DETERMINING THE FACTORS INFLUENCING OF MOBILE LEARNING

BY

KAZI SULTANA MARGIA

ID No: 213-15-14790

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised by

Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

Co-Supervised by

Amir Sohel
Senior Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH
JULY, 2024

APPROVAL

This Project titled **"Detemining the factors influencing of mobile learning"**, submitted by **"Kazi Sultana Margia"**, ID No: **213-15-14790** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on July 16, 2024.

BOARD OF EXAMINERS

Narayan Ranjan Chakraborty (NRC) — **Board Chairman**
Associate Professor & Associate Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Naznin Sultana (NS) — **Internal Examiner 1**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

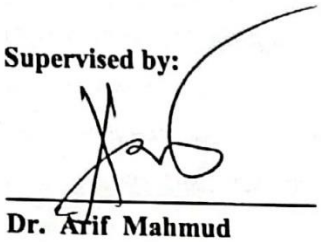
Raja Tariqul Hasan Tusher (THT) — **Internal Examiner 2**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Ahmed Wasif Reza (DWR) — **External Examiner**
Professor
Department of Computer Science and Engineering
East West University

DECLARATION

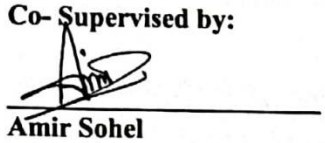
I hereby declare that this project has been done by us under the supervision of **Dr. Arif Mahmud, Associate Professor & Program Director MIS, and Department of CSE** at Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:



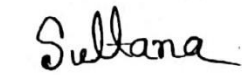
Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

Co- Supervised by:



Amir Sohel
Senior Lecturer
Department of CSE
Daffodil International University

Submitted by:



Kazi Sultana Margia
Id Number: 213-15-14790
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First, i express our heartiest thanks and gratefulness to almighty God for His divine blessing makes me possible to complete the final year project successfully.

I really grateful and wish our profound our indebtedness to **Dr. Arif Mahmud, Associate Professor & Program Director MIS, Department of CSE** Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "Structural Equation Modelling" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

I would like to express our heartiest gratitude to **Dr. Sheak Rashed Haider Noori, Professor & Head**, **Department of CSE**, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

I would like to thank my entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

The huge and rapid development of mobile devices as well as information and communication technology has resulted for modern technology that is Mobile Learning. The prevalence of mobile learning is becoming commonplace day by day in the whole world. M-learning has become an excellent medium of learning. Mobile devices is for Mobile learning that is constantly growing technology and mobile devices have successfully mixed into people's lives, and the use of m-learning is being used more frequently. Educational institutions all over the world are using connectivity, location- based learning, personalized learning, social interaction, and movability, increasing interest in creating mobile learning (ML) environments due to the benefits of affordability and greater ubiquity. Therefore, it is crucial to determine and explore the factors that can influence the user's interest to use m-learning and the results of its use can affect the nation and its development of any country. Empirical tests have been carried out using the proposed framework especially using questionnaires from students. Its results revealed that effort expectancy, performance expectancy, belief expectancy, self-management of learning, system efficacy, and social influence are significant determinants of m-learning assumption. These findings have important implications for both research and practice in the field of education. Moreover, this study sheds light on the reasons why the use of e-learning has not been adopted before. Smart PLS can identify user satisfaction, loyalty, behavioral, intentions, and practical behavior by using smart PLS, and two other models are used, which are ASE and ISS, with which the given dataset is analyzed.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Technology has become essential in our daily lives these days. Technology contributes to everything we do. And it cannot be denied, that in the education system, it is used incomparably. Using technology helps to gain information and experience extensively and this concept is m-learning. By using M-learning, many opportunities and benefits are available, which were not available in traditional learning methods earlier. M- Learning is a modern method of education. In the education field, m-learning provides a crucial learning environment anywhere, anytime using a Mobile device. Numerous social, technological, cultural, and educational factors influence how widely ML is adopted. It is important to explore the reasons why ML is being influenced as the digital world evolves and mobile technology becomes increasingly prevalent. One ML uses tablets, smartphones, iPads, and other handy devices as learning mediums. Mobile devices are used to create a convenient, adaptable and high-quality learning setting. Rapid development of mobile technology such as mobile devices is necessary to increase the popularity of ML. Availability of the internet, affordability of devices, and features further increase the possibilities of ML. The advent of mobile technology ushers in a new transformative era in the education system. Through mobile learning, anyone can gain knowledge from anywhere in the world. Many factors affect m-learning, among them, determining the special factors is the work of this research. A new age of education has begun with the introduction of mobile technology, where dynamic, learner-centric approaches are replacing old limits. Leading this growth is mobile learning, which is the integration of mobile devices into educational activities. .Considering the prospective for mobile learning to significantly transform the acquisition and distribution of information, this study aims to sort through the complex web of factors influencing its adoption. By highlighting mobile learning as a driver for educational innovation and outlining the variety of components that

enable its effective implementation, the introduction creates the groundwork for a thorough examination. Many factors that affect mobile also affect how well and widely mobile devices are used in learning environments.

1.2 Motivation

The various factors are there that is support the adoption & effectiveness of mobile learning contribute immensely to components of mobile learning such as usability, functionality, design, content, system, and service quality. When the components work properly and effectively and meet and satisfy the needs of the learners, it encourages them to interact with the mobile learning environment, the various creative activities of mobile learning are influenced by the students to realize various economic benefits, social interaction, relevance, usefulness, and enjoyment. And by various factors including convenience of use students tend to use mobile devices for their educational needs when they have positive knowledge and perceptions about these attributes. And the motivating factor is the caliber of the teaching materials. And when students believe that learning through mobile devices is in line with their learning objectives. The information provided by the ML platform is engaging and relevant to their needs, they are more attracted to it and its popularity is growing dynamically. Advances in mobile technology inspire educators, and students to fully utilize the capabilities of tablets and smartphones. Students are motivated to engage with multimedia information, and educators see opportunities to develop innovative educational approaches and enhance the learning process through technology. Many organizations use mobile learning to reduce costs and maximize utilization of their organizations. Due to the cost-effectiveness, scalability of mobile platforms, and digital content delivery that reduces reliance on physical infrastructure, education has become more and more economically viable as technology permeates more and more aspects of everyday life. . Educators also try to encourage students to use it responsibly and ethically and students are motivated to develop digital skills. The popularity of mobile learning has led educators and practitioners alike to test its ability to assist with virtual learning. ML is a special kind of electronic-learning and the independent part where the content is delivered only on mobiles, phones and tablets. ML is a popular medium for studying personal

behavioral motivation. One of the motivations of mobile learning is that it is easily accessible to everyone everywhere with be of service mobile devices.

Through this, it is progressing day by day as one of the world's education systems. Hopefully there will come a time when people will become completely dependent on mobile learning and its influence will be ubiquitous. Mobile learning platforms are proposed to be attractive, flexible, and easy to use. It encourages people for educational purposes. The rapid development of mobile technology inspires educators and students to take full advantage.

1.3 Rationale of the Study

It is necessary to clarify the rationale behind finding the factors influencing ML analysis. Providing meaningful information to students, institutions, educators, and policymakers by explaining these factors after clarifying how significant ML can change existing perceptions of education. In this increasingly international educational world, the purpose is to focus on how ML can be properly represented on global educational platforms. In short, the study's justification derives from its dedication to identifying the various ways in which ML influences. ML will lead to an accessible educational future for all. One of the arguments for ML is its rising popularity. Motivation can be considered a key argument for increasing student engagement in distance learning. Also, through mobile learning, communication with the teacher, distance learning, all become possible, so it is important to study it. Be it for professional training, or for personal reasons in today's daily life everything is available from mobile devices. Hence the interest towards implementation of mobile learning is strong. Mobile learning makes learning accessible and flexible which is lacking in traditional methods. Anytime access means training does not have to be done in the classroom, during office hours or in the office. Access learning resources from home, on commute and during breaks. It's convenient for just-in-time learning. Our technological age is undoubtedly advancing the career. Mobile learning increases completion rates is high. M-Learning courses are bite-sized, which helps the user to complete and switch courses.

1.4 Research Question

RQ1: What steps take to create a dataset?

RQ2: What are the significant factors affecting ML?

RQ3: How does the difference between technology infrastructure and availability affect people's propensity to engage in mobile learning?

RQ4: Which model is useable in this research paper?

RQ5: What kind of thesis is it? Why do you use smart PLS in this thesis?

1.5 Expected Output

This study looks at various factors that influence the reasons for using ML. A distinction is made here between age, gender, finances, and social environment i.e. what makes people prefer ML and what prevents them from using ML. It also explored the factors that make a school or organization suitable for using ML, and what factors might make it more difficult. The study also detailed what people can do to make ML better and more cost-effective. Moreover, this expected information can help teachers, managers, and policymakers how to use mobile learning anywhere, schools, colleges, universities, and other places. Expected Results the expansion of education expected through ML is nothing short of incredible. The only reason behind this is the advancement of technology. As ML is focused on adapting to the technology, the expected results will have a global impact very quickly. The effects of ML are explored based on teacher, student judgments.

1.6 Project Management and Finance

I have used real data for analyzing this research paper. So I have collected data and these data are survey- based & collected data from academics and students. I was pay some money for it. Then I used a special program called smart PLS to analyze the data and find patterns. And collected data through Google forms. There were many attributes in the form to ask questions. I shared the Google form with everyone and collected the data.

1.7 Report Layout

In this study, chapter 1 discusses the role and factor of influence ML. Also, chapter 2 discusses related work and previous work and problem quantification. Chapter 3 explains how I did my research, such as the description of the data I collected, data statistics, classifiers and statistical data. Chapter 4 analyzes the result, Using ML in Chapter 5, talks about how society influences our behavior. Finally, Chapter 6 summarizes and concludes everything.

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

Many studies have classified ML at variance ways based on the objective. According to Attwell (2005), "mobile learning and e-learning are the same that use wireless transmission and portable devices such as cell phones, PDAs, laptops and tablet PCs." Again, this doctrine has been given a different opinion by many who depend on technology another way Sharples (2007) states that learning across contexts is another way to characterize mobile learning by focusing on learner mobility while dealing with portable technology. According to Sanchrz al (2007), learning mobile is another way of mobile learning in society. The main focus is on how organizations and educational institutions are potentially adjusted satisfy an increasingly mobile population.

2.2 Related Works

A great number of research studies have looked at the impact of electronic devices & mobile technologies in educational settings on student learning. This section begins with an examination of the theoretical framework that guides such research efforts. Next, a thorough analysis of relevant academic literature and various studies related to mobile computing will identify potential factors that may influence the implementation of mobile learning. The m-learning adoption model used in this study takes these factors into account and is explained in the concluding section of the literature review. Khadija Alhumaid and colleagues (2019) explored artificial neural network (ANN) models for adaptation in mobile learning, resulting in a squared value of 0.487. This study used data analysis to simulate the impact of the COVID-19 pandemic situation. Qadri Nurul Hasan Naveed and others (2020) used the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) models, with core co- efficient values ranging from start 0.1 to 0.2.The study reveals significant values for all hypotheses, sheds

light on the external factors influencing the mobile-learning environment, and explains how both macro and micro factors influence m-learning adoption. The test employed Smart PLS and Structural Equation Modeling (SEM) using SPSS (V.25). ARAIN++ and AIJAZ (2021) using the UTAUT2 model and Smart PLS 3, show r squared values ranging from 0.1279 to 0.3086.

2.3 Comparative Analysis and Summary

Table 2.1. Comparative analysis results with earlier work

SL NO	Author Name	Used Model/Algorithm	outcome
1.	Khadija Alhumaid et al. [1]	ANN model.	R^2=0.487
2.	Amir Chavoshi. et al. [2]	TAM, UTAUT	Beta =0.1 to 0.2
3.	Quadri Noorulhasan Naveed. et al.[3]	TAM, UTAUT	Beta = 0.1 to 0.2
4.	AIJAZ. A. ARAIN++ et al. [4]	UTAUT2	R^2= 0.1279 to 0.3086
5.	Mary Helen Fagan et al. [5]	UTAUT	R^2=0.222 to 0.747
6.	Kallaya.et al. [6]	UTAUT	Beta=0.095 to 0.398
7.	Ahmad Abu-Al-Aish. et al. [7]	UTAUT	P= 0.01 to 0.03

8.	Mohamed Sarrab. et al. [8]	TAM	CR=0.729 to 0.846
9.	Yaneli Cruz. et al. [9]	UTAUT	Composite Reliability=0.92 to 0.96
10.	Said A. Salloum. et al. [10]	UTAUT	R^2=0.338 to 0.432
11.	Sailong Hu. et al. [11]	UTAUT2	Beta =0.1 to 0.2
12.	Mohammad Qasem Al-Hamad. et al. [12]	TAM	composite reliability= 0.759 to 0.889

2.4 Scope of the Problem

Here are drawbacks to m- learning that must be considered, just like with anything else. Mobile learning can expose students to distractions due to its lack of social interaction, excessive reliance on technology, lack of customization and exclusion of students without access to high-quality technology. Adoption of mobile learning is a wide-ranging topic that touches on a variety of facets of the learning environment. The disparities in learners' access to and utilize mobile devices is one of the main barriers to digital equity. The issue is made worse by differences in socioeconomic status, geographic location, and demographic traits, all of which have an impact on how fairly educational resources are distributed. Pedagogical strategies are another facet of the problem that necessitates research into effective teaching methods that take into account a variety of learning preferences and styles. Cultural adaptation raises the complexity even further, thus it's critical observe ways to improve the effectiveness of m-learning content and make it resonate in a range of cultural contexts. The importance of teacher preparation is highlighted by the need for educators to acquire the skills and knowledge required to effectively use mobile technology. The breadth of the issue includes developing frameworks for policies that provide equitable, inclusive, and moral ways to include mobile

learning devices into classrooms at all levels of education. By addressing this wide range, the study hopes to offer nuanced insights that assist direct strategies, policies, and practices for a more equitable, successful, and culturally sensitive adoption of mobile learning.

2.5 Challenges

Successful integration of mobile learning functionality can be challenging. One issue involves protecting data and data privacy, as it is critical to ensure the protection and preservation of sensitive information when using mobile devices for educational purposes. Overcoming these barriers requires students to secure data, implement suitable encryption protocols, and establish strong processes to maintain stored data. One of the challenges posed by mobile devices is content compatibility, ensuring that learning materials are compatible with the various screen sizes, operating systems and capabilities of these devices occur a daunting task. To find this problem solution it is very important to adapt the screen size, optimizing the work across platforms considering bandwidth limitations. Another obstacle to effective ML is the limited screen size of mobile devices. To overcome this challenge, students may engage in activities that require larger screens. Different content, UI design must take into consideration the smaller screens available on mobile, various distractions and unreliable internet access hinder the functionality of both platforms. Social media and app advertisements create distractions for students during distraction. Internet connection inconsistencies pose a significant challenge. Additionally, the limited battery life of mobile devices raises another real-world problem for ML. Battery life of mobile devices can reduce students' learning time. It is not always possible to study sitting in the charging zone Thus, there are challenges in providing educators and students with the necessary technical support and training for mobile learning research.

CHAPTER 3

RESEARCH SUBJECT AND INSTRUMENTATIONS

3.1 Research Subject and Instrumentations

The primary and principal objective of this research is to observe how and why students are interested and adapted to use mobile devices. This chapter provides an outline of the methodology/strategy utilized in this research, which is divided into several parts. First, the research presents evidence supporting paradigm choice. Secondly it conducts pre-primary examination and provides details including questions relevant to the population. The 3rd section deals with primary and minor issues including techniques used for sampling, determination of suitable sample size, data collection methods. The 4th section explores how to deal with data preparation, also including computation of missing data and common data technique. Difference treatment. Finally, instructions for executing data and information analysis are provided. In addition, the sixth and final stage highlights the software equipment used to analyze the data. Namely: using UTAUT(unified theory of acceptance and use of technology), ANN(Artificial Neural Network),PAM(Privileged Access Management),ISS(Information System Success) & ASE(Acceptance of Software Engineering) models, testing , was evaluated using the SMARTPLS platform for observation and training methods.

Variables	Codes	Ques.
System Quality		I find mobile learning quite intuitive to use.
		I find mobile learning to be flexible and easy to interact with.
		My engagement with mobile learning is clear and comprehensible.

Information Quality		M-learning disseminates up-to-date and contemporary knowledge.
		Mobile learning delivers reliable and accurate knowledge.
		Mobile learning offers pertinent knowledge.
		Mobile-learning provides comprehensive knowledge.
		Mobile learning supplies systematized knowledge.
Service Quality		I can access m-learning services whenever and wherever it is convenient for me.
		Mobile learning offers multimedia (audio, video as well as text) course content.
		M-learning facilitates interactive communication.
Intention to adopt	IA1	If given the opportunity, I would opt for m-learning.
	IA2	I am inclined to use m-learning.
	IA3	I am enthusiastic about embracing m-learning soon.
	IA4	I would embrace m-learning when the opportunity presents itself.
Attitude	ATT1	Using m-learning would be a beneficial idea.
	ATT2	The utilization of m-learning would be the wiser idea.
	ATT3	I would grab the opportunity of using m-learning.
	ATT4	I look forward to the enjoyable experience of adopting m-learning.

Social influence	SI1	I am eager to use m-learning because someone significant in my life encourages me to do so.
	SI2	I would use m-learning because my friends recommend it.
	SI3	I would utilize m-learning since it is strongly recommended by people who are important to me.
	SI4	I would like to use m-learning because it is advocated by people who inspire me.
	SI5	I am intrigued to use m-learning because my family members encourage me to do so.
	SI6	I would use m-learning because the majority in my social circle recommend it.
Self-efficiency	SE1	I would have complete control over the use of m-learning.
	SE2	I would be equipped with the tools and knowledge to apply m-learning.
	SE3	The use of m-learning would be convenient for me.
	SE4	I feel capable of using m-learning by myself.
Personal innovative ness	PI1	Ever since I learned about m-learning, I have been eager to find ways to experiment with it.
	PI2	In my peer group, I want to be the first to try mobile learning.
	PI3	Generally, I am open to experimenting with mobile learning and do not uncertain to give it a try.

	PI4	I would be like to study with m-learning
Perceived trust	PT1	I would be trust that m-learning would keep the and agreements and commitments they make
	PT2	M-learning is worthy of trust.
	PT3	I would rate m-learning to be honest.
	PT4	I believe that the mobile-learning will be responsible
	PT5	I would Generally say, I will have confidence in the m-learning
Symbolic adoption	SA1	I am very enthusiastic about utilizing mobile-learning
	SA2	I am enthusiastic about using m-learning.
	SA3	It is my wish to see full implementation of m-learning
	SA4	Do you use mobile-learning? (like notepad, short videos, online Q&A forums)

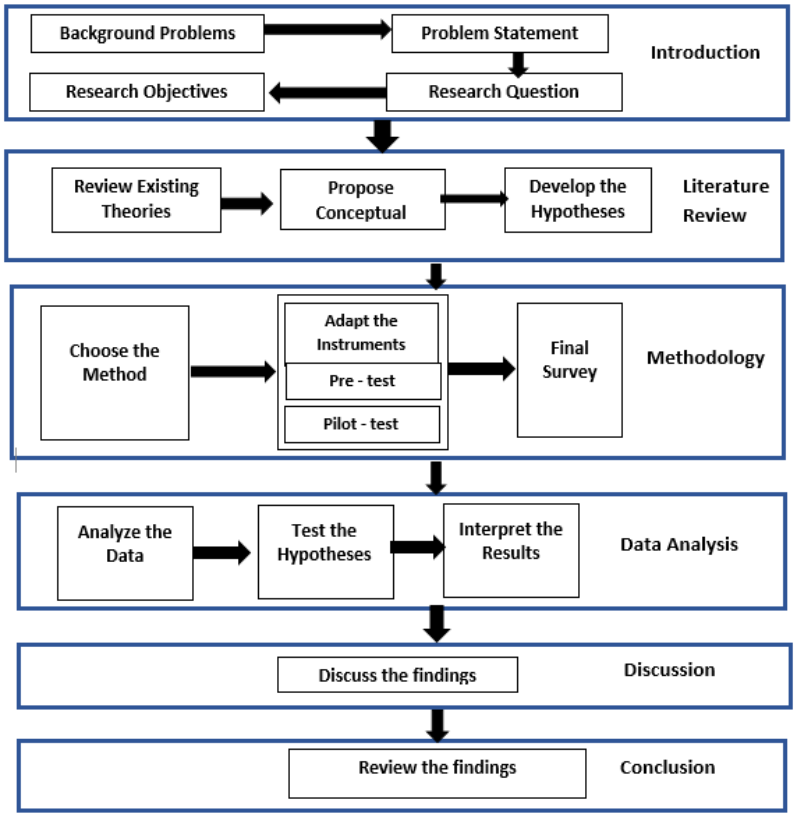


Figure 3.1: Research processing steps

3.2 Data Collection Procedure/Dataset Utilized

This study shows that it is important to collect the appropriate data. For this, I have collected the necessary data. Best data collection approach can include surveys, interviews, experiments, analysis of data, observations and more. Ethical issues associated with data collection are discussed, such as protecting participant rights, anonymity, consent, and confidentiality. First, a small sample of data collection instruments was pretested to detect and resolve any phrasing, clarity, or comprehensibility issues. Which is known as a pilot test. I made a Google form to collect the information through which I collected the data. I got about 348 responses from different students. All these data were collected from various sources. To collect the final data first 44 data sets were tested for pilot testing.

3.3 Statistical Analysis

The primary Statistical analysis is required for the elements required for ML acquisition. Various statistical methods have been used to verify data and extract important information. Factor analysis is one of the best commonly use of statistical analysis methods. It has made it easier to discover the many factors, factors, or dimensions involved that influence ML adoption. Regression analysis is also often used to evaluate the relationship between independent factors of human decision-making (like as perceived usefulness, ease of use, or attitude) through factor analysis. SMARTPLS Used for Statistical Analysis SMART PLS for SEM is a popular tool to use for test the association among latent variables. By inputting the collected data into SMART PLS, the measurement model was established by assigning the indicators to the appropriate latent variables. The validity of the measurement indicators was examine. In addition, the quality of the measurement model is determined by index loading, discriminant validity, convergent validity, (average variance extracted or AVE), relationships between variables can be expressed using the SEM model, and s SMART PLS is also used. Path coefficient, R-squared values, and other pertinent statistics to estimate the significance of the latent variable. SMART PLS is used in this thesis to predict how users will adapt to m Learning. There are 348 data collected.

Besides, 44 data for pilot test. As a result of statistical study, the essential variables can be known. Which has a great impact on people's decisions and successful impact on education environment.

3.4 Proposed Methodology/Applied

Methodology is the most important and essential part of a research. Methodology can easily achieve its objective successfully if it is used and planned properly. The technology used in learning ML is Smart PLS. There are two ASE and ISS models are used here. Also, Cronbach's Alpha, R Square, F Square and Path coefficient are used. Two well-established models are used here, ASE and ISS, which are proposed to find out the factors affecting

ML adoption. Since 2 models are used here. Each model has its own goals. The models offer a framework for evaluating and considering different aspects that motivate the utilize the learning of mobile. The objective of ISS model is quality of system & information, quality of services, personal attitude as well as user satisfaction. Besides, evaluating the effectiveness of the information system by considering many factors. We will further refine the ISS model to evaluate the acceptability, effectiveness of ML. It will help identify the essential elements of user satisfaction, ease of use, acceptability, system usability, content engagement with the ML platform in a thorough manner. Another used model is ASE.

Software engineering processes and acceptance are emphasized in the ASE model. The main purpose of the ASE model is consider factors including social influences, behavioral intention, favorable conditions, perceived functionality, and perceived simple use. ASE models are used to facilitate the adoption of mobile learning technology. To use these models, we can learn in detail about the ways in which people's preferences are influenced. Students and teachers will be given forms to complete to collect quantitative data on how they view various aspects influencing the assumption of mobile learning. A deeper qualitative discernment into participants' experiences and the reasons they are adopting or rejecting the use of ML will be obtained.

Here, regression analysis and structural equation modeling (SEM) have been used as statistical methods to analyze data. These analyses are used to explore the variables that have a major impact on ML. This methodology combines the ISS and ASE models with interview statistical analysis and literature review data to offer a holistic perception of the components influencing mobile learning assumption.

Demographic data:

Table 3.2. Demographic data

Items	Categorization	Occurrences
Uses of Mobile Learning	YES	323
	NO	25
Gender	MAN	261
	WOMAN	87
Age	15 to 20 Years	164
	21 to 26 Years	184
Academic Qualification	No admit Academic Degree	0
	SSC or Equivalent	7
	HSC or Equivalent	125
	Diploma or Equivalent	0
	Honours or Equivalent	216
	Masters or Equivalent	0
	PhD or Equivalent	0

3.4.1 Factor Loading

The variable items have been modified from the body of current literature. The degree to which the construct affects the indicators is measured by factor loading, known as "indicator loading". Additionally, it assesses the percentage of variance described by the respective latent variables (Urbach and Ahlenmann) requiring a minimum loading value of 0.7 for good outcomes. And if the loading value is less than 0.5, the factor should be removed from the measurement model.

3.4.2 VIF

Indicator Validity When 2 or more exogenous variables interact within a regression model that is known as indicator validity. Notably, the variance inflation factor (VIF) can be identified using the value. If VIF = 1 then VIF is not acceptable. That is not correlated and VIF is moderately correlated if 1<VIF<5 and if VIF> 5, then It is strongly related to VIF, any VIF value greater than 5 should be rejected otherwise, Urbach & Ahlemann, argue that 10 is the cutoff value for VIF.

.3.4.3 Internal Consistency Reliability

It is also known as internal consistency occurs when the indicator varies based on the underlying variable. This can be assessed using composite reliability. Significantly, the Composite Dependability value should be at least 0.7

3.4.4 Convergent Validity

The degree to which discrete module are related to appliances measuring discrete variables is known as convergent validity (Urbach & Ahlemann, 2010). Additionally, Average Variance Extracted (AVE) is average of squared factor loadings of a set of values, which is used as a convergent validity test. AVE is accepted.value is 0.5 .

3.4.5 Discriminating Validity

The degree of measurement of many variables is an aspect of discriminant validity (Urbach and Ahlenmann, 2010). This study decided discriminant validity according to Fornell and Larcker's (1981) method. Along with proceed towards, a latent variable could provide and difference more variance than any other variable with the specified indicators. To assess this restriction, the least squared correlation of each variable must be greater than (Hair et al, 2014).

Table 3.3 Summary of Validity Standards for the Measurement Model

Validity and Reliability	Criteria	Threshold Value and Guideline
Indicator reliability	Factor loadings (FL)	FL > = 0.5
Indicator validity	Variance inflation factor(VIF)	VIF < = 5 or, VIF < = 10
Internal Consistency Reliability	Composite reliability(CR)	CR > = 0.7
Convergent validity	Average variance extracted (AVE)	AVE > = 0.5
Discriminant validity	Fornell and Larcker(1981)	The AVE of each variable has to be larger than the maximum squared correlation of any other variable

3.4.6 Path Coefficient

Sometimes referred to as a weighted beta or standardized beta coefficient. Path coefficient is (Komalasari et al, 2015) which is a traditional relationship between components. Additionally according to Hair et al 2015 this coefficient has a range of +1 to -1, with both values potentially great significance. It is important to note that the minimum root coefficient value needs to be greater than 0.2 (Chain, 1998) or 0.1 (Lohmoller, 1989).

3.4.7 Coefficient of Determination

The association among describing a latent variable and its total variance is evaluated by the coefficient of determination or R2. According to Chin (1998) a poor, moderate and substantial explanatory power with weak, moderate and significant levels of 0.25, 0.5 & 0.75 respectively as per, hair et al (2014).

3.4.8 Cross Validated Redundancy

The predictive importance of the internal model can be confirmed using the cross validated redundancy (Q2) approach. The measured is predicated on the resampling method, whereby the parameters of the model are estimated and then the deleted category is predicted using the estimates Rindon, 2, specifically, the proposed threshold value is Q2>0 (Urbach & Ahlemann, 2010, hair et al, 2014)

3.4.9 Effect Size

Effect size assurance that a dependent variable is crucially affected by an independent variable (Urbach & Ahlenmann,2010). By ensuring f2 the researcher can calculate the effect size of each path in the structural equation model. Based on the f2 er value, the effect size can be classified as small (when 0.02<=f2<0.15), medium (when 0.15<=f2<0.35) or high(when f2>=0.35) (Hair et al, 2014). Additionally Sawilowsky 2009) notes that 0.01<0.02 can be considered a very small effect size.

Table 3.4 Summary of Validity Standards for the Structural Mode

Validity	Criteria	Threshold Value and Guideline
The validity of the model	Path coefficient (β)	$\beta > 0.1$ or, $\beta > 0.2$
	Coefficient of determination (R^2)	Substantial 0.67,moderate 0.33, weak 0.19 or, Substantial 0.75,Moderate 0.50, Weak 0.25
	Cross validated redundancy (Q^2)	Q2>0
	Effect size (f^2)	$0.01 <= f^2 < 0.02$ very small effect $0.02 <= f^2 < 0.15$ small effect $0.15 <= f^2 < 0.35$ medium effect $f^2 >= 0.35$ large effect

3.4.10 Hypotheses

H1: System quality is influenced by a positive attitude.

H2: Information quality has positive influence on attitude.

H3: Positive attitude is influenced by service quality.

H4: Attitude is influenced by self- efficiency.

H5; Social influence has positive influence on attitude.

H6: Attitude has positive influence on symbolic adoption.

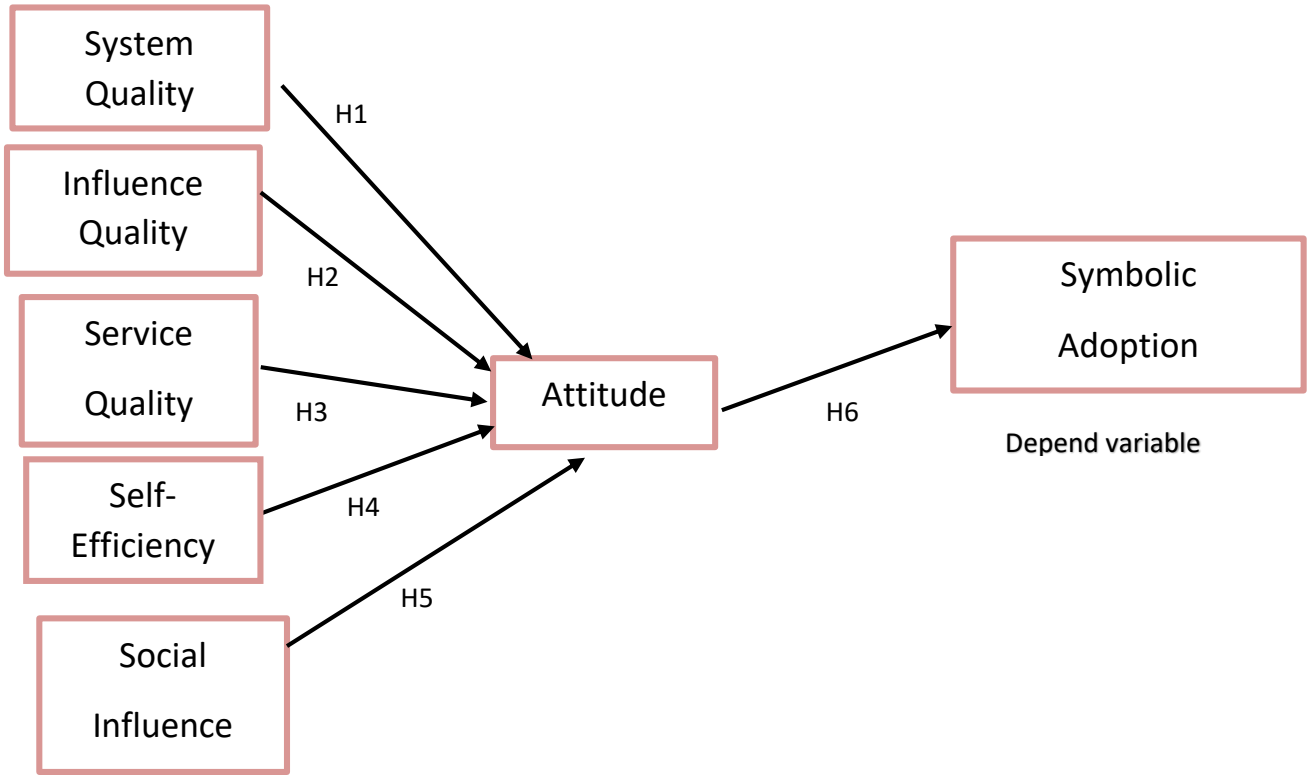


Figure 3.2: Proposed Research Mode

Here 6 hypothesis are used. Attitude and dependent variable are also used. All hypothesis depends on attitude and attitude depends on dependent variable. H1 hypothesis value is 0.292 which is connected with attitude. H2 value provides 0.195 attitude. In that same case H3, H4, H5 hypothesis values connected to attitude with the value 0.0205, 0.243, 0.161 respectively.

3.5 Implementation Requirements

The research requirements are:

- Windows 10 or above OS
- SSD/HDD of minimum space of 100GB
- Minimum 8 GB RAM

The developing Tools requirements are:

- Smart PLS
- PLS-POS, IPMA
- Complex Bootstrapping routines
- Browser

CHAPTER 4

EXPERIMENTAL RESULT AND DISCUSSION

4.1 Experimental Setup

A trained model is used for distinguishing correct and incorrect data from an experimental setup. Necessary and important steps for preprocessing after data collection are described. These include defining the models and scaling all survey data to fit the models' results. Provide empirical results to test the hypotheses of this study.

4.2 Experimental Results & Analysis

4.2.1 Factor Loading

Model reliability is assessed by looking at item loadings. Table 4.1 indicates that the factor loading values of the items are adequate and there is a strong correlation between the data.

Table 4.1: Indicator Reliability (Outer Loading)

	ATT	INFQ	SA	SE	SERQ	SI	SYSQ
ATT1	**0.917**						
ATT2	**0.884**						
ATT3	**0.920**						
ATT4	**0.888**						
INFQ1		**0.779**					
INFQ2		**0.840**					
INFQ3		**0.876**					
INFQ4		**0.875**					
INFQ5		**0.838**					

SA1			**0.881**				
SA2			**0.909**				
SA3			**0.866**				
SE1				**0.808**			
SE2				**0.890**			
SE3				**0.855**			
SE4				**0.910**			
SERQ1					**0.879**		
SERQ2					**0.918**		
SERQ3					**0.862**		
SI1						**0.858**	
SI2						**0.894**	
SI3						**0.889**	
SI4						**0.870**	
SI5						**0.877**	
SI5						**0.877**	
SYSQ1							**0.891**
SYSQ2							**0.834**
SYSQ3							**0.877**

4.2.2 Indicator Reliability

Validity is assessed using VIF. All components of the measurement model are checked to see if they are less than 10. (See Table 4.2).

Table 4.2: VIF value

	VIF
ATT1	**3.847**
ATT2	**2.782**
ATT3	**3.941**
ATT4	**2.784**
INFQ1	**1.821**
INFQ2	**2.356**
INFQ3	**2.877**
INFQ4	**2.823**
INFQ5	**2.239**
SA1	**2.230**
SA2	**2.565**
SA3	**2.011**
SE1	**2.029**
SE2	**2.901**
SE3	**2.371**
SE4	**3.244**
SERQ1	**2.341**
SERQ2	**2.707**
SERQ3	**1.964**

SI1	**2.715**
SI2	**3.420**
SI3	**3.245**
SI4	**2.816**
SI5	**2.937**
SYSQ1	**2.265**
SYSQ2	**1.740**
SYSQ3	**2.050**

4.2.3 Internal Consistency Reliability & Convergent Validity

CR (Composite Reliability) assesses internal consistency reliability. Table 4.3 shows that if greater than 0.7, greater is consistent and more reliable.

Convergent validity is assessed by measuring the AVE value, shown in Table 4.3

Table 4.3: Constant Reliability

	Cronbach's Alpha	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
ATT	**0.924**	**0.925**	**0.946**	**0.814**
INFQ	**0.897**	**0.899**	**0.924**	**0.710**
SA	**0.862**	**0.863**	**0.916**	**0.784**
SE	**0.889**	**0.897**	**0.923**	**0.751**
SERQ	**0.864**	**0.870**	**0.917**	**0.786**

SI	**0.925**	**0.926**	**0.944**	**0.770**
SYSQ	**0.836**	**0.838**	**0.901**	**0.753**
INFQ	**0.897**	**0.899**	**0.924**	**0.710**

4.2.4 Discriminant Validity

Discriminant validity was assessed by applying criteria developed by Fornell and Larcker Table 4.4 diagonal elements also indicate square root of AVE.

Table 4.4: Discriminate Validity

	ATT	**INFQ**	**SA**	**SE**	**SERQ**	**SI**	**SYSQ**
ATT	**0.902**						
INFQ	**0.712**	**0.843**					
SA	**0.753**	**0.649**	**0.886**				
SE	**0.738**	**0.656**	**0.716**	**0.867**			
SERQ	**0.724**	**0.685**	**0.641**	**0.712**	**0.887**		
SI	**0.700**	**0.606**	**0.750**	**0.660**	**0.572**	**0.878**	
SYSQ	**0.768**	**0.630**	**0.765**	**0.714**	**0.646**	**0.735**	**0.868**

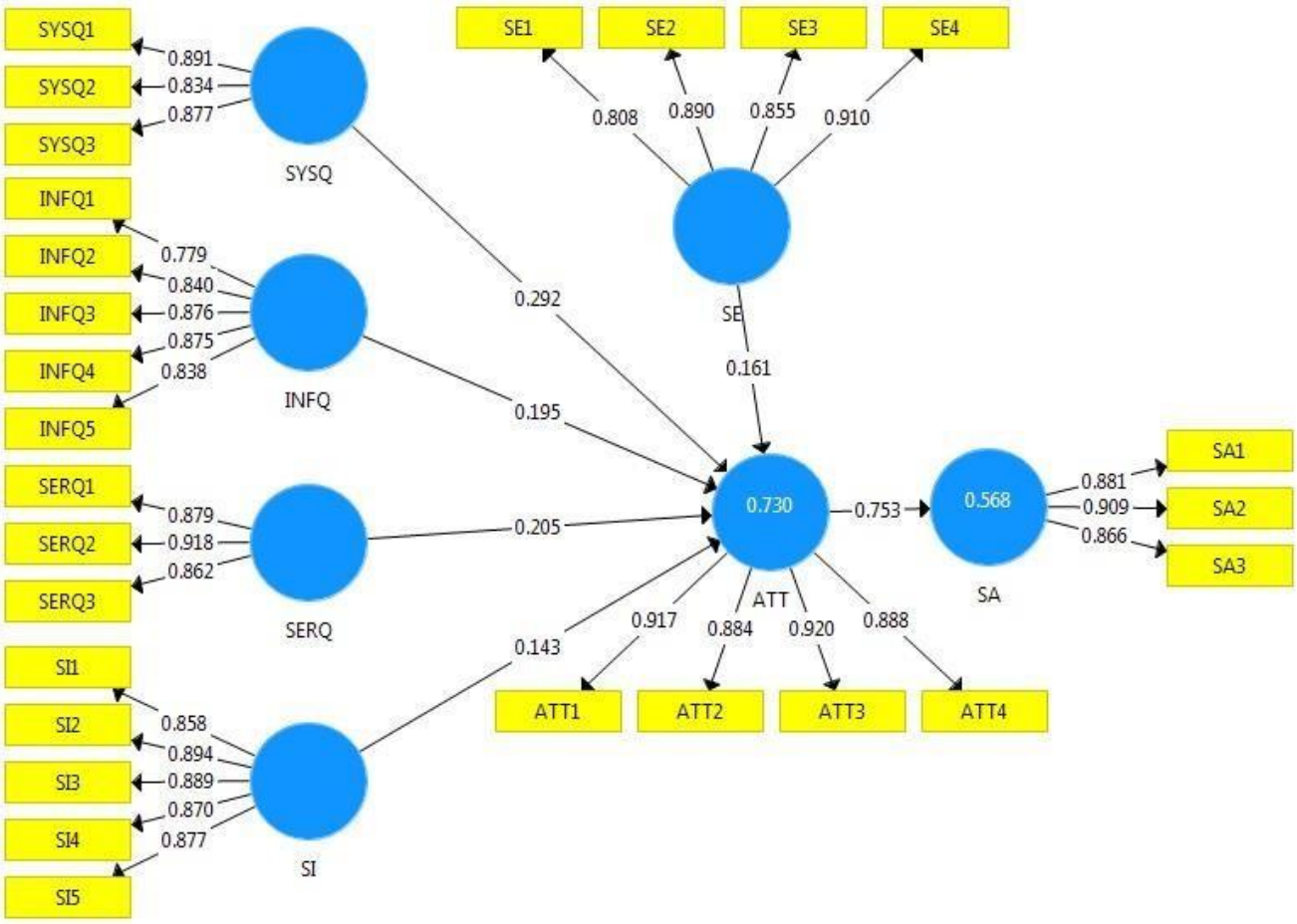


Figure 4.1: Research and analysis Measurement Model Results from the Smart-PLS Tool

4.2.5 Coefficient of Determination

The R2 value is calculated using Smart PLS tool is shown in Table 4.5

Table 4.5: R^2 (square)

	R^2	R^2 Adjusted
ATT	**0.730**	**0.727**
SA	**0.568**	**0.566**

4.2.6 Cross Verified Redundancy (Q^2)

The model is adequately predictive. The values of Q are shown in Table 4.6

Table 4.6 Predictive Relevance results

	SSO	SSE	Q^2 (=1-SSE/SSO)
ATT	**192.474**	**83.118**	**0.568**
INFQ	**248.480**	**100.831**	**0.594**
SA	**126.203**	**63.896**	**0.494**
SE	**218.281**	**102.929**	**0.528**
SERQ	**164.713**	**76.047**	**0.538**
SI	**215.789**	**93.579**	**0.566**
SYSQ	**138.089**	**82.069**	**0.406**

4.2.7 Effect Size

Table 4.7 displays the values of F2 using the smart PLS tool.

Table 4.7: F square

	ATT	INFQ	SA	SE	SERQ	SI	SYSQ
ATT			**1.312**				
INFQ	**0.061**						
SA							
SE	**0.034**						
SERQ	**0.062**						
SI	**0.031**						
SYSQ	**0.109**						

4.2.8 Path Coefficient

Path coefficient values (sample mean, standard deviation & T values) results are shown in the table 4.8. Furthermore, any association with a p value greater than 0.05 is indicated in red. Table 4.8 Path Coefficient

Table 4.8 Path co-efficient

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ATT -> SA	**0.753**	**0.752**	**0.033**	**22.686**	**0.000**
INFQ -> ATT	**0.195**	**0.198**	**0.057**	**3.398**	**0.001**
SE -> ATT	**0.161**	**0.161**	**0.061**	**2.623**	**0.009**
SERQ -> ATT	**0.205**	**0.201**	**0.056**	**3.692**	**0.000**
SI -> ATT	**0.143**	**0.142**	**0.048**	**2.992**	**0.003**
SYSQ -> ATT	**0.292**	**0.293**	**0.058**	**5.061**	**0.000**

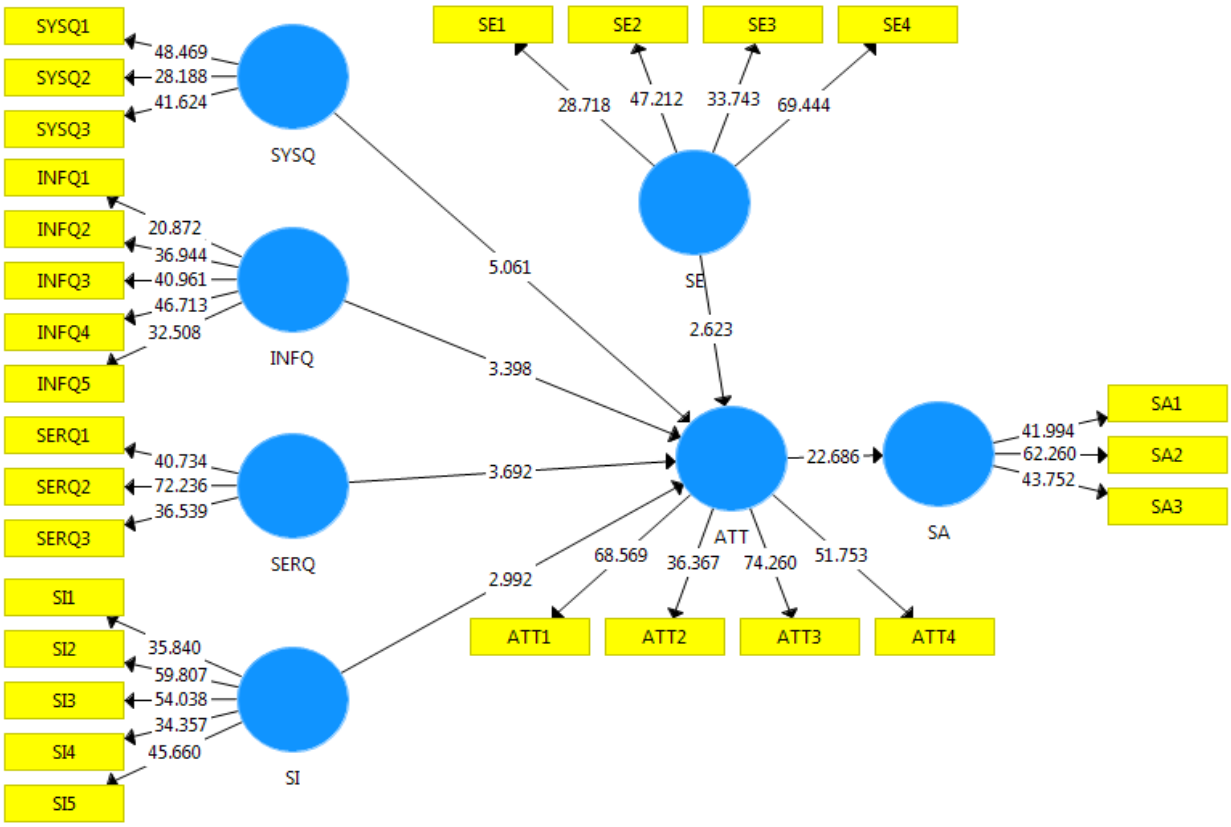


Figure 4.2: Research Structural Model results from Smart PLS tool.

4.2.9 Hypothesis Testing Results

Table 4.9: Hypotheses Testing

No.	Hypotheses	Results
H1	System quality has an impact that is positive on the Attitude for influencing mobile learning.	Supported
H2	There has a positive impact on the attitude for influencing mobile learning in information quality.	Supported
H3	Service has a positive effect on the attitude for influencing mobile learning.	Supported
H4	Self-efficacy has a positive impact on the attitude for influencing mobile learning.	Supported
H5	Social Influence has a positive the attitude for influencing mobile learning.	Supported

4.3 Discussion

In m learning structural and measurement model is used and hypothesis value and test is done using smart pls. Partial least square (PLS) analysis is use for analyze the research model. Various validity & reliability are interpret beginning at viewpoint of measurement model such as: indicator validity, convergent validity, internal consistency reliability, discriminant validity and reliability. And structural model includes effect size (f2), coefficient of determination (R^2), and path coefficient (β), cross verified redundancy (Q^2) and hypothesis testing. In this research it is observed that 5 relationships are very significant. After that, perceived trust and personal innovative skills are tested. Moderators are also used for revaluation of f^2, R^2, Q^2, β and hypothesis testing. Plot analysis is using to deeply understand graphical expressions.

CHAPTER 5

IMPACT ON SOCIETY, ENVIORNMENT AND SUSTAINABILITY

5.1 Impact on Society

After finding factors that influence ML learning, it is necessary to understand the impact it has on society. Modern technology has become a challenging subject in the education sector and is providing many new learning options to students. With the development of technology, the education sector is improving. Technological innovation Smartphones and other smart devices contribute to all sectors of education, entertainment, and communication. Smart devices are part of every part of our life. The direction is completely taken over. The true fact is that 86% of college students now own a smartphone and more than half of them regularly use it for study. According to a recent (Ofcom) survey, mobile devices such as smartphones and tablets account for 50% of all internet browsing activity worldwide. Most of the factors that make mobile learning widely adopted have an impact on society at large.

First, the extensive use of mobile learning has the capability to close the digital inclusion and democratize access to education. As a result of the proliferation of ML in education, those who previously had no access to formal education can now easily access education through mobile or handheld devices. However, the contribution of mobile devices is widespread. It is easily accessible and affordable compared to computers or laptops. Second, the proliferation of ML is increasing day by day. The development of ML encourages ongoing education. Mobile devices facilitate approach to learning at any time, from any location, area. With this flexibility and convenience, students can expand their knowledge, skills, and knowledge to survive in a rapidly changing labor market. In this way society gets a skilled, successful, innovative, and efficient, workforce.

Additionally, ML promotes continuous and collaborative learning. Students using ML can participate in various online forums, develop skills, share information, and materials, and

collaborate on any project through mobile learning. And can get instant feedback from teachers or other students using various Apps and Platforms.

Personalized Learning can be enhanced and developed through experiences and mobile learning. Mobile applications with modern technology can customize the content according to each individual student's needs, interests, and progress preferences, thereby enabling a high level of knowledge retention.

In addition traditional classroom learning, reducing the use of paper and pen. ML use promotes environmental sustainability. In conclusion, society is significantly affected by the adoption of ML. ML has the potential to significantly impact overall social development by creating opportunities in education, supporting educational settings, personal development, and supporting environmental sustainability

5.2 Impact on Environment

Learners these days use mobile devices to keep pace with the times. ML can access many resources that promote learning and skill development. In traditional classrooms, ML has proven to be very beneficial in narrowing the educational gap. The learning environment of students has a major impact on their learning outcomes. Erroneous board placement Crowded, classroom, temperature imbalance, communication condition, noise level in and around the educational institution, air pollution, classroom discomfort are several problems that can cause students to get confused during class. As mobile devices have already made our lives easier. Therefore, a large amount of research is needed to make mobile devices more user-friendly. Mobile gadgets are expected to be very useful for students. However, some studies have shown that M L is ineffective. We hope that this study provides an overview of how mobile devices in teaching and learning will benefit our teachers and students (T&L). There are environmental benefits associated with using mobile learning. One of the main benefits for the environment is the reduction of paper usage, textbooks, Handouts and worksheets can be accessed modernly and successfully through M L. Our education reduces the use of paper and thus we can reduce the deforestation of our country

and protect the environment. It has natural resources. Savings can be made. Furthermore, mobile learning uses less energy than traditional classroom learning, energy use for lighting, heating and cooling can be greatly reduced by using digital devices instead of physical infrastructure such as classrooms.

In addition, ML in distance education provides opportunities or encourages any situation where M L is possible Learning materials can be accessed from anywhere without the need to show the actual place. As a result, transportation needs are reduced and greenhouse gas emissions related to vehicles are reduced. In short ML implementation has a positive and favorable effect on the environment because it reduces the utilizing of paper, pen, energy, resources and encourages distance learning options

5.3 Ethical Aspects

Ethics should be emphasized along with teaching ML. Learn how ML affects ethical aspects. The digital divide and access to mobile learning materials are two ethical issues. Although the mobile devices are readily available, the devices are fragile, and due to socio-economic differences, some people do not have equal access to technology, creating barriers another important factor that should if considered in mobile learning are data security and data privacy. Since mobile learning requires interaction with Internet devices, users should be mindful of privacy and security when disclosing their personal data. A code of ethics should be established to protect data. In addition, they must share secure information and require compliance with regulations. The adoption of m-learning is closely linked to ethical learning that affects individuals and communities. It is important to be respectful and considerate of different cultures and beliefs when using mobile appliance for learning. Ethical strategies for ML ensure that everyone, regardless of their ability, can access and understand learning materials. It is also important to have high-quality educational content that is fair, accurate and follows specific rules. It's important to care about people's feelings, evaluate everyone fairly, and be transparent about how things work. By thinking about all these issues, we can create a learning environment that is fair, inclusive and ethical.

5.4 Sustainability Plan

In order to propose ML in education, the necessary methods and techniques are mentioned to guarantee that the technology is operational and sustainable. The project should be sustainable, so that people of any age, any class can use it easily. So that everyone can be use it effortlessly. So that everybody can use it easily in the future. Such a plan should be kept .Sustainable planning affects individuals and society. As the use of ML is growing day by day, sustainable planning must be implemented .Promote ethical behavior improve digital literacy and ensure users skills with ML.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDSATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Through this research paper, structure, outcomes, and factors influencing ML in the education system have been thoroughly investigated. The principle goal of this analysis was to identify & evaluate factors influencing ML various aspects, implications, and ethical issues influencing ML are looked at. Thoroughly examines the factors influencing ML and brings out the results. The Smart PLS analysis results are aggregated and accepted. The results obtained by using Smart PLS derive the "behavioral results" of ML, in addition, ASE and ISS models are used to identify the significant variables to determine the effect or behavior of the medium. A brief description of this study examines the results in Chapter 4.

6.2 Conclusion

Factors affecting mobile learning were examined using Smart PLS research resulting in a thorough result. This research explores and examines factors including educational outcomes, technological infrastructure, learning institutional practices, and user perspectives. The outcomes of this experiments emphasize the benefits of mobile learning for educational success, skill development, and accessibility, as well as minor issues. The direction has also been highlighted. Here are some innovative techniques to leverage ML.Finally built models that recognize ML behavior with accuracy. Two models are ISS and ASE model to discuss the effect of small and large components of ML eclipses has been used by which p gives a significant and Route coefficient value Range 0.1 or 0.2. Additionally q square gives values of 0.442 to 0.586 and r square also gives values of 0.568 to 0.730

6.3 Implication for Further Study

The evaluation of factors influencing the assumption of mobile learning offers a solid basis for next studies, offering a variety of avenues to deepen our comprehension and enhance the implementation of mobile learning initiatives. I have worked with the ISS and ASE models; in my research report, I may include some more models in the future. This study report will employ moderators in the future. Also including mediator in future. Only students at Daffodil International University provided the data that I gathered. In a subsequent study publication, data from various universities can be gathered, and numerous additional models can be added to check the results in various ways and determine whether or not my results are significant. Subsequent research ought to concentrate on assessing the enduring consequences of implementing mobile learning, including aspects such as skill retention, continuous academic accomplishment, and the enduring influence on students' professional trajectories. Future studies on digital equality and inclusion should focus on lowering barriers to entry and ensuring that mobile learning remains an inclusive teaching tool across a range of socioeconomic contexts. Future study is crucial in this area due to the implications of mobile learning on students' social and emotional well-being, which calls for an analysis of the intricate relationships between the negative effects of technology-mediated education and mental health outcomes

REFERENCE

[1] K.Alhumaid,. M. Habes and S. A. Salloum, "Examining the Factors Influencing the Mobile Learning Usage During COVID-19 Pandemic: An Integrated SEM-ANN Method," in IEEE Access, vol. 9, pp. 102567-102578, 2021, doi: 10.1109/ACCESS.2021.3097753.

[2]. Chavoshi, A., & Hamidi, H. (2019). Social, individual, technological and pedagogical factors influencing mobile learning acceptance in higher education: A case from Iran. *Telematics and Informatics*, *38*, 133-165.3. Naveed QN, Alam MM, Tairan N. Structural Equation Modeling for Mobile Learning Acceptance by University Students: An Empirical Study. *Sustainability*. 2020; 12(20):8618.

[3] Rizvi, Wajid. (2018). Factors Influencing Acceptance of Mobile Learning by Higher Education Students in Pakistan. 50. 10.26692/sujo/2018.1.0025

[4] Mary Helen Fagan (2019) Factors Influencing Student Acceptance of Mobile Learning in Higher Education, Computers in the Schools, 36:2, 105-121,

[5] Kallaya, Jairak, Praneetpolgrang Prasong, and Mekhabunchakij Kittima. "An acceptance of mobile learning for higher education students in Thailand." (2009).

[6] Abu-Al-Aish, Ahmad and Steve Love. "Factors Influencing Students' Acceptance of M-Learning: An Investigation in Higher Education." *International Review of Research in Open and Distributed Learning*, volume 14, number 5, december 2013, p. 82–107

[7] Sarrab, Mohamed, et al. "An Empirical Study of Factors Driving the Adoption of Mobile Learning in Omani Higher Education." *International Review of Research in Open and Distributed Learning*, volume 17, number 4, june 2016, p. 331–349.

[8] Cruz, Y., Boughzala, I., & Assar, S. (2014). Technology acceptance and actual use with mobile leraning: first stage for studying the influence of learning styles on the behavioral intention.

[9] Hu, S., Laxman, K., & Lee, K. (2020). Exploring factors affecting academics' adoption of emerging mobile technologies-an extended UTAUT perspective. *Education and Information Technologies*, *25*, 4615-4635..

[10] Al-Hamad, M., Mbaidin, H., AlHamad, A., Alshurideh, M., Kurdi, B., & Al-Hamad, N. (2021). Investigating students' behavioral intention to use mobile learning in higher education in UAE during Coronavirus-19 pandemic. *International Journal of Data and Network Science*, *5*(3), 321-330.

[11] Salloum, S. A., & Shaalan, K. (2019). Factors affecting students' acceptance of elearning system in higher education using UTAUT and structural equation modeling approaches. In *Proceedings of the*

International *Conference on Advanced Intelligent Systems and Informatics 2018 4* (pp. 469-480). Springer – International Publishing.

[12] Shamsuddin, A., Wahab, E., Abdullah, N. H., & Suratkon, A. (2018, November). Mobile learning adoption in enhancing learning experience among HEI students. In *2018 IEEE 10th International Conference on Engineering Education (ICEED)* (pp. 202-207). IEEE.

[13] Zare, S., Shirdeli, M., Rezaee, R., Niknam, F., Mobarak, S., & Jelvay, S. (2022). Mobile Learning Among University Students: Adoption and Application of MLearning. *Acta Medica Iranica*, 699-706.

[14] Dolawattha, D. D. M., & Premadasa, H. K. (2023). Novel Impact Model for Mobile Learning Adoption in Higher Education. *Asian Journal of Research in Computer Science*, *16*(3), 167-180.

[15] Mac Callum, K., & Jeffrey, L. (2014). Factors impacting teachers' adoption of mobile learning. *Journal of Information Technology Education*, *13*.

[16] Arpaci I. (2015). A comparative study of the effects of cultural differences on the adoption of mobile learning. *British Journal of Educational Technology*, *46*(4), 699-712.

[17] Palos-Sanchez, P. R., Correia, M. B., & Saura, J. R. (2019). An empirical examination of adoption of mobile applications in Spain and Portugal, based in UTAUT. *International Journal of Mobile Communications*, *17*(5), 579-603.

[18] Chatterjee, S., Majumdar, D., Misra, S., & Damaševičius, R. (2020). Adoption of mobile applications for teaching-learning process in rural girls' schools in India: an empirical study. Education and Information Technologies, 25, 4057-4076

[19] Hamidi, H., & Chavoshi, A. (2018). Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the University of Technology. *Telematics and Informatics*, *35*(4), 1053-1070.

[20] Qashou, A. (2021). Influencing factors in M-learning adoption in higher education. *Education and information technologies*, *26*(2), 1755-1785..

[21] Al-Adwan, A. S., Al-Adwan, A., & Berger, H. (2018). Solving the mystery of mobile learning adoption in higher education. *International Journal of Mobile Communications*, *16*(1), 24-49.

[22] Zare, S., Shirdeli,, M., Rezaee, R., Niknam, F., Mobarak, S., & Jelvay, S. (2022)

[23] Mobile Learning Among University Students: Adoption and Application of MLearning. *Acta Medica Iranica*, 699-706.

[24] Nikolopoulou K., Gialamas, V., Lavidas, K., & Komis, V. (2021). Teachers' readiness to adopt mobile learning in classrooms: A study in Greece. *Technology, Knowledge and Learning*, *26*, 53-77.

[25] Sarrab, M., Al-Shihi, H., Al-Manthari, B., & Bourdoucen, H. (2018). Toward educational requirements model for mobile learning development and adoption in higher education. *TechTrends*, *62*, 635-646

[26] Domingo, M. G., & Garganté, A. B. (2016). Exploring the use of educational technology in primary education: Teachers' perception of mobile technology learning impacts and applications' use in the classroom. *Computers in Human Behavior*, *56*, 2128.

[27] S. Bourekkache, S. Tigane, O. Kazar and L. Kahloul, "Mobile and personalized learning system for computer science students," 2020 Sixth International Conference on e-Learning (econf), Sakheer, Bahrain, 2020, pp. 189-193.

[28] D. D. M. Dolawattha, S. Pramadasa and P. M. Jayaweera, "Mobile Learning: Modelling the Influencing Factors on Mobile Devices," 2020 20th International Conference on Advances in ICT for Emerging Regions (ICTer), Colombo, Sri Lanka, 2020, pp. 1-2, doi: 10.1109/ICTer51097.2020.9325494.

[29] Iqbal, S., & Qureshi, I. A. (2012). M-learning adoption: A perspective from a developing country. *International Review of Research in Open and Distributed Learning*, *13*(3), 147-164

Plagiarism Report

MOBILE LEARNING

ORIGINALITY REPORT

23%	21%	11%	16%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	7%
2	Submitted to Daffodil International University Student Paper	4%
3	www.erudit.org Internet Source	1%
4	Submitted to University of South Africa (UNISA) Student Paper	1%
5	link.springer.com Internet Source	1%
6	journal.ugm.ac.id Internet Source	<1%
7	Submitted to University of Ruhuna Matara Student Paper	<1%
8	ebin.pub Internet Source	<1%
9	journals.plos.org Internet Source	<1%