000.

The findings show that students are more inclined to adopt less complicated systems than more complex ones due to the less effort required. Previous studies have also examined the empirically significant relation among application complexity and PEOU such as (Idoga, et al., 2022; Chin et al., 2016; Aypay, et al., 2012) Studies investigated the acceptance of new IS. A correlation that is positive and statistically significant in-between complexity and PEOU offers fascinating evidence that students experience e-learning as easy to use when the chosen software for e-learning is user-friendly and minimally complex. Similarly, the parameter estimation results for hypothesis H5b, which states that "*Application Complexity will have a positive and encouraging effect on Perceived Usefulness*," indicated that the coefficient (β) was 0.322. The corresponding t-value was 6.253, and the p-value was 0.000, showing a significant association between these two constructs. Previous research has found the same significant results in-between application complexity and PU (Idoga et al., 2022; Chin et al., 2016; Aypay et al., 2012). These empirical findings reveal that application complexity is a substantial predictor of PU, as experienced by respondents during COVID-19. In summary, it was discovered that application complexity has an indirect impact on behavioural intention (BI), which is

mediated by PEOU and PU. Consequently, the results of this study imply that students who enrol in online courses may have higher academic accomplishment and more engagement with their instructors when using software with a user-friendly design.

6.2.5.6 Examine the Impact of Social Influence on PU and BI

Social influence can be stated as "a person's view that the majority of persons influential to him or her think that he or she should engage in the behaviour in question." The hypothesis posited that SI would have a favourable impact on BI to adopt e-learning directly and indirectly (via the mediation of PU). Statistical results revealed a strong correlative significance between SI and PU constructs as the coefficient (β) was 0.147, with a corresponding t-value of 3.057 and a p-value of 0.002. These findings further suggest that individuals were more likely to regard e-learning as beneficial during the COVID-19 epidemic when they see friends and relatives using it and receiving recommendations. These findings match numerous earlier investigations (Alami et al., 2022; Nikou, 2021; Economides, 2017; Wu, 2017). As per the finds of this study, it is sensible to assume that social influence has a major effect on students' beliefs regarding the utility of e-learning, and students who were not using e-learning as a learning method may have to value the thoughts of their professors, parents, or others who affect their behaviour.

In the same way, the outcomes of parameter estimation for hypothesis H6b are examined. According to empirical results, the coefficient (β) was 0.129, with a subsequent t-value of 3.045 and a p-value of 0.002 implying a significant correlation between SI and BI. Several previous research reveals the same results (Md Yunus et al., 2021; Muangmee et al., 2021; Kornpitack et al., 2022). Based on the findings, it can be concluded that social influence significantly affects students' behavioral intention to adopt e-learning, specifically during the COVID-19 pandemic. This influence is mostly facilitated by the support provided by instructors, family members, and friends.

6.2.5.7 Examine the Impact of Facilitating conditions on PEOU and BI

Facilitating conditions can be defined as the degree to which an individual perceives that the existing organizational and technological framework is conducive to effectively utilizing technology. In the framework of this study, two hypotheses were developed to investigate the impact of facilitating conditions on e-learning during COVID-19.

Hypothesis **H7a** examined the association among FC and PEOU. As per the empirical results, the coefficient (β) was 0.177, with a corresponding t-value of 2.693 and a p-value of 0.007. Results suggest a favorable association between facilitating conditions and users' attitudes toward adopting e-learning in the COVID-19 epidemic, with ease-of-use observation mediating the influence. The considerable influence of facilitating conditions, which determine the ease of adopting e-learning, supports prior research findings (Fauzi, et al., 2021; Prasetyo et al., 2021). Simply, facilitating conditions such as broadband internet access, uninterrupted power supply, and technical infrastructure exist to facilitate e-learning in Pakistan. In conclusion, the level of FC has a considerable effect on potential students' opinions regarding the ease of use of e-learning.

In contrast, hypothesis **H7b** suggested that *“Facilitating Conditions will have a positive encouraging effect on the Behavioral Intention to adopt e-learning throughout COVID-19”*. According to the empirical results, the coefficient (β) was 0.110, with a corresponding t-value of 1.916 and a p-value of 0.055. The findings suggest a lack of significant correlation between FC and BI. Consequently, the said hypothesis was rejected. Hence, these findings indicate that facilitating conditions do not directly impact the willingness of students to adopt e-learning. However, as previously stated, H7a's proof indicates that Facilitating conditions employ an indirect effect via the mediating role of PEOU. Previous studies (Venkatesh et al., 2003) have shown a strong significant association in-between FC and BI. However, the results of this research study show that, even though FC is not a primary predictor of BI, it strongly affects users' willingness to use e-learning when viewed through the lens of PEOU. One probable justification for this inconsistency among facilitating conditions and BI is that e-learning was a new concept

suddenly imposed on students by higher education institutions in the COVID-19 epidemic; students may have yet to investigate the resources required for this learning method. In summary, results revealed that FC in Pakistan do not directly impact user intention but through the lens of ease-of-use perspective.

6.2.5.8 Examine the Impact of COVID-19 on PEOU, PU and BI

The COVID-19 epidemic has introduced a novel scenario that students have not previously encountered. Consequently, more research studies need to examine COVID-19 as a predictor, particularly within Pakistan. The COVID-19 predictor is one of the major predictors of this study. This variable was examined to assess its impact on the adoption of e-learning among students concerning the circumstances of lockdown, stress, and fear of COVID-19.

A hypothesis **H8a** was proposed “*COVID-19 (lockdown Fear & Stress) will have a negative, discouraging effect on Behavioral Intention to adopt e-learning*” to find out covid direct effect on BI. According to the results, the coefficient (β) was -0.182, with a subsequent t-value of 3.714 and a p-value of 0.000. A negative sign in the beta coefficient signifies a negative relationship in-between the constructs, providing evidence for the acceptance of the hypothesis. According to the findings, during the COVID-19 epidemic, students had significant levels of anxiety, isolation, tension, and fear, as the fatality rate was exceedingly high. Along with these issues, students belong to an underprivileged country like Pakistan, where most of the population belongs to the middle class, and the lower middle class faces financial issues due to lockdown restrictions.

Some research studies have also proven the same results; for example, According to Roman et al., (2021) under the intense analysis of the COVID-19 lockdown, e-learning is less likely to be adopted if the learner is experiencing psychological stress or anxiety. An additional investigation was carried out by Kapasia. et al., (2020) suggest that during lockdowns, students at Indian West Bengal universities suffered various issues, including stress, depression, slow internet, an uncomfortable environment, and anxiety which ultimately influenced the adoption of e-learning. In summary, the COVID-19 predictor

possesses a direct and substantial impact on the adoption of e-learning and the acceleration of e-learning implementation can be facilitated, particularly during a pandemic such as COVID-19, via increased dedication from governmental bodies and higher education institutions in addressing the previously mentioned obstacles by leveraging their available resources to the maximum extent.

Another hypothesis, **H8b**, COVID-19 → PEOU was proposed “*COVID-19 (lockdown Fear & Stress) will have a negative, discouraging effect on Perceived-ease of use*” to check the influence of COVID-19 on Perceived-ease of use. As per the empirical results, the coefficient (β) was -0.144, with a corresponding t-value of 2.840 and a p-value of 0.005. Once again, the negative value in the beta coefficient proves a negative influence of the construct as proposed in the hypothesis. According to the results, students were concerned about the influence of the COVID-19 epidemic on the ease of use of e-learning platforms. Furthermore, increased COVID-19 fear, and stress will likely reduce students' willingness to adopt e-learning as a viable educational option.

Moving on, hypothesis **H8c** COVID-19 → PU was proposed: “COVID-19 (lockdown Fear & Stress) will have an adverse, discouraging influence on PU”. The data analysis results show that the coefficient (β) was -0.195, with a corresponding t-value of 4.256 and a statistically significant hypothesis at a p-value of 0.000. The findings demonstrate a negative association between COVID-19 and perceived usefulness, implying that lockdown, anxiety, and stress during COVID-19 influence the usability of the e-learning system. The researcher conducted a similar type of investigation (Nikou et al., 2021). strengthen the position of COVID-19 as a variable to assess its impact on PEOU, Behavior intention, and PU.

In Summary, the COVID-19 epidemic presented obstacles to students when taking online classes, and the pace of e-learning adoption was lagging. Consequently, it became essential for authorities to address this issue with careful consideration, ensuring a seamless response to any potential future crises like the COVID-19 pandemic.

6.2.5.9 Examine the Impact of Student Learning Motivation on BI

In the context of e-learning, student learning motivation can be defined as the inner drive that students must initiate, sustain, and lead their learning activities employing technology Harandi, S. R. (2015). In this study, Student learning motivation (SLM) intended to have a direct, positive impact on BI for the adoption of e-learning. Hence hypothesis **H9** states *“Student Motivation will have an encouraging positive effect on Behavioral Intention to adopt e-learning throughout COVID-19”*. According to the statical data, the coefficient (β) was -0.06, with a t-value of 1.191 and a p-value of 0.234 suggesting that the hypothesis was rejected. A possible explanation for this can be the slow internet connectivity, power failure, lack of lab access, and improper assessment of students by the instructors.

Previously similar types of explanation were also reported by several scholars for example According to a study, conducted by (Rehman, 2021) while taking online classes during COVID-19, poor connectivity and a lack of electricity were the major challenges for students and teachers. According to a measure developed by the researcher of another study (Ansar et al., 2020), a significant majority of students, specifically 78%, expressed dissatisfaction with their experiences in online learning. during COVID-19 because of issues including problems with student-teacher interaction, examination consistency, and conceptual confusion. In summary, the findings indicated that in the context of Pakistan, students showed a lack of motivation to participate in online learning in the COVID-19 epidemic. Furthermore, it was observed that this factor does not directly influence the intention of Students.

6.2.6 Mediation

A statistical method called "mediation analysis" determines how much a third variable, "the mediator," affects the relationship between two other factors. Mediation analysis assists researchers in determining answers to questions such as.

1. Does the independent variable indirectly influence the dependent variable via Mediator?

2. What exactly is the mediation effect?
3. What is the magnitude of the indirect effect?

The TAM model was chosen as the base reference model for this reach study because it includes two constructs, PEOU and PU, which operate as mediating variables. The subsequent section discusses the impact of these mediating factors on the e-learning behavior intention during COVID-19.

6.2.6.1 Examine how PEOU Mediates e-learning BI during COVID-19

As discussed earlier in Chapter No.3 PEOU can be defined as “It is a degree to which a person believes that there will less effort required to use the specific system or technology”. The mediation impact of PEOU was assessed in this research study for the following relationships among the factors.

- i. PEOU mediates Application Complexity & Behavioral Intention.
- ii. PEOU mediates Facilitating Coniditions & Behavioral Intention.
- iii. PEOU mediates COVID-19 & Behavioral Intention.

6.2.6.1.1 PEOU mediates Application Complexity & Behavioral Intention

The indirect relationship between Application complexity and behavior intention was estimated statistically ($\beta = 0.081$, $t = 3.094$, $p = 0.002$) with a 95% confidence interval (0.032 to 0.134) assumed as significance in terms of statics. This suggests that a significant portion of the effect of application complexity on Behavior intention is directed through users' perceptions of ease of use. Moreover, the direct impact **CO→BI** of Application Complexity on Behavioral Intention was still significant ($\beta = 0.323$, $t = 2.604$, $p = 0.009$) even when considering the mediation pathway which proves that PEOU server as a partial mediator in-between Application complexity and Behavior intention to use. One possible reason for this partial mediation can be that during COVID-19, the use of E-learning was no longer optional; it was required to continue with the education process due to social distance. and

there was external pressure on students to use it, irrespective of the ease of use. (Soni et al., 2020)

6.2.6.1.2 PEOU mediates Facilitating Conditions & Behavioral Intention

The indirect association between facilitating condition and behavior intention was estimated statistically ($\beta = 0.034$, $t = 2.146$, $p = 0.032$) with a confidence range excluding zero (0.008 to 0.070) taken as significance in terms of statics and the direct association between facilitating condition and behavior intention was estimated statistically ($\beta = 0.110$, $t = 1.916$, $p = 0.055$) insignificant. The findings suggest that PEOU fully mediates the correlation between Facilitating Conditions and Behavioral Intention. One potential explanation for the observed full mediation findings can be that when students are provided with sufficient support, resources, and training, they may perceive the technology as more user-friendly, resulting in increased PEOU and a larger intention to engage in the desired action. (Songkram et al., 2023)

6.2.6.1.3 PEOU mediates COVID-19 & Behavioral Intention.

The statistical analysis reveals that the observed indirect effect between COVID-19 (CVD) and BI is considered to be statistically insignificant ($\beta = -0.028$, $t = 1.932$, $p = 0.053$). Therefore, it can be concluded that the PEOU does not serve as a mediating factor in the relationship between COVID-19 and BI, despite the significant overall effect ($\beta = -0.280$, $t = 5.531$, $p = 0.000$) and direct effect ($\beta = -0.182$, $t = 3.714$, $p = 0.000$). Due to limits caused by the pandemic, users may feel like they have to use e-learning, even if they do not think it is easy to use, so the potential reduction of the mediating role of PEOU may arise due to the need for more feasible alternatives. One possible reason for the revealed result could be the limits caused by the pandemic, students may feel like they have to use e-learning, even if they do not think it is easy to use, so the desire for more practicable options may result in a potential reduction of the mediating role of PEOU.

6.2.6.2 Examine how PU Mediates e-learning BI during COVID-19

PU refers to a student's level of trust in a system's ability to enhance their career productivity. In this study, the researcher examined the following associations between variables to determine how perceived usefulness mediated those associations.

- i. PU mediates Application Complexity & Behavioral Intention.
- ii. PU mediates Social Influence & Behavioral Intention.
- iii. PU mediates COVID-19 & Behavioral Intention.

6.2.6.2.1 PU mediates Application Complexity & Behavioral Intention

According to the statical results, the direct effect ($\beta = 0.213$, $t = 5.462$, $p = 0.000$) and indirect effect ($\beta = 0.097$, $t = 3.875$, $p = 0.000$) between Application complexity and Behavior intention is significant with a 95% confidence interval (0.053 to 0.150). It is evident that perceived usefulness serves as a partial mediator between application complexity and behavior intention to use e-learning during COVID-19 and has a considerable percentage of the effect. One possible reason for this partial mediation can be the significance of direct relationship between application complexity and behavior intention to use. As per (Cheng et al., 2012) the partial mediation effect can be observed if the size of the direct correlation between the dependent and independent variables decreases while still maintaining statistical significance. The results show that the beta value of the indirect relationship is greater than the direct relationship, implying that students believed using e-learning during COVID-19 somehow would help them improve their skills.

6.2.6.2.2 PU mediates Social Influence & Behavioral Intention

Like the above observation again Perceived usefulness behaves as a partial mediator between social influence and Behavior intention as the static results of direct association ($\beta = 0.129$, $t = 3.045$, $p = 0.002$) and indirect association ($\beta = 0.044$, $t = 2.723$, $p = 0.006$) are significant with a 95% confidence interval (0.016 to 0.179). The results show that the impact of perceived usefulness on BI may be enhanced by social influence. In other words,

during COVID-19, if students think the e-learning app is helpful, they might be more influenced to follow the advice of their peers. This interaction effect can potentially increase the perceived usefulness of the experience being studied, as it acts as a mediator to some extent.

6.2.6.2.3 PU mediates COVID-19 & Behavioral Intention

Once again in the association between COVID-19 and behavior intention Perceived usefulness serves as a partial mediator as the statical result of direct relation ($\beta = -0.182$, $t = 3.714$, $p = 0.000$) and indirect relation ($\beta = -0.059$, $t = 2.736$, $p = 0.006$) are significant with a 95% confidence interval (-0.106 to -0.023). One possible explanation for this partial mediation can be that traditional in-person learning was severely limited due to the pandemic outbreak, necessitating the usage of e-learning alternatives. Perceived usefulness may somewhat mediate the association between COVID-19 and behavioral intention because it captures the idea that people value the convenience and practicality of e-learning in situations where alternative options are limited.

6.3 CHAPTER SUMMARY

This chapter discusses and reflects on the significant results of the data analysis done in Chapter 5 to answer the research questions and validate the model. The researcher tried to thoroughly discuss and justify the response rate, demographic characteristics, and background information collected from the respondents. Out of 567 responses, 461 were selected for data analysis by deleting undesirable ones. This response rate was reasonable and better than many IS research studies. Then, a discussion of the descriptive statistical findings of every construct and its items was achieved. Additionally, the researcher observed how the proposed research model explained correlations between predictor factors and the outcome factor, i.e., BI, to adopt e-learning during COVID-19. As per the results, the dependent variable (BI) had a total variance of 61.1, which was justified by all its dependent variables. Among the constructs having a direct relation with BI, Perceived Usefulness explained the high variance followed by PEOU, Social Influence SI, System

Quality SQ, Cost CS, and COVID-19 CVD. These findings show that increasing PU, PEOU, social impact, and system quality while decreasing cost and COVID-19 (all of which are negative factors) would improve e-learning adoption among Pakistani students, especially in any pandemic situation like COVID-19. Likewise, PEOU predictors explained 39% of the variance, and Perceived Usefulness predictors explained 54.7% variance in descending order of significance.

This chapter concludes by presenting an in-depth analysis of the outcomes derived from hypothetical paths under the suggested research framework. Based on the results obtained from parameter estimation, fifteen hypotheses were formulated, out of which 13 were accepted, and two were rejected. Furthermore, perceived usefulness demonstrates partial mediation among factors, whereas perceived ease of use demonstrates full, partial, and no mediation among constructs.

CHAPTER SEVEN

CONCLUSION

7.1 INTRODUCTION

The conclusion chapter of this research work provides an overview of the research findings, assessing to what extent the study's objectives have been accomplished. Following the introduction, the researcher examines the study background and imparts a concise summary of the research objectives that have been met. Subsequently, an in-depth analysis resulting in theoretical and practical implications is discussed. Furthermore, this study investigates a comprehensive analysis of the valuable and substantial contributions in terms of theoretical advancements and practical applications. Finally, this chapter includes an overview of the research's limitations, as well as ideas, suggestions, and possible direction for future study.

7.2 REVIEW OF THE RESEARCH CONTEXT AND OBJECTIVES

E-learning can be referred to as the standard educational system which utilizes electronic resources. Here the term electronic resources mainly refers to education through computer and internet technologies (Aboagye et al. 2020). During COVID-19, education through online platforms made significant progress due to the need for more education alternatives. Several researchers predicted that e-learning would be the most feasible solution to continue educational activities in case of pandemic situations COVID-19, where social distancing would be necessary. Authorities recommend that alternative learning methods be considered during emergencies to mitigate the disruption of students' education and reduce the development of the pandemic (Maatuk et al., 2022). e-learning was the most effective method for preventing the spread of epidemics because it ensured physical separation (Lizcano et al. 2020). E-learning plays an essential part in the modern educational environment since it has introduced revolutionary changes to the entire

education system and has emerged as a highly favored subject among academics (Samir et al. 2014)

During COVID-19 e-learning provides several benefits, for example, it provides flexibility, which means that it can be accessed anytime from anywhere if there is connectivity. It saves time, and expenditure means there is no need for a particular place, just like schools and universities so the running cost for these places can be saved (Soni, V. D. 2020). Despite the number of benefits, the adaptation of e-learning has many challenges, particularly in underdeveloped countries like Pakistan; even before COVID-19, the pace of e-learning adaptation was relatively lagging due to the number of problems faced by the Government. Pakistan is a multi-lateral, multilinguistic country in the subcontinent of South Asia that made several efforts to implement information technology in the country so that e-learning can be adopted smoothly (Hussain, Wang & Rahim, 2013). In the past several distance learning programs such as the establishment of the Alama Iqbal open university, Virtual University of Pakistan, IP-based online lectures through video conference system, National Digital Library, and PERN (Pakistan Education Research Network) star to online education (Siddiquei, et al., 2020). Nonetheless, despite various efforts, Pakistan had several e-learning-related issues throughout COVID-19 even before COVID-19 required special attention from the researcher to study further.

The primary goal of the current research was to identify important factors that determine the adoption of e-learning during COVID-19 in Pakistan, using the theoretical foundation of a proposed research model. To fulfill the research objectives outlined in Table 7.1, a model was put forward theoretically, which was established on TAM as a base reference model along with external constructs derived from well-recognized information system theories and models. To formulate a research model for this study, a thorough and systematic review of pertinent scholarly works was undertaken, as detailed in Chapter Two. A thorough examination of prior empirical research investigations was carried out, emphasizing the application of numerous established theories and models in Information Systems and Information Technology. This review assessed the significance of these psychological theories and models to this research study's objectives. A comprehensive

examination of relevant literature has determined that the TAM is the most pertinent and appropriate theoretical framework for this study. The reason behind selecting the TAM as the basis for this current research was primarily driven by its simplicity, closeness, and focused emphasis on Information Systems (IS). However, while conducting a more extensive examination of the literature, it became apparent that the fundamental constructs of the TAM, namely PU and PEOU, were insufficient in identifying the key factors necessary to achieve the research objective effectively. Hence, additional important variables, such as COVID-19, Cost, System quality, Application complexity, Social Influence, Facilitating conditions, and Student learning motivation identified after an extensive literature assessment, were included in the suggested research model as outward constructs. Lastly, in Chapter Three, a proposed hypothetical model of identified endogenous and exogenous variables was given, debated, and validated.

The research model suggested that students' inclination to adopt e-learning during the COVID-19 pandemic can be impacted by many cognitive beliefs, together with PU, PEOU, COVID-19 concerns, cost considerations, system quality, application complexity, social influence, facilitating conditions, and student learning motivation. Furthermore, the constructs of PU and PEOU have been recommended as mediators in the relationship between external factors, such as social influence, application complexity, COVID-19, and facilitating conditions on the dependent variable's behavioral intention to adopt e-learning during the COVID-19 pandemic. Primary data for this research topic was collected by a quantitative cross-sectional field survey utilizing a Likert scale with seven points. The survey tool was put together by modifying items from previous research work on IS/IT adoption. Before conducting the primary survey, it was necessary to perform pre-testing and a pilot study. These first steps were undertaken to prevent potential ambiguities, errors, misinterpretations, or confusion in the survey items. Additionally, the purpose of these preliminary tests was to assess and evaluate the effectiveness of the survey instrument.

The survey instrument underwent revisions and modifications based on the comments collected during the pre-testing phase as stated in Chapter Four. After having a thorough screening of the final survey's data using established statistical tools such as IBM

SPSS and Smart-PLS, a total of 461 responses were incorporated into the analysis. The descriptive analysis, handling of missing values, and investigation of outliers were conducted using SPSS version 26.0. The suggested model was assessed and confirmed through the utilization of a two-stage method in structural equation modeling (SEM), specifically including the measurement model and the structural model. After thoroughly examining the data, the results revealed that the suggested predicted associations in the model received substantial support. Ultimately, the present study has obtained the necessary findings to address the research questions and effectively accomplish the intended aim and objectives specified at the start of the research. See Chapter One for more details. Table 7.1 illustrates the study objectives and the corresponding chapters whereby these objectives are accomplished.

Table 7.1 Achievement of Research Objectives

Research Objective	Achievement
1. To determine the significant factors influencing e-learning adoption during COVID-19.	Chapter 2
2. To propose a research model created on the Extended Technology Acceptance Model (TAM).	Chapter 3
3. To analyze the hypotheses in the suggested research model of e-learning adoption in Covid-19.	Chapters 5 & 6

In addition to the table indicated above, this study includes three research questions that directly correspond to the aims outlined in the same table. The responses to the research questions are deliberated subsequently.

Research Question One.

What are the key factors influencing the adoption of e-learning during the COVID-19 pandemic in Pakistan?

Answer: According to the study, the key factors influencing the adoption of e-learning during the COVID-19 pandemic in Pakistan are Perceived Cost, System Quality, Complexity, Social Influence, Facilitating Condition, COVID-19 (Lockdown and COVID fear), Student learning motivation, Perceived Ease of User (PEOU), and Perceived

Usefulness (PU). These variables were found to impact the behavioral intention to use e-learning in Pakistan during the COVID-19 epidemic. For more details see chapter No. Two

Research Question Two.

How student behavior influences the adoption of eLearning during the COVID-19 epidemic in Pakistan.

Answer: The study found that student behavior was influenced by several factors in their adoption of e-learning during the COVID-19 epidemic in Pakistan. These factors include Perceived Cost, System Quality, Complexity, Social Influence, Facilitating Condition, COVID-19 (Lockdown and COVID fear), Student learning motivation, Perceived Ease of User (PEOU), and Perceived Usefulness (PU). These factors impact the Behavioral Intention (BI) to use e-learning in Pakistan and were measured using a survey questionnaire and Structural Equation Modeling (SEM) analysis. The study revealed that PU, PEOU, SI, SQ, CS, and COVID-19 variables positively correlated with behavioral intention, whereas Cost and COVID-19 had a negative correlation with BI. For more details see Chapter No. three.

Research Question Three.

How to statically validate the proposed research model for identifying the significant factors influencing e-learning adoption during the COVID-19 pandemic

Answer: The study used the Structural Equation Modeling (SEM) analysis technique to validate the proposed research model for identifying the significant factors influencing e-learning adoption during the COVID-19 pandemic. The research model was constructed which is based on the Extended Technology Acceptance Model (TAM) and included external factors, such as COVID-19, Cost, System Quality, and Application Complexity. The hypotheses in the proposed research model were validated by analyzing the relationships among the variables in the model, and the Explanatory power and predictive relevance of the model were evaluated by examining the model predictors (R square, Q square, and F square) of the model. The study employed a range of statistical tests to assess Model reliability, including Factor loading, Indicator Multicollinearity, and the Cronbach's-Alpha test. The Model validity of the study was established using Convergent Validity, which involved measuring the average variance of the components. Discriminant validity

was also assessed by the Fornell and Larcker Criterion, Cross loading, and the Heterotrait-Monotrait Ratio (HTMT) test.

The findings of this study have significant consequences and contributions that are advantageous to the existing body of knowledge on innovation. These outcomes are valuable for scholars, policymakers, and practitioners in the field. The subsequent sections offer comprehensive analyses and essential instructions about these subjects.

7.3 CONTRIBUTIONS TO THEORY AND METHODOLOGY

The findings of this investigation offer several theoretical and methodological advancements. To begin with, this study has contributed to the existing body of knowledge on innovation adoption and the literature on information systems (IS) about the adoption of e-learning in the COVID-19 epidemic, with a specific focus on underprivileged countries like Pakistan. Hence, it has the potential to enhance understanding and expand information relating to the processes of adopting innovations in an era illustrated by the rapid evolution of new technology. Furthermore, this study has assessed and examined the feasibility of several ideas and concepts relating to the adoption and dissemination of innovation, originally formulated for more developed nations, to compare challenges inside developing nations. The present study has analyzed a comprehensive framework consisting of many components derived from prominent and established theories frequently employed in the study of information system adoption. The extended conceptual framework was constructed through an extensive examination of existing literature to gain a thorough understanding of the study on technology adoption.

According to the researcher's best estimates, this study represents a unique attempt to validate the constructs of known theories and models on adopting information systems/information technology (IS/IT) within an underdeveloped country, Pakistan. This research fills a critical gap in the existing literature by identifying the variables that affect students' adoption and utilization of e-learning during COVID-19. This investigation is grounded on theory and employs empirical methods to contribute valuable findings. The

second theoretical proposition of this study suggests that, despite the widespread and influential usage of the TAM and the adoption and usage behavior of new information systems and services, numerous studies have identified certain limitations and areas for further exploration (Mailizar & Damon Burg, 2021; Sarosa, S., 2021; Alkhawaja et al., 2021; Al-Marroof et al., 2021; Al-Rahmi et al., 2019; Prasetyo et al., 2021; Sukendro et al. 2020).

According to these scholars, it has been argued that the ability of the Technology Adoption Model (TAM) to effectively explain user adoption of new Information Systems (IS) should not be assumed. It is recommended that researchers enhance TAM by incorporating pertinent constructs from the existing IS literature to obtainable and valid results. Consequently, the current study expanded the (TAM) Technology Acceptance Model by incorporating pertinent constructs derived from established Information Systems (IS) theories, namely IDT, the TAM2 by Davis and Venkatesh, and UTAUT by Venkatesh. The selected constructs and variables from these theories include Perceived Cost, System Quality, Application Complexity, Social Influence, Facilitating Condition, Student Learning Motivation, the impact of the COVID-19 epidemic, PEOU, and PU examine the influence on behavioral intention for the adoption of e-learning during the COVID-19 pandemic.

Subsequently, the empirical verification of the suggested integrated theoretical framework significantly contributes to academic circles by enhancing knowledge of e-learning adoption during pandemics while also increasing the exploratory ability of the TAM. Therefore, the empirical verification of the model suggests that it is valid and can be frequently utilized to investigate and achieve enhanced results in comparable contextual environments. In addition, no previous research has ever compared TAM with COVID-19 as a construct based on the opinions of both students and teachers in an e-learning context in Pakistan. Generally speaking, the survey instrument that was designed and validated in this study has the potential to be applied in examining the adaptability and usage patterns of other new information systems services and technologies.

Third, the outcomes of this work revealed that the primary constructs of the TAM, namely PEOU, and PU, can be influenced by certain external circumstances. These factors account for 39% and 54.7% of the variation, respectively, in descending order of significance. Moreover, it is observed that perceived usefulness plays a role in partial mediation concerning the constructs being studied. Conversely, PEOU exhibits various levels of mediation, including complete, partial, and no mediation, among constructs. Fourth, to obtain comprehensive and representative results that reflect the perspectives of the entire nation, this study employed a clustered sample methodology. Valuable feedback was gathered from five geographically diverse locations inside Pakistan. The audience of choice consisted of students and teachers from public sector universities, encompassing individuals from various age ranges. Furthermore, concerning methodological developments, this study employed comprehensive statistical methodologies to examine the suggested theoretical framework. The descriptive data analysis was done in SPSS 26, followed by SmartPLS, a more advanced tool, to analyze and validate the hypothetical model. As a result, employing these complicated and advanced statistical methodologies and approaches considerably contributes to examining the adaptability of an information system.

7.4 RESEARCH IMPLICATIONS

This study includes various implications for scholars, e-learning platform service providers, govt. bodies, and higher education institutions. The implications can be categorized into two primary groups, namely practical implications, and theoretical implications. The subsequent section provides a comprehensive analysis of each category.

7.4.1 Practical Implications

The study has yielded significant findings highlighting numerous practical implications of great value for e-learning platform service providers, higher education institutions, government organizations, and other stakeholders involved in e-learning during COVID-19 in Pakistan. The belief elicitation approach has discovered distinct outcomes that have

been further validated through empirical study. These findings serve as crucial guidelines for higher education institutions and e-learning service providers. Identifying key factors that drive students' interest in using e-learning, particularly during a COVID-19 pandemic, can assist stakeholders in properly prioritizing and allocating resources in the future.

The significance of perceived usefulness has become a crucial determinant in shaping the user's behavioral intention toward the adoption of e-learning. To enhance user engagement and motivation, service providers must establish trust among potential users. The development of e-learning systems should prioritize considering learners' needs and preferences. It is required to ensure that the features and functionalities of the platform match with learners' perceptions of usefulness for their educational endeavors.

The identification of system quality construct was found to be a significant factor in e-learning adoption during COVID-19. The term "system quality" pertains to the technical components of an e-learning platform, encompassing its features, reliability, performance, and usability. For the students' significant behavior intention, ensuring a high-quality system is critical. e-learning platform designers should ensure that the e-learning platform is consistently available and reliable. Downtime or technical glitches can disrupt learners' progress and negatively impact their experience. Moreover, they should optimize the platform for fast load times and responsiveness. Slow loading can frustrate learners and hinder their engagement with the content. Their platform should be compatible with various devices and browsers. Learners should be able to access the content seamlessly from different devices. System designers may guarantee that students will have a good time using their e-learning system if they pay attention to these technological details.

It is critical to recognize that this study found that potential adopters of e-learning during COVID-19 were quite sensitive to cost-related factors. This suggests that in the context of a struggling economy in Pakistan, where a significant portion of the student population comes from the middle class, there was notable anxiety regarding the expense associated with using e-learning. The expenses associated with mobile devices, personal computers (PCs), tablets, internet connectivity, and other pertinent computer peripherals

necessary for participating in or facilitating online educational courses are still above the average user's expectations. It is recommended that the government should consider implementing tax incentives for IT hardware importers to reduce the hardware cost. Additionally, it is suggested that the Pakistan Telecommunication Authority be directed to mandate mobile operators to introduce affordable internet packages.

This study identified application complexity as a significant construct, referring to the level of difficulty experienced by students when utilizing e-learning platforms or software during the COVID-19 pandemic. Ensuring a user-friendly and effective learning experience requires application designers to manage their applications' complexity carefully. They should develop a streamlined and user-friendly interface that effectively reduces unnecessary complexities. A user-friendly interface enhances the ease with which learners can browse and engage with the platform.

It is essential to arrange the information and navigation coherently and systematically. Well-organized menu structures and easily navigable pathways facilitate learners in locating the desired information without experiencing confusion or disorientation. Finally, it is recommended to maintain a simplistic and uncomplicated design approach. It is advisable to stay away from overwhelming the interface with an abundance of images, animations, or interactive components that have the potential to perplex learners. By considering these recommendations a better learning experience and higher levels of student engagement can be achieved.

Another construct revealed by this study, COVID-19, has significant practical consequences for e-learning, resulting in the rapid adoption of this method of instruction and a shift in the delivery of educational content. COVID-19 appears as a global health issue and highlights the need to hold digital literacy skills. Students and teachers were expected to improve their proficiency in using e-learning tools and technology to fully participate in distance education. The importance of open educational resources and digital libraries has been highlighted among those affected by the pandemic, as they have supplied a large diversity of materials to support e-learning efforts. Educational institutions and

instructors have conducted trials using unique pedagogical methodologies, educational technology tools, and instructional approaches to effectively engage learners inside the virtual learning environment. Even when the epidemic declines, the experience of widespread e-learning adoption has prompted researchers to investigate long-term hybrid education models that integrate in-person and online learning.

The COVID-19 epidemic has focused attention on the practical implications of e-learning, emphasizing digital education's potential flexibility, adaptability, and transformative capabilities. The pandemic created numerous challenges, but it also accelerated the improvement of teaching approaches and the integration of technology into the educational sector.

This study found that throughout the COVID-19 epidemic, the concept of social influence, including the effects of others' opinions, recommendations, and behaviors on a person's decision process, has proved beneficial in the context of e-learning. The likelihood of learners using e-learning platforms was higher when they received recommendations from their peers. The encouragement from their classmates or friends influenced the learners' engagement with online learning tools. Internet forums, conversations, and social networking platforms have all played important roles in developing social learning communities. Learners can participate in knowledge-sharing by discussing experiences, asking questions, and seeking advice from their peers, resulting in higher levels of engagement. The COVID-19 health crisis has brought to light the importance of collaborative learning. Social influence was critical in motivating students to actively participate in collaborative activities such as group projects, virtual dialogues, and peer-to-peer relationships.

Moreover, COVID-19 produced social pressure that pushed teachers and educational institutions to address students' concerns and reservations about e-learning. Concerns were addressed by providing clear information about the benefits and available support. The concept of social influence emerged as a critical aspect in supporting the timely integration of e-learning within the context of the COVID-19 outbreak. The

recommendations, behaviors, and support of other students, educators, parents, and institutions provided influenced how learners used and engaged with online learning platforms.

To summarize, the belief gathering data approach has discovered distinct outcomes that have been experimentally validated in this research. These findings offer valuable guidance for e-learning service providers, application designers, instructors, government agencies, and higher education institutions. The results of this study guide individuals and organizations involved in developing and optimizing software platforms, prioritizing service provisioning, formulating relevant policies, and improving efficiency. These findings aim to boost the adoption of e-learning in the country.

7.4.2 Theoretical Implications

Taking a theoretical approach, the results of this study revealed significant implications for academics seeking to understand the practical considerations surrounding the implementation of new information systems, mainly in the situation of e-learning during a pandemic.

First, this study expanded upon previous research on the TAM by including extra external factors, namely Application Complexity, System Quality, Cost, COVID-19, Social Influence, Facilitating Condition, and Student Learning Motivation, alongside its essential predictors of PU and PEOU. The investigation specifically focused on the context of e-learning in the COVID-19 epidemic. Including external variables highlights the significance of students' interpretation of the evolving notion of e-learning. At the same time, the fundamental principles of the TAM propose that these beliefs serve as mediators.

Second, this empirical investigation and extensive explanatory models contribute to the structure of understanding in the context of underdeveloped nations. Previous studies on the adaptability of IS have mostly focused on developed nations. For this reason, there is a substantial gap in understanding the extent and reach of modern IS in growing countries

such as Pakistan. As a result, the model tested empirically in this work can be used to evaluate the adoption of relevant information systems, such as software created for online education.

Third, using a multi-method strategy in this research study, which includes numerous data-gathering methods such as WhatsApp, electronic mail, and online web-based questionnaires, considerably improves its scholarly worth. Furthermore, the utilization of the Structural Equation Modeling (SEM) technique, specifically employing the SmartPls4 application pack, to examine and authenticate the hypothetical model in this research provides a supplementary theoretical contribution to the scholarly body of knowledge.

7.5 LIMITATIONS

Although the empirical investigation has shown optimistic results that support the hypothesis elicitation process, it is imperative to recognize the constraints of this study.

The first potential constraint of this research's feasibility is the data collection process, as the information obtained for this investigation was derived exclusively from individuals residing in Pakistan. Additionally, the research design employed a cross-sectional approach, which involved data collection at a singular moment in time and relied on quantitative methods. As per previous research has shown that people's perspectives can shift over time (Davis and Venkatesh, 2000; Davis et al., 1989). Longitudinal data collection could be used in subsequent studies to investigate adoption behavior more extensively before and after the implementation of e-learning, supporting the reliability of the results.

Second, due to the limited sample size and the narrow scope of the investigation, the research's use is limited. As a result, it is recommended that further samples and constructs be collected in order to undertake additional investigations on the relationships before making generalizations based on the obtained data.

Third, the model under consideration was evaluated within the specific perspective of Pakistan, and it is imperative to acknowledge that the results obtained may differ when applied to other developing countries. Furthermore, the data utilized in this study was obtained from volunteer settings, which may need to be revised. This means that its results might not apply to compulsory contexts.

Fourth, the data collection process was limited to major urban locations in Pakistan, primarily due to time and cost constraints. Unfortunately, respondents from rural areas were not included in the survey, resulting in their exclusion from the data analysis. Hence, in order to make comprehensive generalizations, it is imperative to do further research that incorporates feedback from these overlooked areas.

Fifth, because this study was designed to test a particular approach related to a specific field of IS, namely e-learning, carefulness should be exercised before generalizing the results to other information technology and information systems apps and user groups.

7.6 RESEARCH FURTHER DIRECTIONS

The present study has formulated an extensive integrated model that offers an effective understanding of the student's adoption of e-learning during the COVID-19 epidemic. First, the present study has the potential to be transformed into a qualitative research design, employing a case study methodology, in order to explore the user's adoption of technology. Second, the investigation of e-learning adoption during the COVID-19 pandemic can be approached from a broader perspective by considering cross-cultural influences. Third, the present study employed behavioral intention (BI) as the dependent variable within the proposed research framework. Further studies could be undertaken to examine and explore the actual use of e-learning, as opposed to its intended application. Fourth, the present study examined the direct and mediated effects of specific Covid-19 factors. However, future research should consider measuring its moderating impact on many constructs, such as Cost, Social influence, and facilitating settings.

In conclusion, while the research model demonstrates a promising level of explained variance ($R^2 = 61.9$), future studies could benefit from incorporating alternative theories of information systems (IS) adoption, such as UTAUT2. By including additional factors from the IS literature, such as Student engagement, Student satisfaction, Learning Outcomes, Self-Efficacy, Learner Autonomy, Personalization, Assessment, and Digital Literacy, researchers can enhance the overall variance explained by the model.

7.7 CHAPTER SUMMARY

This chapter aims to present the findings and conclusions derived from the research investigation. Initially, a comprehensive examination of the research context and its aims was provided to ascertain the extent to which the objectives of the current study have been achieved. Furthermore, the researcher has identified several valuable methodological and theoretical aspects of this work, as indicated by the research findings. Similarly, an examination of many research implications, both theoretical and practical, was conducted. Finally, it highlighted the need to identify study limits and provide comments and suggestions for future research endeavors.

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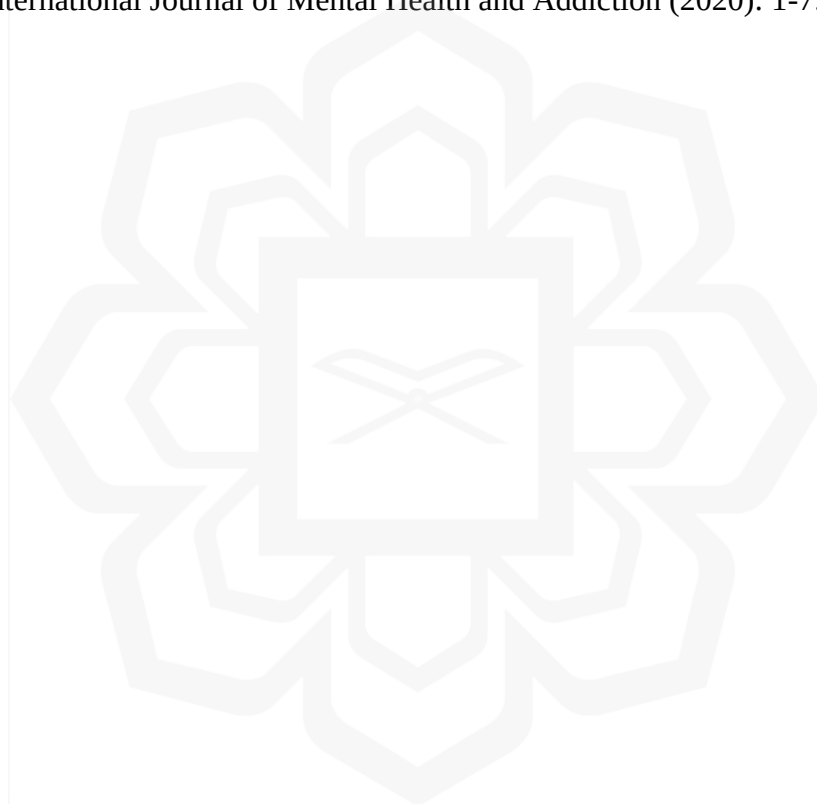
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APPENDIX A

LIST OF PUBLICATIONS AND PRESENTATIONS

1	Paper Title	Moderating Effect of Covid-19 On E-Learning Predictors: An Empirical Study on Student's Perspective in Pakistan
	Journal	International Journal of Membrane Science and Technology, 2023, Vol. 10, No. 4, pp 536-549 (Scopus Index)
	Statutes	Published
2	Authors	Imran khan Keerio, Asadullah Shah, Krishan Kumar Luhana, Najhan Muhammad Ibrahim, Hazwani Mohd Mohadis
	Paper Title	A Framework of E-Learning Challenges During Covid-19 In Higher Education Institutions of Pakistan
	Journal	Journal of Information Systems and Digital Technologies (Non-Index)
3	Statutes	Published
	Authors	Imran khan Keerio, Asadullah Shah, Masoomi Hifazat Ali Shah, Najhan Muhammad Ibrahim, Hazwani Mohd Mohadis and Imran Ahmed Qureshi
	Paper Title	A Conceptual Framework for Moderating Effect of COVID-19 on e-Learning Predictors: An Empirical Study on Student's Perspective in Pakistan
4	Conference	ICETAS 2023 – 8th International Conference
	Statutes	Published
	Authors	Imran khan Keerio, Masoomi Hifazat Ali Shah, Najhan Muhammad Ibrahim, Yaqoob Koondhar, Voltisa Thartori, Asadullah Shah, Hazwani Mohd Mohadis
4	Paper Title	Development of conceptual framework-Teaching quality of academicians towards MOOCs in higher education in Pakistan.
	Journal	Journal of Information Systems and Digital Technologies (Non-Index)
	Statutes	Published

Authors	Hifazat Ali Shah Masoomi, Asadullah Shah, Imran Khan, Norsaremah Bt Salleh and Abdul Abdul Rafiez
Paper Title	Upgrade Student Engagement in Online Discussion
Journal	Global Educational Studies Review, VIII(II), 167-176. https://doi.org/10.31703/gesr.2023(VIII-II).16
Statutes	Published
Authors	Kirshan Kumar Luhana, Imran Khan, Ali Raza



APPENDIX B

QUESTIONNAIRE

Section 1 of 12

Factors affecting the slow adaptation of E-Learning during Covid-19 in Pakistan

Dear Respondent,

This survey is being carried out as part of my Ph.D. research project to understand the adoption of eLearning during Covid-19 and to identify the factors affecting its slow adoption in Pakistan

eLearning during Covid-19 is defined as the activities through online platforms using computing devices to provide learning facilities anywhere and anytime, especially during a covid-19 crisis where social distancing was mandatory.

I want to invite you to be a part of this research study. Please answer the questions freely. You cannot be identified from the information you provide. The questionnaire on the google form should take about 10 - 15 minutes to complete. Please, spend only a little bit on any questions. Your first thoughts are usually your best!

Even if you feel the items covered may not apply to you, please do not ignore them. Your answers are essential in building an accurate picture of the critical issues to identify factors affecting the slow adoption of eLearning during covid-19.

I hope you find completing the questionnaire enjoyable and thank you for taking the time to help. If you have any queries or would like to have further information about this research, please get in touch with me: at i.khan@live.iium.edu.my

Thank you for being so cooperative.

Email *

Valid email address

This form is collecting email addresses. [Change settings](#)

Gender *

☐ Male

☐ Female

Occupation *

☐ Student

☐ Faculty

Age (years) *

☐ Less than 20

☐ 21-30

☐ 31-40

☐ 41-50

☐ 51-60

☐ More than 60

Education *

☐ Less than high school

☐ High school

☐ Intermediate

☐ Diploma

☐ Under graduate

☐ Graduate/ MS

☐ Post-graduate

University Name

Long-answer text

Area

☐ Urban

☐ Rural

Do you use an internet-connected smartphone, tablet, PC, or laptop? *

☐ Yes

☐ No

How long have you been using the Internet on your cell phone/tablet, PC/laptop? *

☐ Less than 1 year

☐ 1-2 years

☐ 3-4 years

☐ 4 years

☐ more than 5 years

Have you ever used eLearning before covid-19? *

☐ Yes

☐ No

How often do you use eLearning during covid-19? *

☐ Daily

☐ Weekly

☐ Monthly

I intend to use eLearning as often as needed during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Some what Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I intend to continue using eLearning in any covid-19 type situation. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Some what Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Assuming I have access to eLearning, I intend to use it. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Some what Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Given that I may have eLearning access, I predict I will use it. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Some what Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I will strongly recommend others to use eLearning in the type covid-19 situation. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Some what Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

In covid-19, using eLearning enabled me to accomplish my academic tasks more quickly. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Using eLearning increased my academic productivity and performance during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Using eLearning make it easier for me to engage in online educational activities during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Using eLearning enabled me to access much information during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Overall, I found practical learning. In covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Through eLearning, I found that what I wanted via eLearning was easy during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

My interaction with eLearning was clear and understandable during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I found eLearning to be flexible in interacting during covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

It was easy to remember how to use eLearning during covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Overall, I found eLearning easy to use. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The eLearning system I used for online classes was always available when and where needed. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The eLearning system I was using for online classes responds quickly during the busiest hours of the day *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The response time of the eLearning system I was using for online classes was consistent *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The eLearning system I was using for online classes was reliable *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The eLearning system I was using for online classes makes Information easier to access *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The equipment cost was expensive for using eLearning during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The access cost was expensive using eLearning during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I think the internet packages cost was expensive for using eLearning during covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

There were financial barriers to my use of eLearning during covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The software platform I was using for online classes was user-friendly. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The software platform I was using for online classes was easy to navigate *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The software platform I was using for online classes was well structured *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The software platform used for eLearning operates sufficient features *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The software platform used for eLearning functions is considered to be satisfied *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

During covid-19, the lockdown affected my financial assets, which involved my use of online education. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

During covid-19, the lockdown affected required facilities for conducting or taking online classes, which involved my use of online education. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

During covid-19, the lockdown affects my online education's ease of use. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I believe that during covid-19, the lockdown put stress and anxiety on me and my colleagues/fellows, which turn into an effect on the use of online education.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I believe that during the covid-19 lockdown, online learning was not helpful to me

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

People who influence my behavior think that I should use eLearning during covid-19.*

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

People who are important to me think I should use eLearning during covid-19.*

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I will use eLearning if my colleagues/fellows use it. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I would use eLearning if people in my community widely use the service. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Mass media reports influenced me to try out eLearning during covid-19. *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I had all the necessary resources available for eLearning during covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

I experienced a power failure which turned to effect on my online classes in covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

The speed of the internet connection was sufficient to take online classes during covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

It was easy to get the knowledge necessary to use eLearning.*

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

A specific Person (or group) was available for assistance during covid-19.*

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Attending online classes through eLearning saves travel time, money, and energy for students *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Through eLearning, students can achieve better grades exceptional in covid-19 type situation *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Online classes were convenient and flexible during covid-19 *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

Through online classes, students can improve their real-time skills *

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Somewhat Disagree
- ☐ Neither Agree Nor Disagree
- ☐ Somewhat Agree
- ☐ Agree
- ☐ Strongly Agree

APPENDIX C

PREESTING

