Addis Ababa University
College of Natural and Computational Sciences
School of Information Science

CUSTOMERS' E-BANKING ADOPTION IN ETHIOPIA

Yemisrach Desta

A Master's Thesis

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CUSTOMERS' E-BANKING ADOPTION IN ETHIOPIA

A Thesis

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Declaration

I, Yemisrach Desta, hereby declare that the thesis work entitled:

"Customers' E-banking adoption in Ethiopia"

is submitted by me for the award of the degree of Master of Science in Information Science from the school of Information science of Addis Ababa University, is my original work and it hasn't been presented for the award of any other Degree, Diploma, Fellowship or other similar titles of any other university or institution.

Name Yemisrach Desta Fenglea

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As an advisor, this thesis has been presented for examination with my approval of its originality with the required level of accepted standard.

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Approval of Examination

This thesis work entitled as ***"Customers' E-banking adoption in Ethiopia"*** has been examined and approved for the award of the degree of Master of Science in Information Science from Addis Ababa University, College of Natural and Computational Sciences, School of Information Science.

Name and signature of Member of the Examining Board

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ABSTRACT

In Ethiopia, E-banking technologies were introduced almost before two decades for the main purposes of reaching new customers and enhance deposit mobilization. Though banks are investing huge amount of money for technological and service enhancements, customers did not yet adopt these technologies to the required level. Despite number of researches conducted on E-banking channels, no study has been undertaken to comprehensively analyze determinant factors of customers' E-banking adoption in Ethiopia. Hence, after an extensive review of literature, this research has developed and tested a model based on the unified theory of acceptance and use of technology (UTAUT2). The research model has been built to explain how UTAUT2 constructs influence behavioral intention and the actual use behavior of E-banking adoption from the point of customers' perspective. A cross-sectional survey research has been conducted to collect data from 321 respondents of four different banks across the country. Partial Least Square Structural Equation Modelling (PLS-SEM) has been used to test the proposed model and identify the key determinant factors of customers' behavioral intention and the actual use behavior of E-banking technologies. The research revealed that performance expectancy, habit, hedonic motivation, price value, and facilitating conditions are the main influential factors of customers' behavioral intention to adopt E-banking technologies in Ethiopia. Moreover, habit and facilitating conditions has been found to be the influential factors on determining the actual use behavior of E-banking technologies in Ethiopian context. Practitioners can use the findings in such a way that they focus on the functionalities of E-banking technologies that increases customers' performance expectancy and creating a conducive environment to users that exposes them to experience these benefits and built habit of using these technologies for everyday activities. However, it is still demanding to study further for identifying other factors that affect E-banking adoptions and testing the model in similar technology adoption areas.

Keywords: UTAUT2, PLS, E-banking adoption, PLS-SEM, partial least square, structural equation modelling, unified theory of acceptance and use of technology

for my beloved wife

for all your love, care and support!

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nothing is done without you, thanks my Lord!

Yemisrach Desta

Table of Contents

List of Tables

List of Figures

List of Acronyms

Abbr.	Full text
ABP	Automatic Bill Payment
ANOVA	Analysis of Variance
ATM	Automatic Teller Machine
AVE	Average Variance Extracted
BI	Behavioral Intention
CBE	Commercial Bank of Ethiopia
CB-SEM	Covariant Based Structural Equation Modeling
CORE	Centralized Online Real-time Exchange
CSV	Comma Separated Value
DOI	Diffusion of Innovation
E-banking	Electronic banking
EE	Effort Expectancy
EFT	Electronic Fund Transfer
Ethiopay	Ethiopian National E-payment System
Ethswitch	Ethiopian National E-payment Switch
FC	Facilitating Condition
HM	Hedonic Motivation
HT	Habit
ICR	Internal Consistency Reliability
ICT	Information Communication Technology
IDT	Innovation Diffusion Theory
KYC	Know-Your-Customer
LV	Latent Variable
MM	Motivational Model
MPCU	Model of Personal Computer Utilization
MS	Microsoft Office
PCI	Perceived Characteristics of Innovation
PDA	Personal Digital Assistant

PE	Performance Expectancy
PEOU	Perceived Ease of Use
PLS	Partial Least Square
PLS-SEM	Partial Least Square-Structural Equation Modelling
POS	Point of Sale
PSS	Premier Switch Solution
PU	Perceived Usefulness
PV	Price Value
SCT	Social Cognitive Theory
SEM	Structural Equation Modelling
SGC	School of Graduate Committee
SI	Social Influence
SMS	Short Message Service
SN	Social Norm
SPSS	Statistical Package for Social Sciences
SV	Social Value
TAM	Technology Acceptance Model
TOE	Technology-Organization-Environment
TOT	Training of Trainers
TPB	Theory of Planned Behavior
TRA	Theory of Reasonable Action
TTF	Theory of Task-technology Fit
TVET	Technical and Vocational Education and Training
UK	United Kingdom
US	United States
USD	United States Dollar
USSD	Unstructured Supplementary Service Data
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
XLSX	Excel Workbook (MS Excel file format)
XHTML	Extensible Hyper Text Markup Language

List of Symbols

α (Greek small letter Alpha)	used to represent Cronbach's alpha
β (Greek small letter Beta)	used to represent path coefficient values between two latent variables
λ (Greek small letter Lamda)	used to represent path coefficient values between indicator and latent variables
p (Latin small letter p)	used to represent probability significance
t (Latin small letter t)	used to represent T-statistic value
n (Latin small letter n)	used to represent number of samples

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CHAPTER ONE

I. Introduction

1.1. Background of the study

Electronic banking (*commonly referred as E-banking*) is one form of modern electronic payment systems which adds new flavors of cash payment transactions in addition to facilitate the traditional bank services like Cash-deposit and Withdrawal (Datta, 2010). The term is used in different ways. For instance; Natasha, Faiza, Maryum and Atta (2014) used the term for representing all systems and procedures that enables a customer to complete banking transactions electronically without visiting a physical institution. This explanation is considered as the working definition of E-banking in this document.

Technology adoption is a common term used to describe the stage or level in which a technology is selected for use by an individual or an organization (Carr, 1999). In this thesis context, E-banking adoption is specifically referred to the stage in which E-banking technology is selected and used by individuals or customers of banks.

E-banking was introduced in Ethiopia for the first time in 2001 by the state owned Commercial Bank of Ethiopia (CBE) using Automatic Teller Machines (ATMs) (Worku, 2010). However, it was lagged to successfully address the services to its customers mainly due to infrastructure related problems. Following the State pioneer bank, Dashen and Wegagen Banks have started to offer E-banking services through card payments in 2006 and 2010 respectively (Kindie, 2016; Worku, 2010; Zeleke, 2016). Currently, almost all commercial banks in Ethiopia provides E-banking services in one or more ways. Card based payment through ATM and Point of Sale (POS) machines, Mobile banking, Internet banking and Agent banking are some of E-banking services exercised in Ethiopia.

Though it took nearly two decades, E-banking is not fully adopted in Ethiopia; and Cash is the most dominant medium of exchange (Girma, 2016). While the basic transactions, Cash withdrawal and Fund transfer, can be done using other electronic channels, people are still preferring to visit the narrow teller windows. The number of transactions using E-banking channels comparing to the traditional way of banking is remarkably very low. This situation doesn't meet business specialists' expectation of returns on huge investments, which in turn might negatively affect further expenditures on new technology acquisition.

There are different factors associated with this problem. Demographic factors, lack of awareness, security issues and low levels of computer literacy are among the most common factors (Girma, 2016; Muche, 2017; Zeleke, 2016). Moreover, factors related to customers' behavioral intention towards using E-banking technologies are the likely reasons for poor E-banking adoption (Alalwan et al., 2017). In this research paper, further exploring of these factors that influences customers' E-banking adoption in Ethiopian context has been conducted.

1.2. Statement of the problem

Even though modern technology-based banking service has offered many advantages over the traditional systems, E-banking usage in developing countries is very poor (Natasha, Faiza, Maryum, & Atta, 2014). Customers' intention to involve in and use of E-banking services in Ethiopia is also very poor. Zeleke (2016) mentioned that Ethiopian Banks' customers are not yet entertaining the benefits of E-banking technologies. Kindie (2016) also analyzed that customers of CBE pay no attention for its newly deployed mobile banking services. Moreover, Muche (2017) strengthen the above idea by mentioning the stage of E-banking as infant in the Ethiopian banking industry.

Different reports from the bank industry also showed that the adoption rate of E-banking by users is very low. As an example; Wegagen bank, which is one of the giant and pioneer private banks in E-banking adoption, reported that its registered number of ATM card holders is nearly 16 % of the total account book holders[1]. This document also mentioned that the rate of subscribed users of ATM banking to the total card holder in CBE is about 29%. Similarly, the rate of their Mobile banking subscribers is less than 10% of the total account book holders.

The transaction rate by subscribed users is also very small compared to the total bank account holders. Total card usage in the year 2015/16, considering minimum of one transaction per a

[1] E-banking directorate annual report for the year 2015/16, Wegagen Bank S.C

month, is about 26.8% for CBE card holders[2]. According to the national payment switch monthly reports, the number and amount of transactions made using ATMs is also very small compared to the total number of card holders. The unsatisfactory level of number of Mobile Banking users is the other indicator of low rate adoption.

In addition to the above research findings and document analysis; the researcher also noted noticeable knowledge gap and lack of experience on the available E-banking services during a panel discussion made among three Wegagen bank district's representatives as part of a three days TOT plan of the year 2016/17. In general, all the above problems on preceding paragraphs indicate the tenacity of the problem on the mentioned area.

Since the paradox between the availability of sophisticated E-banking systems and very poor adoption takes much attention, number of studies were conducted to improve the situation. For instance; a study conducted by Gemechu (2014) on adoption of E-banking in Ethiopia, found that security risk, lack of trust, lack of legal and regulatory framework, lack of ICT infrastructure and absence of competition between local and foreign banks as major barriers.

On the other hand, from customer point of view, Tesfaye (2016) found perceived usefulness (PU) and Trust as most significant factors affecting customers' intention towards using E-banking services while perceived ease of use (PEOU) and Subjective Norm (SN) negatively affect usage behavior in customers of Bank of Abyssinia. Merga (2017) also indicated that performance expectancy (PE), effort expectancy (EE) and price value (PV) are major influencing factors of behavioral intention (BI) whereas social value (SV), facilitating conditions (FC) and hedonic motivation (HM) are insignificant on BI of customers for Mobile banking in CBE.

On the other hand, Yohannes (2010) study on key factors of Internet banking adoption in Ethiopia revealed that demographic factors including age, income and occupation status have a relationship with the adoption of internet banking. On contrary, Muche (2017) found that except for gender, the remaining demographic variables such as age, income, educational level and occupational status have no significant influence on users' E-banking usage behavior.

[2] Annual Process Presentation for the year 2015/16, Commercial Bank of Ethiopia (CBE)

However, most of these studies focus on one form of E-banking services like on ATM or Mobile banking independently. However, Lai (2007) suggested that E-banking technologies are highly interrelated to each other that requires comprehensive study of technology adoption. Since ATM and Mobile banking are the most widely used E-banking services in Ethiopia and Internet banking is the promising future prospect, comprehensive study of E-banking adoption that includes these three channels will help to have more general idea than study conducted independently.

Furthermore, most previous researches done in Ethiopia are focused separately on customers of a single bank. As a result, findings in regarding to E-banking adoption factors shows inconsistency that makes it difficult to generalize for all bank customers. The findings of Tesfaye (2016) and Merga (2017) also revealed the above idea that different authors found different factors in similar topic. One reason for their different findings might be due to the nature of electronic channel they focused or the behavior of specific bank customers.

Moreover, most of prior studies conducted to identify E-banking adoption factors focused on behavioral intention rather than measuring the actual use behavior. However, examining factors that influence the actual use behavior of E-banking along with factors that influence the customers' behavioral intention will make the research more inclusive. To the researcher's level of understanding on previous related works, no such study that analyze both the intention and actual use behavior of E-banking adoption by encompasses many alternative channels together among different commercial bank customers in Ethiopia has been done.

In general, this research is aimed to further shed light on the E-banking adoption in Ethiopian context and overcome previously mentioned problems by conducting comprehensive study of E-banking adoption factors among different commercial bank customers located in different areas of the country. For attaining this purpose and framed the research problem, candidate variables and associated positive relation with respect to customers' behavioral intention and the actual usage behavior are hypothesized to be tested based on intensive literature in chapter two.

1.3. Objective of the study

The general objective of this study is to assess and analyze factors that affect E-banking adoption among the customers of commercial banks in Ethiopia. Putting this main objective at the head, the specific objectives are to:

- review related literatures on the E-banking adoption factors;
- analyze the association and influence of PE, EE, SI, FC, HM, PV and HT on BI of customers' E-banking adoption in Ethiopia;
- analyze the association and influence of FC, HT and BI on the actual use behavior of customers' E-banking adoption in Ethiopia;
- analyze the association and influence of these variables with respect to specific E-banking channel in Ethiopia;
- put forward useful recommendation for practitioners of E-banking technologies in Ethiopia to focus on factors that strongly influences customers' E-banking adoption.

1.4. Significance of the study

Analyzing customers' E-banking adoption in Ethiopia will enable us to recognize factors that influence E-banking adoption by customers. This recognition in turn will add new findings to the existing knowledge of E-banking adoption factors in Ethiopian commercial banks context. Since Ethiopia is one of the sluggish countries in technology adoption, such kinds of researches are very important to build the existing knowledge.

This research is also significant for practitioners in Ethiopian banks to consider findings of this research in their strategies to increase deposit mobilization and earning profit through E-banking channels. It will be very valuable in addressing the needs of bank customers and taking measures to improve poor situations. Findings of this research are also very likely to be used as an input for strategic decisions in fostering E-banking adoption among their customers. Customizing and presenting E-banking services according to the customers' desire will used to capture and retain more customers so that the bank will be benefited from profits of large number of E-banking users.

1.5. Scope and limitations

This research focuses on identifying and analyzing of E-banking adoption factors among the commercial banks' customers. For manageability, only four sample commercial banks have been selected for conducting the study. Customers of other non-commercial banks, other financial organizations, payment associations and switch providers will not be included. The scope of this study is also limited to ATM banking, Mobile banking and Internet banking only. The other two ways of E-banking services in Ethiopia (Agent banking and POS terminals) are not in the focus of the study for their unique nature of involving third parties (agents or merchants). Moreover, since the scope of this research focuses on ATM, Mobile and Internet banking, bank customers who are not subscribed for at least one of these services are not included in the target population.

1.6. Ethical Considerations

The proposal of this research was approved by Addis Ababa University, School of Information Sciences Graduate Committee (SGC) with acceptable ethical considerations. Moreover, all basic principles of ethical considerations and standards have been noted during all phases of the research process that includes, but not limited to, respect for participants, respect to the organizations involved, keep confidentiality and avoiding any acts of misconduct like intentional misinterpretations and using findings for harming the whole or part of the society.

1.7. Thesis Outline

This thesis is organized into five chapters. Chapter 1 introduces E-banking services and define statement of the problem, objectives and significances of the research. Scope, limitation and ethical considerations to conduct this study are also the focus points. Chapter 2 exhaustively review about E-banking technologies and their trends in Ethiopia. Brief explanation of technology adoption theories and models with marking related works in the area are presented. Chapter 3 presents the proposed research model along with a research method to collect and analyze data. Chapter 4 is all about the research findings and discussions based upon the empirical tests on the structural and measurement models. Chapter 5 conclude all the key points of the thesis and presents some recommendations.

CHAPTER TWO

II. Literature review and Related works

To exemplify the importance of current study, this chapter started with providing a background of E-banking technologies and the trend in Ethiopia. To visualize the status of E-banking services in Ethiopia, four banks are selected for detail discussion. The second main part of this chapter is the review made on different technology adoption theories and models from which one is selected in the next chapter to build the research model. This chapter ends with adequate marking of related works in the area from the world, the continent and the country perspectives.

2.1. Literature review

2.1.1. E-banking Technology

The advent of information technology to every aspect of human life and business has brought a lot of changes. These technological innovations not only improved the day to day life, but also brought totally new ways of doing things in which they were not even imagine before. Being non-exceptional, information technology brought a great essence in banking system. One of these core contributions are E-banking technologies.

Electronic technologies innovation in the banking industry can be traced back to the introduction of ATM in 1970s. Later, banks were started to offer E-banking services through personal computers using intranet proprietary software for corporate customers in 1990s. Through time, with dramatic enhancements and innovations, today's banks offer multidimensional services through online technologies across the world. However, using a technology is an optional where having access to the technology by no means ensures it will be used effectively unless customers are intended to use it in their day to day life (Thompson, Higgins, & Howell, 1991).

The term E-banking is used in different ways in different contexts. While most authors used the term for similar meanings, some authors used the term as synonym for online banking or internet banking. For example, E-banking was defined as "an internet portal, through which customers can use different kinds of banking services ranging from bill payment to making investments" (Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004). Here, they define the term E-banking from the internet perspective only. Datta (2010) used the terms online banking and internet banking interchangeably to refer E-banking. DeYoung (2001) also associated E-banking with the internet banking by explaining its use as providing clients accessibility to nearly any kinds of transactions except for instant cash withdrawal. This seems to exclude ATM services. However, other authors describe the word E-banking in its generic form as follows.

Al-samadi (2012) adopted the definition of E-banking in his study as the delivery of both retail banking products and services and large value electronic payments through electronic channels. These products and services can extend from electronic deposit to the provision of electronic money including the provision of financial device and electronic bill payment. On his empirical research, Aderonke (2010) also used the term to represent various technologies that used to perform banking transactions through electronic channels including electronic cards, internet banking and mobile banking services.

E-banking technology represents a variety of different services that include ATM services like , Automatic Bill Payment (ABP), Electronic Fund Transfer (EFT) and Computer banking (PC banking) (Kolodinsky, Hogarth, & Hilgert, 2004). In this explanation, the term is used to represent different electronic forms of banking services other than those using the internet platform. For Gemechu (2014), the term was considered as multi-channel service provided through ATM, internet, mobile, POS and telephone. According to Daniel (1999), E-banking was explained as an electronic connection between the bank and customer to prepare, manage and control financial transactions.

In this research context, the term E-banking adopts the explanation of Natasha et al. (2014) as it is a term representing all systems and procedure by which a customer may complete banking transactions electronically without visiting a physical institution. This definition includes any form of banking transaction completed electronically including but not limited to ATM banking, PC banking, phone banking, home banking, internet banking, remote E-banking, POS and mobile banking. This definition is also much close with Muche's explanation of E-banking as a generic term for the process by which customers can conduct various banking transactions electronically without time and place limit (Muche, 2017). The most common forms of E-banking technologies are briefly explained below.

2.1.1.1Common forms of E-banking technologies

PC banking: it is form of E-banking using proprietary software distributed and installed by the bank on customers computer (PC) to access their bank. This can be completed through online banking where banking transactions are directed inside a closed network or through Internet banking (Natasha et al., 2014). It is also sometimes called home banking when the customers are accessing the bank through dedicated links from their home.

Telephone banking: Customers access their bank via telephone. In this case customers will call to their bank call centres to receive payment or fund transfer services. The customers must have their own access pass codes to commit these transactions. In early times, Telephone banking was popular in western countries before mobile and internet banking become common. Today such kinds of services are commonly offered to loyal customers who runs huge investments.

ATM banking: it is the process of cash withdrawal, deposit and transfer services using Automatic Teller Machines placed on any convenience places for customers like in malls, hotels and highways (Fenuga, 2010). ATMs are the oldest and the most widely used forms of E-banking technologies across the world starting from the early 1970s (Fikru, 2011). Initially they were used to replace the basic banking transactions of cash withdraw. Nowadays, ATMs provide many more services including cash withdrawals, fund transfers, inquiries about account balances, requests for account statements, direct deposits and foreign currency exchanges. Observability is their unique marketing benefit for banks in which customers are easily attracted by looking them standing in hotels and malls. However, some customers do not like to be exposed during extracting money from ATMs for psychological, social and security reasons (Fenuga, 2010). When discussing about ATMs, what comes to mind is that about payment cards.

Payment cards are smart cards that used to access customers bank account using ATMs and POS terminals. These cards can be debit cards, credit cards, prepaid or gift cards. The basic difference is that Debit cards require the customer to have pre-opened bank account with sufficient balance to be link with and accessed by the card. Whereas the others do not necessarily require it. Credit cards enable customers to use their card without having positive balance in their credit account. Usually they need some sort of guarantee during the account opening procedure to have trust between the issuer bank (it might be another company too) and the card holder. Normally, credit cards have limit on the accessible amount called floor limit where the card holder is forced to neutralize it before the credit limit is elapsed. Prepaid cards are smart cards which are used on ATMs and POS terminals. Their nature is like debit cards, but they do not need to have pre-opened bank account. One can have prepaid card for any amount he/she has paid during the request of the card. Gift cards are like prepaid cards without any association between the card holder and the card. No labelling or KYC requirement is required and anyone who acquire the card can use them while all other types require some sort of authentication that proves the card holder is the actual owner of the card.

POS (Point of Sale terminal): it is an electronic channel to manage selling process by providing an interface for a sales person most commonly in hotels, shops, gasoil stations or any other merchants who have links with the banks (Shittu, 2010). POS terminals are used to accept payment cards like ATMs, but they are very portable and convenience to use unlike ATMs which need much space and are stagnant in relative permanent places. However, since they require the interaction between the merchant personnel and the customer, they are not as such fully self-service like ATMs. In case of transactions using POS machines, there is no need of carrying the actual cash notes. Hence, POS terminals are much preferable than ATM to create cashless society and increase deposit mobilization. It is also used to shorten the transaction process since the customer can pay its bills directly to the merchant on the spot. Specially for ON-US[3] transactions the bank will be more benefited from deposit mobilization without losing the actual cash notes from the bank's treasury through ATMs. In addition, in case of ON-US transactions, since both the customer and the merchant are the same bank account holder, the bank will be beneficiary from service charges of such payment circulations that makes it much preferred deposit mobilization without losing the actual cash. Though POS terminals are much common to see everywhere in developed countries and some African cites like Nairobi, it seems restricted to big Hotels and Supermarkets in Ethiopia. Moreover, mostly they are seen giving service for foreigners while most Ethiopians prefer to pay cash instead of using them.

[3] ON-US transaction is a transaction where the card issuing and acquiring bank is the same.

Mobile banking: it is an alternative channel using mobile phones to perform banking transactions like checking balance, fund transfer, paying bills, air top up and other services. According Shittu (2010), it is used for performing balance checks, account transactions, payments, credit applications and other banking transactions through a mobile device such as a mobile phone or Personal Digital Assistant (PDA). This might be through SMS, USSD or mobile aps (Shittu, 2010). In short, Mobile banking can be defined as accessing a bank to conduct financial transactions through a mobile device (Cruz, Neto, Munoz-Gallego, & Laukkanen, 2010). Since more than 62% of the world population is using mobile phones (Statista, 2017), mobile banking is much convenient way to address E-banking for large number of users. Besides that, while it is fully self-service and convenient to use, it doesn't associate additional costs like internet banking. Moreover, most SMS notifications are free of charges.

Internet banking: it is an access of the bank to perform financial transactions through a secured portal using the Internet (Natasha et al., 2014). Customers can use Internet banking to see one's account detail, cash transfer, paying bills and related banking services through the Internet platform to access their banks. Except for cash withdrawals, Internet banking gives customers access to almost any type of banking transaction at the click of a mouse (Pikkarainen et al., 2004). As Natasha et al. (2014) emphasize, providing an easy access of the bank through the website with few clicks is one special feature of Internet banking. This uniqueness which enables customers to utilize their time very efficiently makes it widely acceptable. In addition to that cross-country accessibility is unique nature of Internet banking that makes it preferable by international business men who want to access their bank and make transactions from any corner of the world.

2.1.1.2Benefits, drawbacks and challenges

All electronic payment methods have their unique nature. However, most of them have common characteristics of independence, interoperability, portability, security, anonymity, divisibility, ease of use and less transaction fees (Worku, 2010). These characteristics enable E-banking to offer benefits to both banks and customers. Since banks are at the hub of any business, such advanced systems play very important roles on facilitating fast and convenient financial transactions. Moreover, such E-banking technologies are very essential for least developed countries to overcome financial exclusion and physical distance barriers (Baptista & Oliveira, 2015). Hence;

merchants, agents and other intermediaries are beneficiaries of such advanced systems. Normann's justification (as cited in Fikru, 2011) listed out five main reasons for companies to provide technology-based service for their customers. These main reasons are cost reduction, quality control, direct customer connections, higher level of quality service and the use of technology as moderator of behavior towards the intended purpose. According to Pikkarainen et al. (2004), significant operational cost reduction and less branch expansion are the two fundamental reasons for E-banking development. These authors also argued that, self-service channel provides customers freedom from time and place constraint to access their banks. These time and place freedoms enables customers to follow up their bank transaction detail easily in daily bases (Natasha et al., 2014). Time and cost saving with additional convenience are also cited as relative advantages of E-banking (Kolodinsky et al., 2004). In addition to providing the utility of time and place (Zahid, Mujtaba, & Riaz, 2010), it has also psychological impact in reducing stress customers from keeping long queues in boring branches (Aderonke, 2010).

On the other hand, there are some drawbacks and challenges associated with E-banking adoption. As both banks and customers share the benefits of these innovations, both faces some challenges in deploying and using these technologies. One of the main challenge for adoption of new technologies by organizations is the initial investment (Sharma & Mishra, 2014). Most E-banking systems requires huge amount of money for initial investment. This burden limits banks from fast adoption of latest technologies. More specifically small banks couldn't cope up the competition of adopting these technologies with the big banks. Infrastructure related problems like lack of adequate ICT infrastructure, poor internet, lack of governmental regulations and lows are main challenges of E-banking adoptions in general and more particularly for developing countries (Gemechu, 2014). Cost related problems are not challenges for banks only, but also customer require an access to the Internet or mobile banking facilities which costs additional money (Venkatesh, Thong, & Xu, 2012). Difficulty to use electronic channel, lack of comprehensive access and lack of social dimensions are other challenges for customers (Mattila, Karjaluoto, & Pento, 2003). It is also obvious that E-banking environment doesn't create conducive environment for those who desire to have face-to-face relations with branch customer service personnel to acquire some social and psychological benefits. Moreover, privacy and security issues are among the major concerns of E-banking technologies for customers E-banking adoption (Fikru, 2011).

2.1.2. E-banking trend in Ethiopia

The history of E-banking in Ethiopia has been starting by the giant state-owned bank called CBE in 2001 by starting ATM banking (Worku, 2010). However, the service was not successful and had been interrupted for years until the famous Dashen bank gives life for it in 2006 (Kindie, 2016; Worku, 2010; Zeleke, 2016). Dashen bank has paid a lot sacrifices to introduce ATM banking to the society though it was also acquired the competitive advantageous of having such technologies which were almost not known before (Gemechu, 2014). In 2010, Wegagen bank announced the starting of ATM banking services which make it the third bank to use E-banking technologies (Zeleke, 2016, p. 14). Afterward, other private banks start to deploy such innovations with different varieties to compute for the market share.

According to Kinfe (2016), the main driving forces of E-banking adoption in Ethiopian banks include high competition among banks, improving organizational performance, cost reduction, wide geographic coverage and building organizational reputation. Currently all commercial banks of the country involve in E-banking services in one or other forms. On the following paragraphs the experience of E-banking adoptions in some selected pioneer banks will be discussed to have a general picture of the adoption level in the country.

2.1.2.1E-banking trend in selected banks

E-banking trend in CBE

CBE, which is mentioned repeatedly as a pioneer bank in Ethiopia, is legally established in 1963 (Tefera, 2017). Currently, it is the only state owned commercial bank which plays significant role in the country's financial economy. The bank is known for its variety of banking services from which E-banking is among the core banking services offered to its customers. Many studies showed that while the bank was pioneer in E-banking technology by deploying few ATMs during the early 2001, it was stagnant for number of years without successful enhancement (Gemechu, 2014; Kindie, 2016; Tefera, 2017; Worku, 2010; Zeleke, 2016). However, after privately owned commercial banks like Dashen and Wegagen banks started to compute in E-banking services, CBE turns to pay more attention for its E-banking development. Currently it is a leading bank in terms of number of ATMs, POS and Payment card users.

In CBE, the E-banking service is governing by E-payment directorate level under the direct supervision of the bank president. According to the bank's structure there are three divisions for Mobile and Internet banking, ATM banking, and POS channel management. This shows that how much the bank is giving focus to its E-banking service in general. According to its official website, the bank is adopting the following technologies for corresponding E-banking services:

Payment Cards: CBE issues different types of payment cards with generic name called 'Reliable Card'. These cards include debit card for the bank account holders and pre-paid cards for non-account holders. Using these cards, customers can get different services using ATMs and POS terminals as mentioned below (CBE, 2017). According to the bank's communication publication, there were 2.8 million payment card holders to use 889 deployed ATMs and 6,269 POS terminals as of September 30, 2016 (CBE Communication, 2016, p. 5).

ATM: for cash withdrawals, bill payments, forex (foreign exchange), fund transfer, mobile top up and balance inquiry using payment cards of all its and other local bank cards, Visa international cards, Mastercard. The website further mentioned that the number of ATM card holders exceeds 3 million from which, about 61% are active ATM users[4] (CBE, 2017).

POS: for cash advance (taking cash from branch tellers), purchase (payments in hotels, supermarkets, shops, …), fund transfer, mobile top up and bill payment using payment cards of its own cards and; cash advance, balance and purchase for Visa international and Mastercard (CBE, 2017; CBE Communication, 2016).

Mobile banking: for fund transfers, payments and balance inquiries as well as get instant notifications on all CBE accounts linked with Mobile banking services using the SMS, XHTML and mobile Apps. CBE Communication (2016, p. 5) mentioned that, among around 13 million account holders, the number of Mobile banking users was only 716,454 as of September 30, 2016. CBEbirr is the other form of Mobile banking service provided by the bank by opening special type of account with some amount only for this purpose. This service is commonly associated with Agent banking in which customers can deposit or cash withdraw from any nearby agent or branch

[4] Active cards are defined in internal reports as a card which make at least 12 transactions per year.

of the bank along with fund transfer to any other user, pay bill, top up air and related services using their mobile phone.

Internet banking: as its motto "*why inline when you can be online*", it gives instant service of accessing the bank anytime from anywhere including viewing account balances and transactions, making fund transfers between a customer's own current accounts and savings accounts, effecting payments to third parties predefined CBE customers within Ethiopia, viewing and downloading Current and Saving account statements, requesting for Stop Payments on cheque, and other services. However, according to CBE Communication (2016, p. 5) report, the number of Internet banking users was only 15,481 as of September 30, 2016, which was less than 1% of the total account holders. According to Kinfe (2016, p. 30), though the bank has started Internet banking since 2012, the service didn't show progress other than providing services of viewing financial reports and checking balances until 2016.

E-banking trend in Dashen Bank S.C

Dashen Bank S.C, which is mentioned as a 'forerunner' in the E-banking services by many authors, has been in delivering E-banking services since 2006. It is also mentioned many times as it gave renaissance for ATM banking after five years of ATM introduction to the country by the pioneer state owned bank (Fikru, 2011; Kindie, 2016; Worku, 2010; Zeleke, 2016).

According to Zeleke (2016), Dashen bank is the first bank to provide a comprehensive payment card service as a principal for its own labeled card and for the other internationally recognized VISA, MasterCard, Union Pay and American Express card associations. In addition to acquiring these international payment cards, Dashen bank also had an integration with Zemen Bank S.C to create interoperability under the umbrella of its Visa membership right to allow both bank's card holders access both Dashen and Zemen bank's ATMs. Kinfe (2016, p. 30) also mentioned that the bank is working to effectively implementing both the branch based and impersonal banking through various electronic delivery channels, though it faced many challenges.

Currently, the bank delivers cash withdrawal, balance inquiry, mini-statement, fund transfer between accounts attached to a single card, changing and unblocking PIN services for its ATM card holders (Dashen Bank S.C, 2017a). The 21st annual report of the bank shows that it has deployed 205 ATMs and 837 POS terminals across the country to provide its customers convenience service (Dashen Bank S.C, 2017b). As the report further shows, the total number of the bank's card holders reached to 556,688 that makes the percentage of its card holders to the total number of depositors around 32%.

Dashen bank has started Internet banking starting from the last quarter of 2014 with an access to view financial statements followed by fund transfer functionality as the banks E-banking service department annual report for 2015 (as cited in Zeleke, 2016). The latest functionalities added to Internet banking as of today includes account information, mini statement, full transaction statement, daily exchange rate, loan statement, fund transfer within Dashen bank and to other local banks accounts, salary and provident fund upload, electronic bill payment (utility payment), and to stop cheque payment services (Dashen Bank S.C, 2017a). The bank's Internet banking subscribed users number shows remarkably growth in 2017 and reached to 10,353 which shows 33% increment from the precedent year registered number (Dashen Bank S.C, 2017b). However, comparing to the total number of depositors the total percentage of subscribed users is only nearly 1% which is significantly small number.

In regarding to Mobile banking, Dashen bank has started to give the service starting from 2015 using USSD in which customers can use the service by dialing to*996# or by installing Dashen bank mobile Apps. Dashen bank's Mobile banking enables customers to fund transfer within own bank account and wallet account, fund transfer to account holders but not Mobile banking users, fund transfer for non-account holders using their mobile phone number, mini Statement and checking of account history of wallet account, balance enquiry on bank account and wallet account, PIN change, merchant payment, bill payment and other services (Dashen Bank S.C, 2017a).

E-banking trend in Wegagen Bank S.C

Wegagen bank incorporate electronic payment systems along with its ordinary banking services in 2010 (Worku, 2010).The bank has deployed one of internationally known Latvian based card suit system called “Tieto Card Suit” for switching card payment transactions. The deployment project was initially made by Kenyan based agent called Technology Associate which signed the agreement on December 30, 2008 (Gemechu, 2014).

This multi-functional payment system has enabled customers to get different banking services using payment cards in ATM and POS machines. Currently the bank owns 200 ATMs for cash withdrawal, balance inquiry and mini-bank statement of the last five transactions services. Similarly; balance inquiry, goods purchase and cash advance services are available using its 300 POS terminals located in different hotels, supermarkets and other shops (Wegagen E-banking Services Directorate, 2017).

The bank issues different types of payment cards. Debit cards labeled as ‘Agar Visa card’, are the major one in which there are more than 140,000 customers registered for them. The bank also issues pre-paid cards, gift cards and co-branded cards with other organizations. In addition to issuing its own payment card, the bank acquires Visa and Mastercard from any international banks using the Visa and Mastercard payment networks. It also acquires any other local banks’ payment cards using the national payment switch (Wegagen E-banking Services Directorate, 2017).

Mobile banking is the other form of E-banking channel started in August 2014 (Wegagen Bank S.C, 2015). While the bank uses SMS for notification of any account related transactions, it uses USSD for the actual Mobile banking operations. Through this service, it provides fund transfer to own and other account holders in the same bank, fund transfer to non-account holders using their mobile phone number, request cheque book and monitoring its status, viewing loan and other account balances, viewing mini-statement of the last five transactions and requesting for daily foreign exchange rate. Customers of Mobile banking service can avail these services by dialing *866#. According to Wegagen E-banking Services Directorate (2016, p. 8) report, there were 9,417 subscribers of mobile banking and 6,714 transactions were made by these customers with transaction value of Birr 16,974,192 until September 30, 2016. Recently, the bank also started ‘hello cash’ service integrating with Agent banking to provide Mobile banking service using the special account opened for this purpose without having the bank account necessarily. This new form of service enables users to deposit and withdraw cash from any nearby branch or registered agent of the bank. Fund transfer to other customers having this type of account, fund transfer to any other mobile phone user, air top up and paying bills are other services availed to the users by the bank (Wegagen Bank S.C, 2017a).

The third type of E-banking services adopted by Wegagen bank, though it is still not popularly utilized by retail banking users, is Internet banking. The bank provides this technology to enable customers to follow their account detail from anywhere using the Internet (Wegagen Bank S.C, 2017a). The bank is promising to provide more enhanced services using its Internet banking services after the new Centralized Online Real-time Exchange (CORE) banking system project go live in the early 2018.

E-banking trend in Zemen Bank S.C

Zemen bank S.C, which is known for the idea of single branch banking, is also known for its high-level adoption of E-banking technologies (Tefera, 2017). Since the bank followed distinctive business model that is focused on corporate clients and technologically-driven banking services delivered via multiple channels (Zemen Bank S.C, 2017a, p. 12), rapid adoption of E-banking technologies is a primary option. Currently the bank uses four main channels of E-banking services that include ATM, POS, Mobile and the Internet channels (Zemen Bank S.C, 2017b). The list of services offered by these channels is discussed below as it is presented on the bank’s official website cited above.

Mobile banking is one of the alternative channel using SMS in which Zemen bank users access it by dialing *844#. Like other banks Mobile banking, Zemen bank also offer services including balance inquire, mini-statement, view daily exchange rate, fund transfer and follow up on loan accounts. One specialty in Zemen bank is its second type of Mobile banking service which is called Phone banking. It is interactive voice response service where customers can make balance check, review their transaction and make fund transfer by calling to 8700 dedicated line from which specialized personnel gives the service from the bank side.

ATM banking is the other dominant channel using by the bank for its customers. The specialty of the bank in this service is its capability of providing the debit card immediately upon opening the bank account. Most of other banks take 15 to 30 days to offer debit cards to their customers. Moreover, the bank is the only bank that make all its customers to be cardholders. Though the bank does not have much number of ATMs it seems took the advantage of the interoperability with Dashen Bank ATMs and the national payment network. Like most banks do, Zemen bank also provide services cash withdraw, balance check, and fund transfer to another account in the same bank. According to Zemen bank S.C (2017a) report, 57 million birr withdraws from its ATMs in average per month.

In regarding to payment cards, the bank launched pre-paid type of cards in early 2012 before other banks introduced it. This card is used to access pre-loaded amount without the need of link with Zemen bank account. Users can deposit up to Birr 50,000 with any time top up feature to purchase from the bank's POS terminals found in big hotels or to withdraw cash from ATMs like debit cards. As it is mentioned in early paragraphs of this chapter, pre-paid cards additional advantage is their capability to be prepared without personalization to use as a gift card. The bank also uses special type of card called Payroll card which is linked to employees account to those whose salary is directly credited to their Zemen bank accounts. According Zemen bank S.C (2017a) report there are 20,000 employees who use this service using the payroll card.

When we come to Internet banking, Zemen bank is mentioned as the first bank to realize Internet banking for its full-fledged service in Ethiopia (Gemechu, 2014). The Bank provided the service which is easy to use with greater control of user's finance. In addition, it is given for free with complete security. According to Tefera (2017, p. 27), during Zemen bank introduce the new technology for the country in 2010, it was used only to check bank statements and foreign exchange information. Later, the bank has started free account to account money transfer which was new service in Ethiopian banks experience. The channel also used to upload payroll by employers to make payments to their individual workers. Currently, the system is used to view and check balance, download and export statements to other accounting formats, fund transfer, exchange rate inquires, request for cheque and much more services (Zemen Bank S.C, 2017b).

2.1.2.2 Local Payment Switches and Processors

Electronic payments require flow of data which represent conventional financial instruments in digital format. A server that handles the process of electronic payment that includes creating digital representation of the conventional money, conduct authorization and forwards payment orders to their corresponding conventional networks and financial institutions is called a Payment switch (Gifford, Stewart, Payne, & Treese, 1995). All local banks discussed above uses their own payment switch. However, there are two other giant payment switches in the country where one is owned by six private banks and the other is a national payment switch.

Premier Switch Solution (PSS)

PSS is a third-party payment processor with a shared payment switch among six private banks (Yiheyis, 2015). Initially it was established as a share company between three private banks, named as Awash International Bank S.C, Nib International Bank S.C and United Bank S.C in February 2009 for comprehensive and equipped payment card processing and payment switching. Later, other three banks: Addis International Bank, Berhan International Bank and Cooperative Bank of Oromia, has joined the PSS consortium (PSS, 2017; Tefera, 2017; Zeleke, 2016). Premier Switch Solution and S2M (as cited in Tefera, 2017) reported that the company adopted the state-of-the art technology which plays significant role in E-banking development and customers' experience enhancement. Moreover, Yiheyis (2015) study found that this interoperable service increased customers satisfaction. That means, such kind of interoperable services play significant role in customers' adoption of E-banking.

According to Zeleke (2016), PSS is a certified third party by National Bank of Ethiopia to provide a payment switch solution and certified for membership of Visa, Mastercard and Union pay which enables it to acquire Payment cards from international banks which has a membership relation to one of such international brands. Beyond providing a common payment network for six banks with relatively less initial investment, it enabled customers of these banks to use variety of services from ATMs that includes cash withdrawal, balance and mini-statement check, fund transfer, check back request, E-top up and cash deposits (PSS, 2017).

Ethiopian National Payment Switch (EthSwitch)

The national E-payment switch named as EthSwitch S.C is formed by all Ethiopian commercial banks through their association and the country's National Bank of Ethiopia. It has started its operation to provide common payment network for all seventeen commercial banks on May 12, 2016 (BPC Banking, 2016). This interoperability enables customers of any bank to perform payment card related transactions using any bank's ATM. With successive similar projects, the interoperability is expected to include banks' POS terminals in near future.

According to Ethiopian Bankers Association 2009 report (as cited in Tefera, 2017), the interoperability among all banks facilitates the national bank strategy to expand technology-based transaction which in turn helps to create cashless society. It is also used as an interface for five new banks which were neither member of PSS banks nor have their own payment switch. Moreover, having a national payment switch increase availability and convenience of payment service throughout the country that facilitates customers' adoption of E-banking which is key component of any electronic commerce (BPC Banking, 2016; Tefera, 2017).

2.1.2.3Summaries of E-banking services in Ethiopia

E-banking services in Ethiopia has been dormant for number of years though it took more than 15 years. Passing through sluggish change, currently all banks started to give E-banking service in one or more forms. ATM is the first and still the most dominant type of E-banking service in Ethiopia. Most banks provide cash withdrawal, balance inquiry and mini-statement as common services through ATMs. Few banks started to use additional service like fund transfer and foreign currency exchange. Other services like bill payment and air top up are introduced as available services in the above literature even if the researcher, as a customer of about five banks, has found none of these services were fully functional through ATMs.

In case of Mobile and Internet banking, most banks are giving services like fund transfer to the same bank account holder, fund transfer to non-account holder, balance inquiry and mini-statement. Some banks also offer additional services like bill payment to specific organizations and air top-up services by integrating Mobile banking with Agent banking. Few banks are also giving advanced services like payroll upload, full account follow-up and bill payment using Internet banking.

As we see in the above paragraphs, yet it takes several years, E-banking service adoption by banks is increasing from time to time. Remarkable progress is observing in recent years specifically after PSS and EthSwitch create an expanded payment network to facilitate interoperability among banks. However, customers' adoption rate is still very poor comparing to the total account holder in each bank. Except for Zemen Bank, other banks' customer adoption rate is below one third of their total account holders for ATM banking. For other E-banking channels, the rate is even much lower than the above. For instance, the total number of Mobile banking users, for the country having 57.34 million mobile subscribers (Ethio telecom, 2017) is significantly low. For Internet banking, the rate becomes even much severe. Though there are different researches made to study the reason behind the slow adoption of E-banking, the area is still very sensitive that demands such kinds of study which particularly focus on customers' E-banking adoption factors in Ethiopia.

2.1.3. Technology adoption Theories and Models

Due to the highly immerging nature, number of information science researches are conducting over time. Technology adoption is one of well addressed areas of Information Science domain result in developments of several theories and models (Sharma & Mishra, 2014). Among several theories and models investigated to determine acceptance and use of new technologies, widely accepted and used theories and models include, but not limited to, Roger's 1960 Diffusion of Innovation Theory (DOI) (as cited in Sahin, 2006), the Theory of Task-technology Fit (TTF) (Goodhue & Thompson, 1995), the Theory of Reasonable Action (TRA) (Fishbein & Ajzen, 1977), Theory of Planned Behavior (TPB) (Ajzen, 2011), the Technology Acceptance Model (TAM) (Davis, 1989), Technology Acceptance Model 2 (TAM2) (Venkatesh & Davis, 2000), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), and extension of UTAUT, UTAUT2 (Venkatesh, Thong, & Xu, 2012). In the following paragraphs, some of the most widely used theories and models will be discussed.

2.1.3.1 Diffusion of Innovation Theory

Technology acceptance theories and models traced back to the 1960's Everett M. Roger's Diffusion of Innovation Theory (Sharma & Mishra, 2014). The main idea of this theory is about how diffusion of a new idea (innovation) will take place through four main elements named as 'an innovation', 'communication channels', 'time' and 'social' (Rogers, 1983, p. 10). The four main elements are extracted from the definition of Diffusion by Rogers as "the process by which an innovation is communicated through certain channels over time among the members of a social" (p. 5).

For Rogers innovation doesn't mean necessarily new finding or technology, rather it is something that is perceived as new by an individual, society or an organization (p. 11). A communication channel is how messages get from one individual or unit of adoption that has knowledge or experience with the innovation to other individual or unit that doesn't have that knowledge of the innovation. In general, the basic notion of the diffusion of innovation process is the exchange by which one individual communicates a new idea to one or several others (Rogers, 1983, p. 17).

As shown in ***Figure 1,*** this process passes through five stages named as: Knowledge, Persuasion, Decision, Implementation and Confirmation. The process imitated when an individual or adopting unit learns new idea (forms knowledge). Then knowledge of an innovation changed to forming an attitude toward (persuasion) the innovation. Third a decision stage will have occurred to adopt or reject that new idea. Fourth, an implementation of the new idea occurred. Finally, it comes to confirmation of reaffirmation or rejection decision (Rogers, 1983, p. 20).

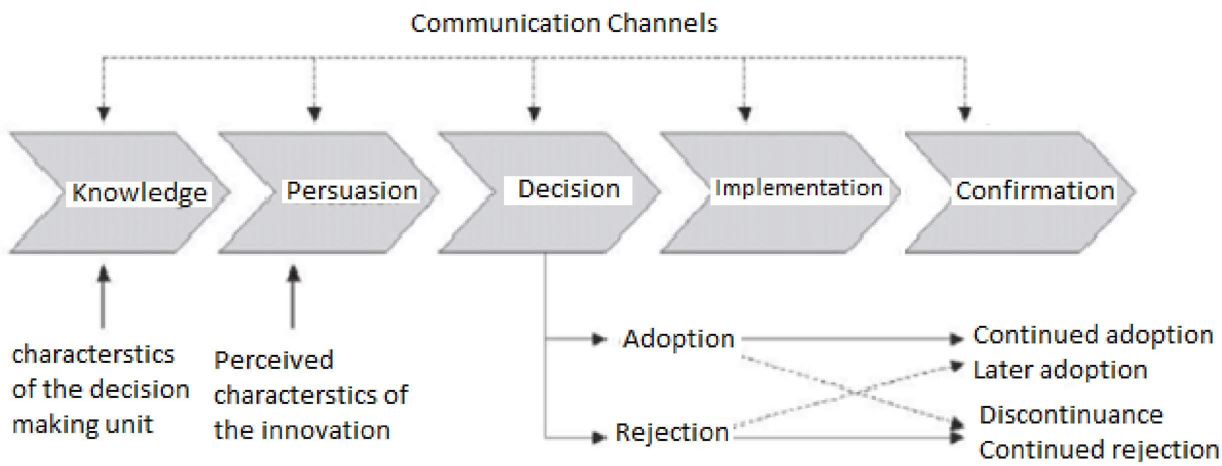

Figure 1: Diffusion of Innovation Theory.

Reprinted from Sharma and Mishra (2014)

According to Sharma and Mishra (2014), the Innovation Diffusion Theory (IDT) has S-shaped curve of adoption. Initially the rate of speed is slow since very few are exposed to the new idea. Then, the rate of speed start to accelerate as more people start accepting the innovation through communication. Finally, the rate of diffusion decreases as there are no more members left for accepting the innovation. Rogers 1995 (as cited in Lai, 2017) explained that the S-shaped adoption curve is characterized by five group of users named as innovators, early adopters, early majority, late majority and laggards, in which early and late majority takes about 68%.

DOI theory is one of the most popular adoption models used by many researches in variety of disciplines (Sahin, 2006). Several of these disciplines include political science, public health, communications, history, economics, technology, and education. Dooley, 1999 and Stuart, 2000 (as cited in Sahin, 2006) argues Roger's theory as a widely used theoretical framework in the area of technology adoption and diffusion.

2.1.3.2 Theory of Planned Behavior (TPB)

Theory of planned behavior (TPB) was developed in 1991 by Ajzen based on review of his 1985 and 1987 works on behavior and TRA which was proposed by Martin Fishbelin and Ajzen in 1975 (Sharma & Mishra, 2014). According to Lai (2017) literature review, Ajzen developed TPB by adding one crucial factor called ‘perceived control’ behavior on the TRA two factors known as attitude and social norm as shown in ***Figure 2*** below.

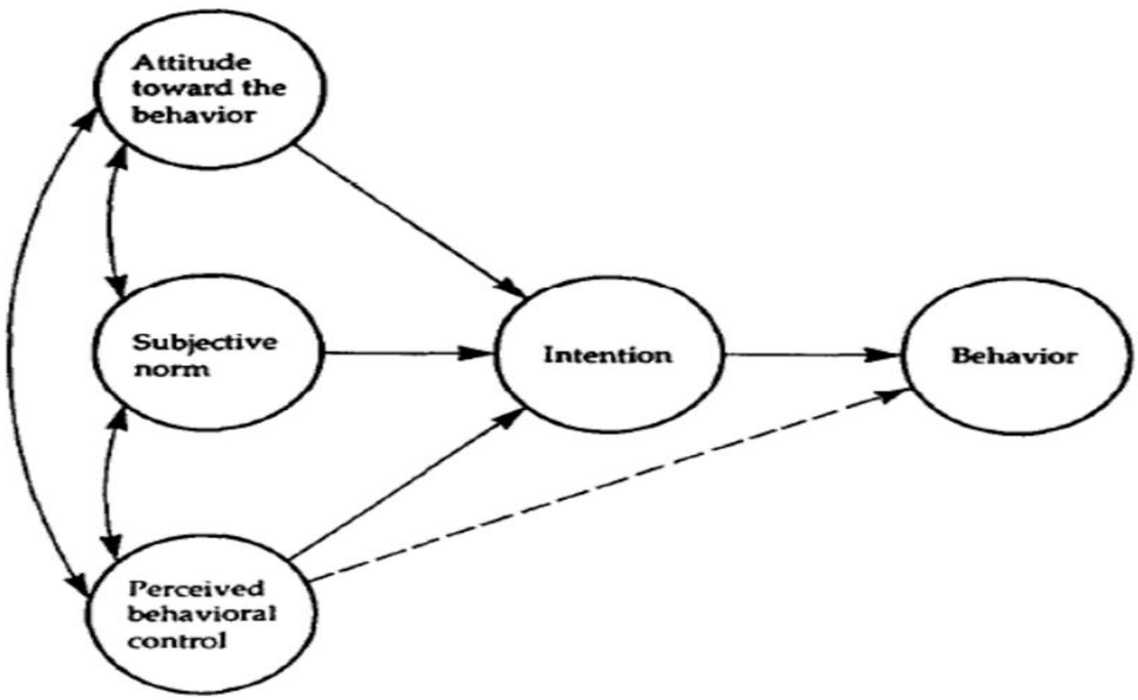

Figure 2: Theory of Planned Behavior (TPB).
Reprinted from Ajzen (1991)

TPB provides a useful conceptual framework for dealing with the complexities of human social behavior that have been shown in different dimensions of previously made studies on social and behavioral sciences. The combination of BIs and perceived behavioral control has been found for their significant behavior variance in TPB. The theory also gives value for determinants of BIs like attitudes towards the behavior, subjective norms and perceived control over the behavior. In general, TPB revealed that Intention, perception of behavioral control, attitude toward the behavior, and subjective norm used to indicate a different aspect of the behavior. So that it is at the level of beliefs that we can learn about the unique factors that induce one person to engage in the behavior of interest (Ajzen, 1991).

2.1.3.3 Technology Acceptance Model (TAM)

TAM was introduced by Fred Davis in 1986 by tailoring TRA for modeling users’ acceptance of information systems or technologies (Lai, 2017). It is basically built up on the association between two primary independent variables (PU and PEOU) and one dependent variable (Attitude towards use) (Liu, 2014) as shown in ***Figure 3.***

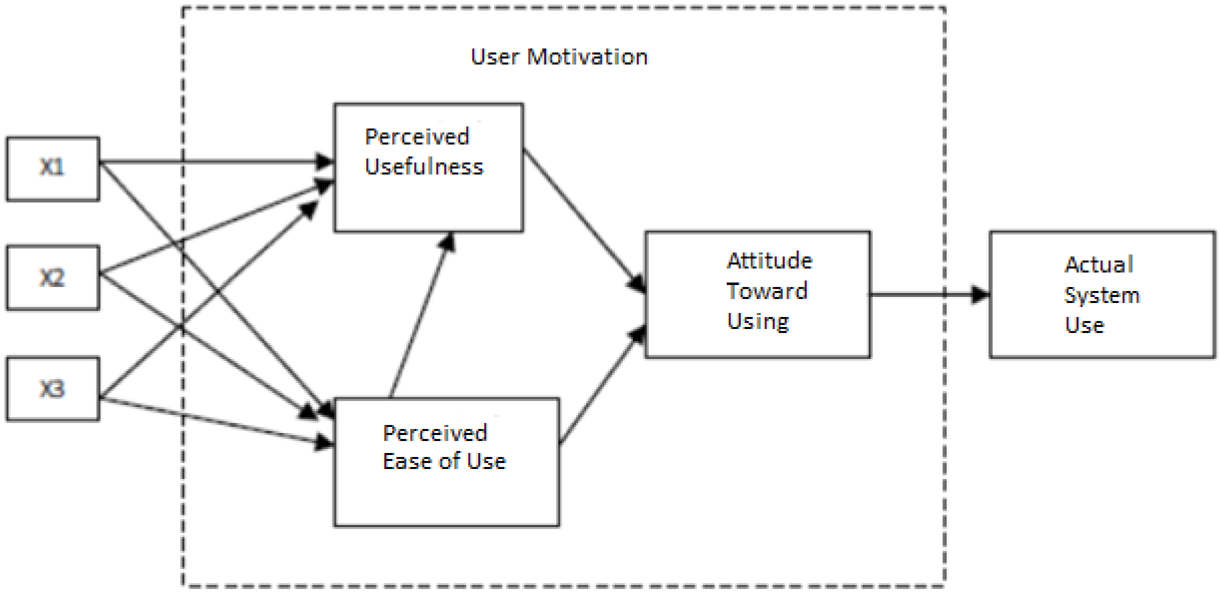

Figure 3: Original TAM model by Davis (1986).
Reprinted from Lai (2017)

In 1989, Davis modified TAM to explain the general determinants of computer acceptance and usage behavior (Lai, 2017). According to Davis (1989), PU is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" and PEOU as "the degree to which a person believes that using a particular system would be free of effort". These constructs are basically derived from Bandura's Self Efficacy Theory (1982) and Rogers and Shoemaker (1971) definition of complexity (Sharma & Mishra, 2014).

Davis (1989) study revealed the strong relationship between the two determinants, PU and PEOU, and usage behavior. Moreover, PU has showed more strong correlation with system use than PEOU. He justified that users are willing to adopt new technology with some extent difficulty if they have got it useful to improve their performance. However, being easy to use will not be a determinant factor to use a system unless it brings some improvement (usefulness) on performance. Hence, designers and implementers should pay much attention on PU for successful adoption.

TAM has been stayed so robust and powerful model for predicting user acceptance for about ten years (Sharma & Mishra, 2014; Maditinos, Chatzoudes & Sarigiannidis, 2013). Moreover, King and He 2006 (as cited in Sharma and Mishra, 2014) presented a meta-analysis of TAM to show its robustness in wide application areas. However, there were some arguments on the influence of other external variables for a person belief on a system use. For instance; social factors, cultural factors and political factors are some of the major external influence of TAM (Surendran, 2012). There are also other extended models of TAM (Maditinos et al., 2013; Podder, 2005) which are modified by other researchers.

Final version of TAM was formed by Venkatesh and Davis in 1996 (as cited in Lai, 2017). This final version showed the influence of external variables on the two constructs of the original TAM model and the direct influence of both PU and PEOU on BI for which it is direct determinant of usage behavior as shown in ***Figure 4***.

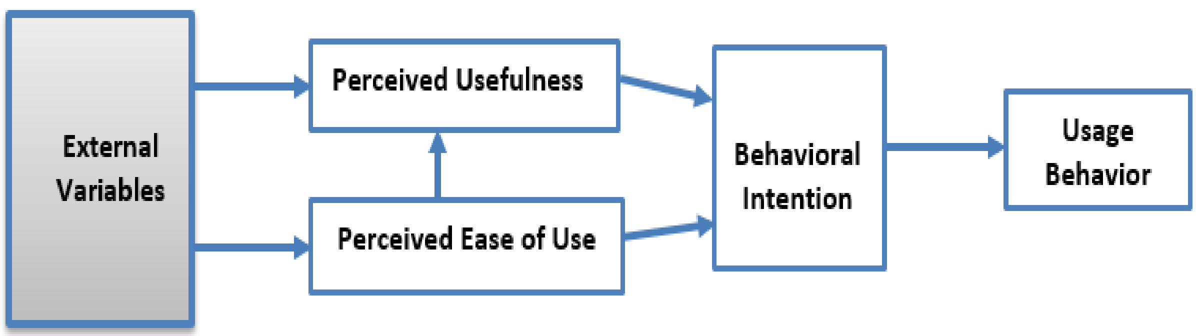

Figure 4: Final version of TAM by Venkatesh and Davis (1996).
Adapted from Lai (2017)

TAM2 is a theoretical extension of Technology Acceptance Model (TAM) (Venkatesh & Davis, 2000). This study explained further about PU and usage intentions in terms of social influence and cognitive instrumental processes. As shown in ***Figure 5***, the model integrates additional three variables (subjective norm, voluntariness, and image) from social influence processes and four variables (job relevance, output quality, result demonstrability, and PEOU) from cognitive instrumental processes that significantly influenced user acceptance. TAM2 proved that cognitive mental assessment of important goals at work with their consequence of successfully performing job tasks using the system used as a basement for forming usefulness perception.

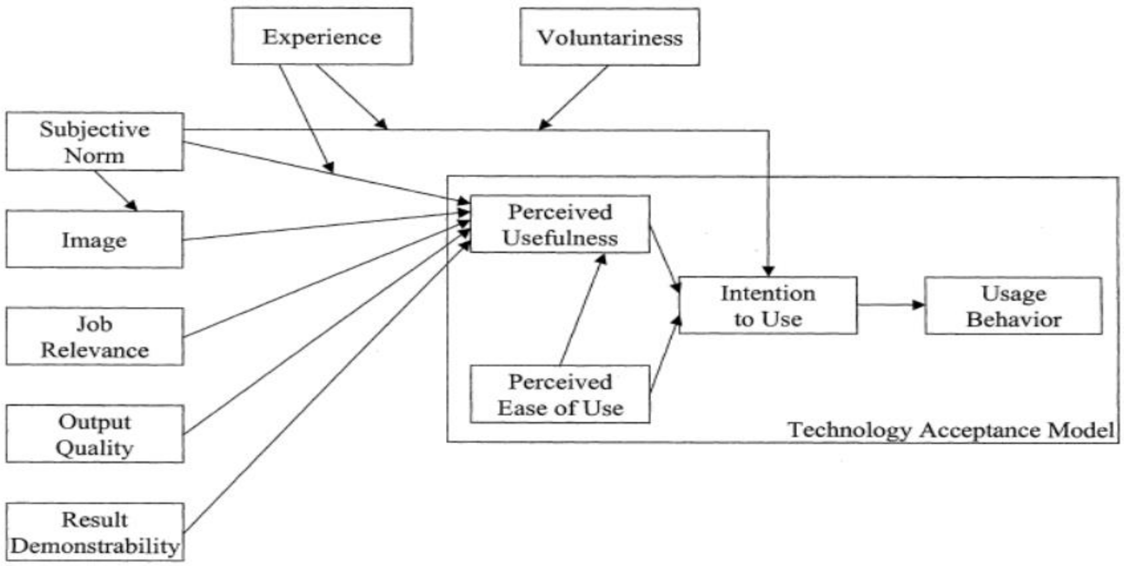

Figure 5: Extended Technology Acceptance Model (TAM2).
Reprinted from Venkatesh and Davis (2000)

TAM3 is further extension of TAM developed by integrating different determinants of PU in TAM2 and the model of the determinants of PEOU by Venkatesh, 2000 (Venkatesh & Bala, 2008). As shown in ***Figure 6***, in TAM3 research model, PEOU to PU, computer anxiety to PEOU and PEOU to BI were moderated by experiences. The model includes other external four different types of conditions: the individual differences, system characteristics, social influence, and facilitating conditions which are determinants of both PU and PEOU (Venkatesh & Bala, 2008).

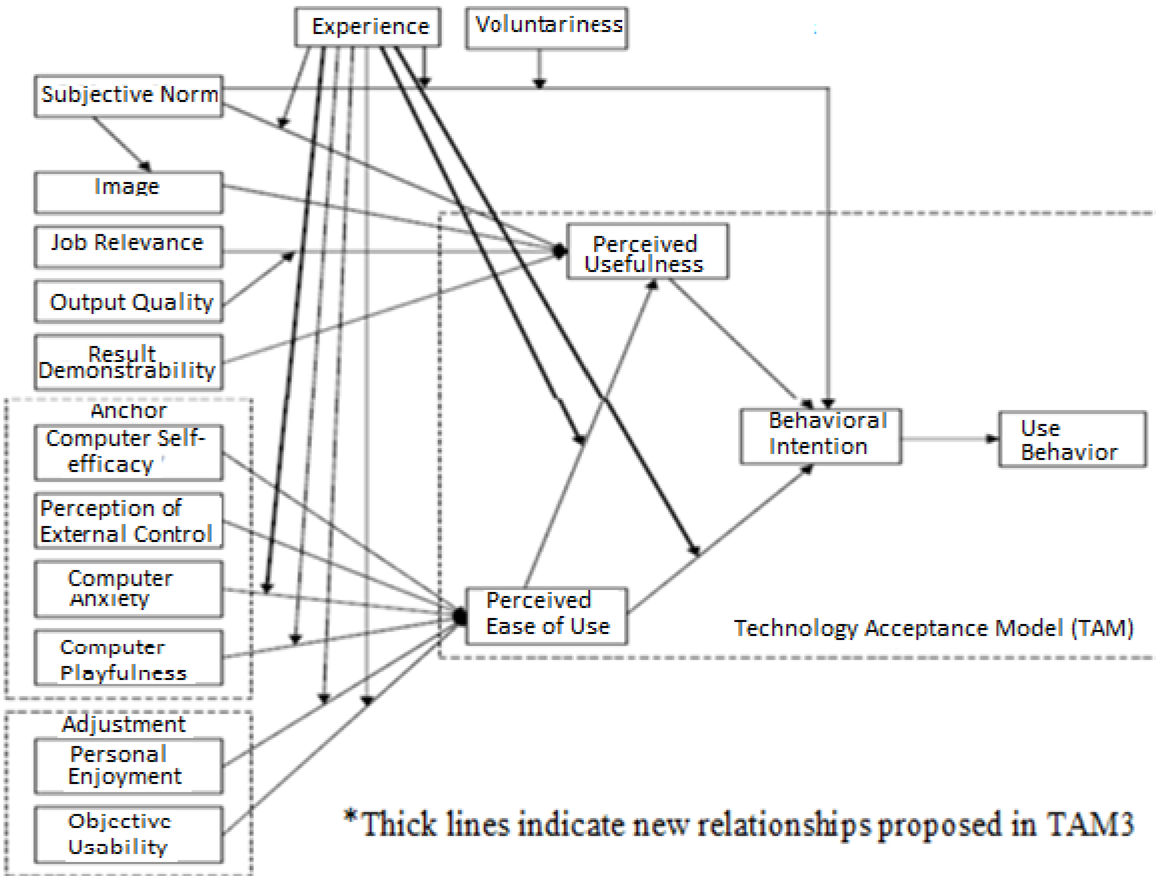

Figure 6: Technology Acceptance Model (TAM3).

Adapted from Venkatesh and Bala (2008)

2.1.3.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT is a conclusive model formed by considering the concepts of eight [TRA, TAM, MM (Motivational Model), TPB, TAM2, IDT , SCT (Social Cognitive Theory) and MPCU (Model of Personal Computer Utilization)] models of the determinants of intention and usage of information technology (Venkatesh et al., 2003). As shown in ***Figure 7,*** UTAUT model has four main independent variables (PE, EE, SI and FCs) moderated by age, gender, experience and voluntariness. Its comprehensiveness provides a refined view of how the determinants of intention and behavior evolve over time. Moreover, UTAUT highlights the importance of contextual analysis in developing strategies for technology implementation within organizations (Venkatesh et al., 2003).

UTAUT serve as a comprehensive model that can be applied in many applications (Sharma & Mishra, 2014). Despite each of previously developed models in the domain are quite successful in predicting technology usage behavior, UTAUT emphasized the importance of consideration of complex range of potential moderating influences that make more complete picture of the dynamic nature of individual perceptions about new technology adoptions (Venkatesh et al., 2003).

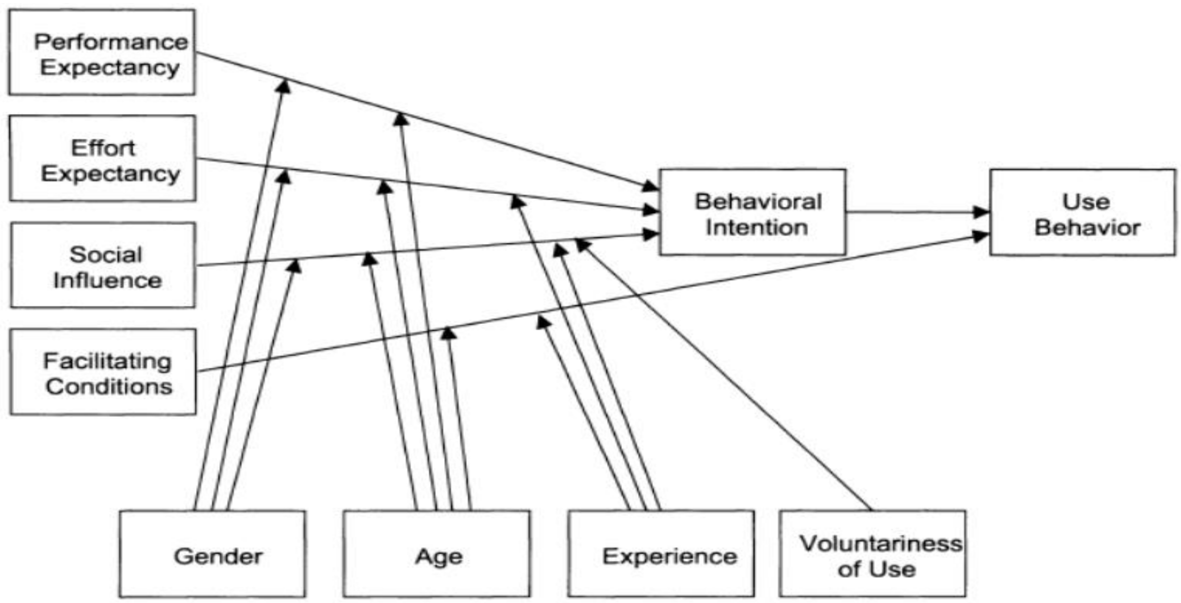

Figure 7: Unified Theory of Acceptance and Use of Technology (UTAUT)
Reprinted from Venkatesh et al. (2003)

2.1.3.5 Unified Theory of Acceptance and Use of Technology (UTAUT2)

UTAUT2 is an extension of UTAUT for applying the model to study acceptance and use of technology in a consumer context while UTAUT and other previous models focused on acceptance and use of technology in organization context. On their study of consumer acceptance and use of information technology, Venkatesh, Thong and Xu (2012) used three additional constructs into UTAUT as shown in ***Figure 8***.

These three additional constructs are HM, PV and HT. HM conceptualized as perceived enjoyment that has been found as major determinant of consumer's BI to acceptance and use technology. PV is referred to consumer's cognitive tradeoff between the perceived benefits from a given technology and monetary cost required for using it. Unlike UTAUT, which is on organization context, UTAUT2 focuses on consumers who has to pay associated cost for the technology use.

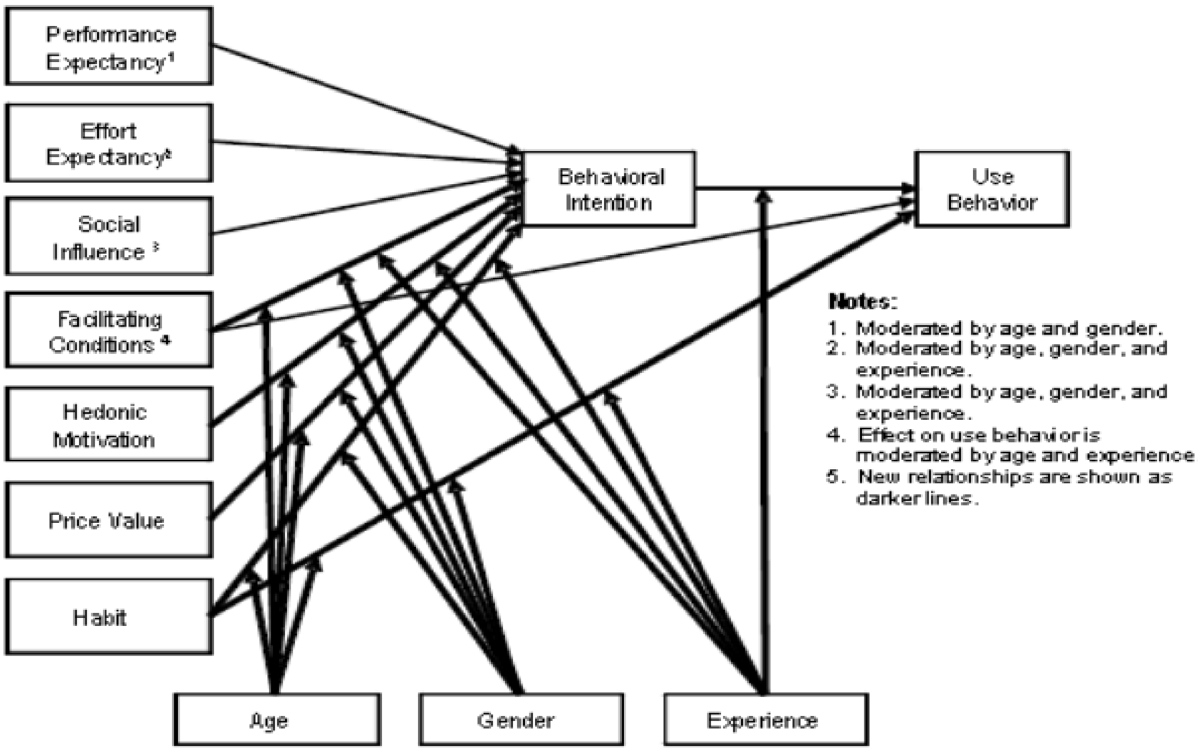

Figure 8: Unified Theory of Acceptance and Use of Technology (UTAUT2).
Reprinted from Venkatesh, Thong and Xu (2012)

Hence, PV will have a significant impact, in which users' intention will be positive for the benefits of using a technology are perceived to be greater than the monetary cost for using the technology. HT is the third construct added in UTAUT2. While experience is associated with the passage of time from the initial use of a given technology, HT is operationalized in UTAUT2 as the extent to which an individual believes the behavior to be automatic. One of the basic assumptions in UTAUT2 about HT is that repeated performance of a behavior produces habituation and behavior can be activated directly by stimulus cues. Hence, the prior use of a given technology is a very likely indicator of using technology in the future (Venkatesh et al., 2012).

2.2. Related works

Technology adoption in different organizations is one of the dominant research area studied by many researchers. With respect to technology adoption in banks, E-banking technologies are among the most concerns of many studies done so far. Being one of the core competitiveness strategy for today's markets, significant enhancement has been observed in E-banking technology innovation and adoption since 1950s. Correspondingly, many researches have been done in the area to study the adoption factors and levels, model and theories, benefits and drawbacks, opportunities and challenges and so on. In this section, we will try to see some closely related works reviewed for this research.

Daniel (1999) argue that E-banking as the newest delivery channel provided by many banks in developed countries during the end of 1990s. In her study of provision of E-banking in the UK and the Republic of Ireland, new insights were found by exploring organization's approach to innovation and their view of current and future markets. As a result, it is found that organizations prediction of customer acceptance was very low and organizational culture of innovation and future vision are the most important factors in the adoption of electronic delivery. In similar country, Shah, Khan and Xu (2005) have made a study to find critical organizational factors of E-banking adoption. Accordingly, quick responsive products/services, organisational flexibility, services expansion, systems integration and enhanced customer service have found as the main critical factors and further recommended that integration of E-banking channels are mandatory along with the integration of technology and business process.

An international comparison of technology adoption was also conducted by Im, Hong and Kang (2011) to examine the relationship of constructs with culture in technology adoption. Two technologies: MP3 media player and Internet banking were examined for the purpose to see the impact of culture on construct variables that are likely to affect the behavioral intention on use behavior. During their empirical test of culture as moderator factor they have found that EE on BI and the effect of BI on use behavior had significant difference for U.S and Korean customers. This research revealed that nationality has stronger impact on moderating users' technology adoption that enforces conducting researches to test different technology adoption models and theories in different cultural contexts (Im et al., 2011). Baptista and Oliveira (2015) also provided new insights into how culture influences individual use behavior by combining Hofstede's cultural moderators with UTAUT2. These rationale supports the importance of conducting similar researches in countries like Ethiopia where wide cultural difference is existed.

Podder (2005) study on factors influencing the adoption and usage of Internet banking in New Zealand context by modifying two models. The first one was TAM (Davis, 1989) with addition of two other variables called risk and self-efficacy. The second one was perceived characteristics of innovation (PCI) (Moore & Benbasat, 1996 as cited in Podder 2005) without the image and voluntariness constructs. This study finally has got that the intention of customers to use Internet banking in New Zealand was low. Moreover, it revealed that PU, PEOU, Self-efficacy, relative advantage, compatibility and result demonstrability have significant association with intention to use internet banking while risk, visibility and trial-ability have not. Podder (2005) also suggested that other models should be tested on the intention or usage studies of Internet banking.

Similarly, in Africa several researches are conducted among which works of Aderonke (2010) from Nigeria, Gikandi and Bloor (2010) from Kenya; Maduku (2014) from South Africa are reviewed below.

Aderonke (2010) has made an empirical investigation of the level of users' acceptance of E-banking in Nigeria. Using survey of 500 questionnaires in Lagos, test of hypothesis was conducted to measure the impact of Perceived Credibility, Computer Self-Efficacy, PU, and PEOU on customer attitude and adaptation. The investigation of this paper showed that PU and PEOU are not sufficient to determine the consumer's BI to use information system, though they have significant roles on other studies. Hence, extending TAM seems reasonable to study user's acceptance and usage of technology.

Gikandi and Bloor (2010) agree on the explosion of researches globally associated with the vast amount of electronical exchange of monetary value, though very little has been done in developing countries to investigate factors that influences the adoption and effectiveness of E-banking. As a result, they made a consecutive study on 2005 and 2009 to see the change in the adoption of E-banking by Kenyans. As a result, they have got significance change from 2005 in 2009 attached with E-banking adoption. Influential factors of E-banking adoption were also showed change over time. For example, lack of legal regulations will never remain the same while time changes.

A study conducted on customers' adoption and use of E-banking services in South Africa also showed that TAM constructs are important factors of E-banking adoption (Maduku, 2014). However, this study showed that, customers' trust in the E-banking system was found to be the strongest predicator of Internet and Mobile banking adoptions. This result contradicts other previous studies where PU and PEOU were widely held to affect the adoption of Internet and Mobile banking strongly. These arguments show that factors of E-banking adoption have variance in different environmental-contexts.

Like in most other developing countries, the attention paid to E-banking adoption in Ethiopia seems very minimal both in terms of adoption rate and researches made on related issues. Worku's (2010) study on electronic banking in Ethiopia is one of the widely cited article that has been done to investigate practices, opportunities and challenges of E-banking in Ethiopia. His investigation showed that Ethiopia were too late to introduce E-banking technologies. Though number of years elapsed from this study, the main challenges of E-banking adoption in Ethiopia seems continued until today. These includes low level of internet penetration, poorly developed telecommunication infrastructure, lack of suitable legal and regulatory framework for e-payment, political instability, high rates of illiteracy, high cost of Internet, frequent power interruption, resistance to changes in technology, fear of risk, and cyber security issues.

One of the other earlier researches, a case study by Fikru (2011) on ATM users of Dashen Bank in Addis Ababa to assess customers' attitudes and satisfaction levels with technology-based self-service is mentioned. This study was conducted to provide better understanding of customers' attitudes and preferences with technology-based self-services. Accordingly, he has used both qualitative and quantitative methods of data collection and found that most of the users were male, younger, educated and earns higher income. Moreover, while most of them had positive attitudes for ATM services in terms of speed, risk, ease of use and physical appearance, they had negative attitudes towards efficiency, convenience and reliability.

Regarding to E-banking adoptions, Gemechu (2014), Girma (2016), Kinfe (2016), Zeleke (2016) and Tefera (2017) are mentioned as some of the recent researches on E-banking adoption studies from organizations' perspective. From these studies, Girma (2016), Kinfe (2016) and Zeleke (2016) studies focused on the opportunities and challenges aspects while Tefera (2017) focused on adoption of E-commerce framework for Ethiopian banks. Gemchu (2014) has developed a research framework based on Technolohy-Organization-Environment (TOE) model that articulates factors of E-banking adoption from the three dimensions.

There are also few researches conducted to E-banking adoption in Ethiopia from customer point of view. Yohannes (2010) conducted a research on specific type of E-banking technology to identify key factors of Internet banking adoption in Ethiopia. He has used DOI theory as a research framework and data has been collected from 400 respondents. As a result, he has found age, income, education level and occupation as demographic factors that influence the adoption of Internet banking. From psychological factors, perceived relative advantage, perceived compatibility, perceived complexity, perceived risk, and perceived cost were found to influence the adoption of internet banking while opinions of friends, parents and colleagues were not found influential to determine Internet banking adoption.

With related research, Yiheyis (2015) has made a study on evaluation of customer's satisfaction on ATM services on PSS member banks' customers located in Addis Ababa. The cross-sectional survey on purposively selected 384 respondents were addressed to collect the required data. This survey result revealed that most of PSS member banks' customers were moderately satisfied with PSS ATMs services. As a result, he suggested to attempt similar studies on more number of banks and large sample groups. Moreover, this study lacks to incorporate behavioral factors that influence customer satisfaction on the available ATM banking services.

A research work to identify factors that affect intention to use E-banking at Bank of Abyssinia in the case of Addis Ababa branches (Tesfaye, 2016) is one of the recent studies. Tesfaye has used an integrated TAM with TPB and Trust as additional construct which yields totally seven constructs: PU, PEOU, attitude, subjective norms, perceived behavioral control, trust and intention. His overall result showed that the level of E-banking services' usage in Ethiopia is still low and PU and trust are the most significant factors affecting customers' intention towards using

E-banking services. Though these findings are aligned with other findings, in contrary, PEOU and subjective norm were found negatively affecting the usage of E-banking that calls for further verification. This discrepancy might be because the study was conducted on the capital city where most user are likely to have knowhow of using such technologies. Therefore, similar studies are expected which covers wider geographical coverage to avoid biasness. Tesfaye (2016) also suggested that culture might have an impact in E-banking adoption specially in countries which have variety of cultures like Ethiopia.

Muche (2017) has also studied influence of demographic factors on user's adoption of E-banking in Ethiopia. She has made a descriptive study using survey of 600 users of E-banking technologies. Findings of this study, which was analysed by using independent sample T-test and one-way analysis of variance (ANOVA), showed that except for gender, the remaining demographic variables such as age, income, educational level and occupational status have no significant influence on users' E-banking usage behavior. However, this result contradicts with other researches mentioned above that require further investigation.

Among local studies on single form of E-banking channels, a case study on Mobile banking adoption behavior is one of the recent researches (Merga, 2017). Merga has used UTAUT2 to identify factors influencing customers' BI in case of CBE. A total of 110 questionnaires were collected and analysed using a partial least square (PLS) method with the help of the SmartPLS software. The empirical evidence of his study revealed that PE, EE and PV were found as major influencing factors of BI while SI, FC, and HM were found to have insignificant effect on BI of customers for mobile banking adoption. Findings are partially aligned with Venkatesh et al. (2012) in which results of the impacts of PE, EE and PV with BI are similar, results in relation to BI and the other three (SI, FC and HM) factors are different. Hence, Merga suggested similar researches to be conducted with additional variables and wider geographic coverages.

In general, few related works are identified in the regard of E-banking adoption in Ethiopia. This study can be categorized with these previous researches as it studies E-banking adoption factors from customer point of view. However, it will be unique to the extents of considering three E-banking channels together, considering four different banks' customers in wider geographic coverage and encompassing both the intention and actual use behaviours in the model.

CHAPTER THREE

III. Research Design and Methodology

The research design facilitates research to be as efficient as possible in terms of effort, time and cost (Kothari, 2004). Since this research is aimed to be conducted within a specified period and place to explore the cause and effect of factors in E-banking adoption, it follows the cross-sectional study design.

Technology adoption is not only related to technological aspect, but also, it is much complex process which involves individual and organizational aspects (Sharma & Mishra, 2014; Venkatesh et al., 2012). According to Sharma and Mishra (2014), two major streams of research have evolved on adoption of technologies. One stream pertains to adoption at individual and the other at organizational level. This research inherits the characteristics of researches which studies technology adoption from individual (consumer) perspective. Several theories and models have been proposed to explain acceptance of new technologies and their intention to use.

In this chapter, a research model will be defined based on well-practiced technology acceptance theories and models discussed in chapter two. Then, a detail of cross-sectional survey research methodology has been discussed up on a positivist epistemological philosophical ground. The research type, sampling and data collection procedures along with the systematic way of doing the analysis are the other key points of this chapter.

3.1. Research Model

3.1.1. Hypothesis Development

Combination of two or more theories and models is believed to have better use than single approaches due to their individual unique strengths. UTAUT is a result of such combination of widely accepted theories and models (Venkatesh et al., 2003). UTAUT2 is a modified model of UTAUT that is customized to fit for individual context (Venkatesh et al., 2012). One unique addition of this model is its flexibility for assessing technology adoption from end users (consumers) perspective. Due to this advantage and its recentness, UTAUT2 is used as a basis for this research conceptual model.

Accordingly, main variables are directly taken from UTAUT2 and its precedent UTAUT models with additional justifications and supports from other researches. These variables include Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit and Behavioral Intention that significantly affect technology adoption. As mentioned earlier, while other variables are adopted from UTAUT, Hedonic Motivation, Price Value and Habit are unique additions of UTAUT2 by Venkatesh et al. (2012). Based on the assumption of exogenous latent variables can directly affect endogenous latent variables in PLS path analysis (Hair, Hult, Ringle, & Sarstedt, 2014), the impact of three moderators (age, gender and experience) in UTAUT2 is not considered in this research model. Hence, the brief explanations of main latent variables and associated hypothesis are presented as follows.

Performance Expectancy (PE)

Originally, Venkatesh et al. (2003) defined PE as "the degree to which an individual believes that using the system will help him or her to attain gains in performance". However, Venkatesh et al. (2012) modified the definition as "the degree to which using a technology will provide benefits to consumers in performing certain activities" to make it much suitable for consumer technology acceptance and use context. The second definition is considered as the working definition of PE in this document as it fits to the main intention of studying customers' E-banking adoption. To make it much specific the term can be understood here as the degree to which using E-banking technology will provide benefits to consumers in performing financial related activities.

According to Venkatesh et al. (2003), PE, which is made up of five constructs named as PU, extrinsic motivation, job-fit, relative advantage and outcome expectation, remains significant in their measurement and considered as the strongest predictor of BI to use. From the above five constructs PU is dominantly found to be significant in BI and use of new technology (Davis, 1989; Lai, 2017; Podder, 2005; Venkatesh & Davis, 2000; Venkatesh et al., 2003). PU is defined as " the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Moreover, there is significant relation among PU and the other four constructs (Davis et al.,1989; Thompson et al., 1991) that makes PU as a critical component of PE. On related researches, using an extended TAM model, Podder (2005) revealed that PU has a significant association with user's intention to adopt Internet banking. Likewise, Jahngir and Begum (2008) identified a significant and positive relation between PU and customer adaptation of internet-based E-banking technologies.

Venkatesh et al. (2012) associates PE with utilitarian value that can be measured in terms of other measures like performance speed, productivity and usefulness. From their experiment they revealed that if someone perceived a new technology as it is useful to perform some activity more quickly and productively, it will arouse BI to use that technology. Huang and Kao (2015) also identified PE as one of the most important dimensions to be considered for concept developments, marketing strategy and new products design of Phablets. Merga's (2017) experimental analysis also identified PE as a strong factor of BI to adopt Mobile banking aligned with the result of (Alalan et al., 2017). Based on these previously made researches, theories and models we can draw the following main and specific hypothesis.

H1: PE has a positive impact on customer's BI of E-banking adoption in Ethiopia

Effort Expectancy (EE)

Effort Expectancy is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003) which is slightly modified by Venkatesh et al. (2012) as "the degree of ease associated with consumers' use of technology". In the original UTAUT, EE was constructed from three other existing models which consists of PEOU, complexity, and ease of use (Venkatesh et al., 2003). The basic notion of these three constructs is aligned with the definition of PEOU, which is defined as a believe on a system being free from difficulty to use (Davis, 1989). According to Thompson et al. (1991) conceptual model of utilization, a negative relation has been identified between complexity and adoption rate.

The analysis made by Podder (2005) on factors influencing the adoption and usage of Internet banking showed that PEOU has a significant association with user's intention. The significant relation between PEOU and customers' adaptation of E-banking was also perceived from New

Zealand bank customers (Jahangir & Begum, 2008). In Finland, (one of the countries which has vast E-banking users), perceived difficulty in using computers combined with the lack of personal service in E-banking were found to be the main barriers of Internet banking adoption among mature customers (Mattila, Karjaluoto, & Pento, 2003).

The impact of EE on BI in UTAUT further approved by UTAUT2 with better applicability and validity of UTAUT constructs as a theoretical base to predict consumers'BIs and technology use (Venkatesh et al., 2012). Strong association between EE and intention to use innovative products has been tested by Huang and Kao's (2015) in Phablets use. EE was also identified as a significant determinant of BI on a study conducted to examine factors that determine the adoption of e-government services in Kuwait (Alawadhi & Morris, 2008). According to Merga (2017), there is also a positive association between EE and customers' BI to adopt Mobile banking. Hence, we can draw the following hypothesis accordingly.

H2: EE has a positive impact on customers' BI of E-banking adoption in Ethiopia

Social Influence (SI)

Social Influence is "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" (Venkatesh et al., 2012). In the original UTAUT, SI has taken its root from different models that represent the term in different ways like subjective norm in TRA/TPB/TAM2, social factor in MPCU and image in IDT (Venkatesh et al., 2003). The strong positive association between SI and BI to use a technology in UTAUT is also verified in UTAUT2 (Venkatesh et al., 2012).

Ajzen (1991) theorized intentions to perform behaviors of different kinds can be predicted with high accuracy from subjective norms, attitudes toward the behavior and perceived behavioral control. Thompson et al. (1991) also identified the strong influence of social factors on BIs, though the degree might differ among gender and age differences. Venkatesh et al. (2003) considered SI as a composed construct of subjective norm, social factor and image is a significant variable that influences BI to use. Moreover, SI has been found as the second strongest determinant predictor of behavior in a study conducted to asses secondary school teachers' acceptance of digital learning environment in Belgium (Pynoo, et al., 2011).

In contrast, Merga (2017) has found SI insignificant on BI of customers for Mobile banking in CBE. However, his consideration of specific group of customers from a single bank might limit the chance to see the impact of social influence on BI among various members of the country located in different social and cultural contexts. Hence, we hypothesized the relation between SI and customers' E-banking adoption in Ethiopia as:

H3: SI has a positive impact on customers' BI of E-banking adoption in Ethiopia

Facilitating Conditions (FC)

Venkatesh et al. (2003) defined FC as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system". In consumer context the term can be explained as consumer's perception of availability of all required resources, infrastructures and support to perform a behavior (Venkatesh et al., 2012). In the original UTAUT, FC was identified as a direct determinant factor for usage behavior in which the relationships between each of the three constructs and intention are similar (Venkatesh et al., 2003). Venkatesh et al. (2012) also validated the UTAUT constructs in such a way that FC has significant impacts on use from consumer perspective.

On the other hand, Venkatesh et al. (2012) theorized a strong positive association between FC and BI though it is strongly moderated by gender and age. Huang and Kao (2015) also identified FC as positive determinant factors for BI and usage behavior of new Phablets. Despite the fact that many researchers agreed on the influence of FC on BI, Merga (2017) has found FC as insignificant factor to influence the behavioral intention of customers' behavioral intention to adopt mobile banking in CBE context. However, the condition is not enough to generalize for other E-banking technologies due to the different level consumers' familiarity on Mobile devices and other E-banking channels like ATM. Hence, in this research we hypothesized the positive relation of FC with E-banking adoption as follows:

H4.1: FC has a positive impact on customers' BI of E-banking adoption in Ethiopia

H4.2: FC has a direct positive impact on customers' E-banking adoption (Use) in Ethiopia

Hedonic Motivation (HM)

Hedonic motivation can be defined in short as the fun or pleasure derived from using a technology (Brown and Venkatesh, 2005 as cited in Venkatesh et al., 2012). HM is related to the essence of individual's psychological and emotive experiences which can be triggered by both the individual behavior and the cognitive states (Magni, Taylor & Venkatesh, 2010 as cited in Huang & Kao, 2015).

Venkatesh et al. (2012) argued HM as important determinant of technology acceptance and use factor to influence consumers' behavioral intention to use a technology. Therefore, they added HM as a construct in UTAUT2 and found it as a critical determinant of behavioral intention whose driver power is even greater than PE in non-organizational contexts. These results were aligned with Huang and Kao (2015), who found HM as crucial factor for Phablet adoption. Alalwan et al. (2017) also revealed that BI is strongly and positively influenced by HM in their study of Jordanian bank customers mobile banking adoption. Therefore; we can posit HM as one of influential factor to E-banking adoption in Ethiopia as:

H5: HM has a positive impact on customers' BI of E-banking adoption in Ethiopia

Price Value (PV)

There are costs associated with E-banking channels use either in the form of service charge fee or data transmission fee by internet service providers. Hoehle (2011) justified that customers intention to use E-banking channels significantly affected by cost. According to Sohrabi, Yee and Nathan (2013), examination of critical success factors for the adoption of E-banking in the context of Malaysia, cost has been found to be significant determinant for customers' adoption of E-banking. On the other hand, other authors give more emphasis for price vale than the direct cost. PV is defined as "consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Dodds et al., 1991 as cited in Venkatesh et al. 2012). Unlike UTAUT, which is on organization context, UTAUT2 focuses on consumers who have to pay associated cost for the technology use. For this reason, Venkatesh et al. (2012) added PV as one of important behavioral determinant factor. Moreover, they justified that the PV is positive when the benefits of using a technology are perceived to be greater than the monetary cost and such price value has a positive impact on behavioral intention.

Merga (2017) has found PV as a third most significant factor to determine BI to adopt Mobile banking in CBE's customers context. This result is further aligned with the empirical test of UTAUT2 by Alalwan et al. (2017) on the adoption of Mobile banking by Jordanian customers. Huang and Kao (2015) also verified the importance of PV consideration based on their investigation of crucial relation between quality, value, and price with a tendency to adopt the Phablet. These studies revealed that PV is an important factor to influence successful technology adoption. It is therefore, very rational to hypothesize PV as likely determinant of customer's BI for E-banking adoption in Ethiopia as:

H6: PV has a positive impact on customers' BI of E-banking adoption in Ethiopia

Habit (HT)

Habit is the second unique factor added in the original UTAUT by Venkatesh et al. (2012) to make the theory more fit to consumer context. They basis on prior researches conceptualization of experience and habit where experience is related with the passage of time from the initial use of a target technology and habit was operationalized as a self-reported perception. Further investigation of prior researches convinced the authors of UTAUT2 to generalize two causal pathways by which HT ultimately influences use directly and through the influence on BI. Their result also showed support for accepting HT as a determinant factor for both BI and Use (Venkatesh et al. 2012).

Thompson et al. (1991) also strongly recommended consideration of HT in determining behavior. Their review mentioned the work of Sugar in 1967 (as cited in Thompson et al. 1991) who found HT as the strongest predictor of college students' cigarette smoking behavior. Habits are believed to occur without self- instruction because of frequent (repeated use) situation-behavior sequences (Triandis, 1971 as cited in Thompson et al., 1991). In related research conducted to test the impact of HT on behavior, Huang and Kao (2015) also found HT as very important to influence users' behavior to adopt Phablets. An application of UTAUT2 to explain Internet banking use by the elderly revealed HT as the strongest determinant factor to influence BI and as strong factor to directly influence the actual use behavior (Arenas-Gaitan, Peral-Peral, & Ramon-Jeronimo, 2015).

Accordingly, we draw the following two hypotheses showing the relation between HT and E-banking adoption in Ethiopia.

H7.1: HT has a positive impact on customers' BI of E-banking adoption in Ethiopia

H7.2: HT has a direct positive impact on customer's E-banking adoption (Use) in Ethiopia

Behavioral Intention (BI)

Behavioral intention is defined as "a person's subjective probability that s/he will perform intention some behavior" (Fishbein & Ajzen, 1975, p. 288). Aarts et al. in 1998 (as cited in Huang & Kao, 2015) referred the term BI to the degree of a person's formulated conscious plans to perform or not perform some specified future behavior(s). Ajzen (1991) stated that intentions are assumed to capture the motivational factors that influence a behavior and BI is a core determinant factor to perform a given action. Moreover, BI is indicator of the persons willingness to try a behavior. Hence, it is accepted that the stronger the intention to engage in a behavior yields the likely mood to perform an action.

Consistent with the underlying theory of the intention models, Venkatesh et al. (2003) theorized that behavioral intention will have a significant positive influence on technology usage. Venkatesh et al. (2012) also validated the relation between BI and technology use in UTAUT2 constructs with stronger positive influence of BI on technology use. An experimental result of Huang and Kao (2012) study to analyze factors for Phablet adoption also align with the above idea that the use intention is one of the most crucial factors for Phablet adoption. Following these theories and tested results, we can infer BI as a positive determinant of E-banking adoption in Ethiopia customers context.

H8: BI has a positive impact on customers' E-banking adoption (use) in Ethiopia

3.1.2. Proposed research model

The proposed conceptual research model for this research will be composed of nine variables and ten relations as shown in the ***Figure 9***.While the variables are represented by rectangular blocks, relation are represented by using arrows where the head represent the dependability direction.

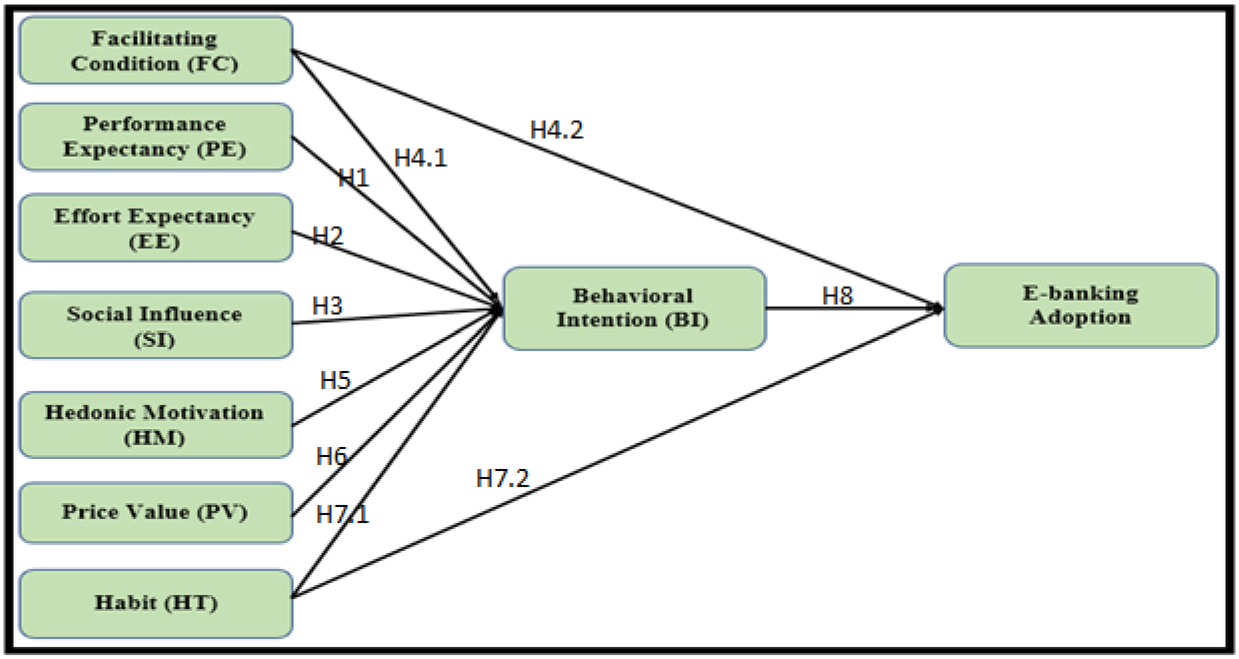

Figure 9: Conceptual model for this research.
Adapted from Venkatesh et al. (2012)

As exhaustively discussed above, this research has drawn the hypotheses from Venkatesh et al. (2012) UTAUT2 model. Moreover, they are also supported by other researches. The independent variables include PE, EE, SI, HM, PV, FC and HT. While these variables influence Behavioral Intention (BI), FC and HT also directly influence the use behavior (E-banking adoption). Hence, E-banking adoption is directly dependent on FC, BI and HT as shown in ***Figure 9***.

3.2. Research Methodology

Behavioral science paradigm seeks to develop and verify theories that explain or predict human or organizational behaviour (Hevner & Chatterjee, 2010). This research seeks to identify factors that lie on human and organizational behaviour which categorize it under the behavioural science paradigm. It is also founded on positivist epistemological belief as it matches characteristics of a positivist research that assumes objective, physical and social world exists independently of humans where the nature of the world can be characterised and measured (Orlikowski & Baroudi, 1991 as cited in Urbach & Ahlemann, 2010). Moreover, as these authors characterized a positivist epistemology with empirical testability of theories, it corresponds the aim of this research to identify customer's E-banking adoption factors in Ethiopian context by testing constructs of UTAUT2 model.

Research type, method and data gathering tools

Any scientific research adopts one or more scientific approaches, methods, techniques and tools that used to collect and analyze data properly (Dawson, 2002, p. 27; Kothari, 2004, p. 7). To address the main purpose of identifying factors for customer's E-banking adoption in Ethiopian context, this research considers a large group of E-banking customers from sampled commercial banks in the country. In such cases a quantitative research is much preferable (Dawson, 2002, p. 15). Dawson explained quantitative research as a research that generates statistics using different methods like survey using questionnaires or structured interviews (p. 15).Survey is one of widely used scientific research method for hypothesis formulation and testing. It is also commonly used in social and behavioural sciences that supports the applicability of quantitative approach for this research which is behavioural in nature (Kothari, 2004, p. 121). Hence, this research is basically quantitative which follows a survey research method.

Questionnaires are the most widely used data collection tools for quantitative survey research. One of the main advantage of using questionnaires is that many people can be reached relatively easily and economically. In addition to that, a standard questionnaire provides quantifiable answers for a research topic that can be scanned straight into a computer for ease of analysis (Kothari, 2004, p. 100). Accordingly, this research used self-administrable closed questionnaire as primary data collection instrument. The questionnaire had two components one for demographic data and other for main items to measure each construct items.

The demographic component is composed of age, gender, income and education level which are likely to influence E-banking adoption. The second group of items are designed to be presented in three sections as it will be suitable to organize items based on the E-banking type (ATM banking, Mobile banking and Internet banking). A group of 28 items adapted from Venkatesh et al. (2012) has been modified and presented in each section to suit each channel type *(see **Table 1** for constructs in unified format)*. Aligned with the previous researches (Alalwan et al., 2012 and Venkatesh et al., 2012), these items are measured using a 7-point Likert scale, ranging from “[1] = strongly disagree” to “[7] = strongly agree”. “Use/E-banking adoption” construct has been measured in terms of frequency and variety using 7-point Likert scale from “[1] = never used” to “[7]= every time”.

The questionnaire was first outlined using English language as it is the language used for writing this research and the original constructed items adapted from Venkatesh et al. (2012). However, Amharic, which is one of the dominant languages spoken in the country, is the national language of Ethiopia where this questionnaire was administered. Hence, the original questionnaire prepared in English language was translated into Amharic language by a licensed official language translator. However, the translation had some limitations of properly converting some key terms in to equivalent Amharic versions. Hence, it was mandatory to further support the translation process by language professional and domain experts for more accepted translation of some technical words. Moreover, the Amharic version was translated back into English language by independent language expert and equivalency of the two versions was confirmed for meaning consistency. Before distributing the final copies, nine copies of both Amharic and English questionnaires were given to different E-banking technical staffs for pre-test of its content completeness, language difficulty and presentation quality. According to their feedback, no significant problems were found. However, it was difficult to find exact meaning for the original very close terms with slight meaning difference like the words “fun”, “enjoyable”, and “entertaining”. After all these procedures, the Amharic version of the questionnaire has been finalized to collect the required data from nominated respondents.

The reliability and validity of the data gathering instrument is granted from the Venkatesh et al. (2012) measurement model results. According to their measurement test using the SmartPLS software, the internal consistency reliabilities of multi-item scales modelled with reflective indicators was greater than or equal to .75 which is adequate for reliability. The average variance extracted was greater than .70 and it was greater than the square of the correlations for all cases that indicates well discriminant validity. The pattern of loadings and cross-loadings were also supported internal consistency and discriminant validity with very few exceptions. Moreover, document analysis of electronic sources as secondary data collection was incorporated for strengthen the data analysis and discussion.

Table 1:Basic variables and construct items.

Source: *Adapted from Venkatesh et al. (2012)*

Variables	Item Code	Construct Items
Performance Expectancy (PE)	**PE1**	I find E-banking useful in my daily life
	PE2	Using E-banking increases my chances of achieving things that are important to me
	PE3	Using E-banking helps me accomplish things more quickly
	PE4	Using E-banking increases my productivity
Effort Expectancy (EE)	**EE1**	Learning how to use E-banking is easy for me
	EE2	Interaction with E-banking is clear and understandable
	EE3	I find E-banking easy to use
	EE4	It is easy for me to become skillful at using E-banking
Social Influence (SI)	**SI1**	People who are important to me think that I should use E-banking
	SI2	People who influence my behavior think that I should use E-banking
	SI3	People whose opinions that I value prefer that I use E-banking
Facilitating Condition (FC)	**FC1**	I have the resources necessary to use E-banking
	FC2	I have the knowledge necessary to use E-banking
	FC3	If I have got problems, I can get support from the bank
	FC4	I can get help from others when I have difficulties using E-banking

Hedonic Motivation (HM)	**HM1**	Using E-banking is fun
	HM2	Using E-banking is enjoyable
	HM3	Using E-banking is entertaining
Price Value (PV)	**PV1**	E-banking is reasonably priced
	PV2	E-banking is a good value for the money
	PV3	At the current price, E-banking provides a good value
Habit (HT)	**HT1**	The use of E-banking has become a habit for me
	HT2	I am addicted to using E-banking
	HT3	I must use E-banking for daily financial activities
	HT4	Using mobile E-banking has become natural to me
Behavioral Intentions (BI)	**BI1**	I intend to continue using E-banking in the future
	BI2	I will always try to use E-banking in my daily life
	BI3	I plan to continue to use E-banking frequently
Items to measure Adoption/Use	a) request remaining balance	
	b) request financial mini-statement	
	c) withdraw cash	
	d) exchange foreign currency	
	e) transfer money to own account	
	f) transfer money to another person's account	
	g) transfer money to non-account holder	
	h) request foreign exchange information	
	i) pay bills (like bus / movie ticket, etc)	
	j) buy mobile air time (mobile card)	
	k) request for other services like stop/initiate cheque, Card, etc.	

3.3. Sampling Design and Target Population

The overall population of this research includes all E-banking customers of commercial banks who are subscribed for one or more of ATM banking, Mobile banking or Internet banking services in Ethiopia. Since the scope of this research focuses on ATM, Mobile and Internet banking, bank customers who are not subscribed for at least one of these services have not be included in the target population.

Sampling design to select banks:

Since this research is aimed to identify and analyse factors for E-banking adoption among commercial banks in Ethiopia, considering all commercial banks in the country would have been better. However; due to the constraints mentioned in the research scope section, only the following four banks has been selected from the available seventeen commercial banks. These are CBE, Dashen Bank S.C, Wegagen Bank S.C. and Zemen Bank S.C which are selected purposefully for the following reasons:

First, these banks are some of the giant commercial banks which are pioneer to E-banking adoption in the country and provide more similar services (Gemechu, 2014; Kindie, 2016; Tefera, 2017; Worku, 2010; Zeleke, 2016). Second, these four commercial banks are on the leading truck of the bank industry in Ethiopia and are some of the top profitable banks (Marcopolis LLC, 2017) where their experience is much useful for other banks. Moreover all, except Zemen Bank, has a large geographical coverage in the country that favors inclusiveness to this research. In addition to these common characteristics, the following are specific reasons for each bank to be selected for this research.

CBE is selected as it is the only state owned commercial bank in the country that gives such E-banking services to its customers. The bank is pioneer to introduce E-banking services in the form of ATM banking (Tefera, 2017; Worku, 2010; Zeleke, 2016). Besides that, it has the largest number of customers and branches in the country that makes unworthy of excluding it from such study. The bank is also known for availing different types of payment cards based on gender and business speciality. It is also the leading bank in terms of having large number of ATMs and POS terminals in the country (CBE Communication, 2016, p. 5).

Dashen bank is the pioneer private commercial bank to adopt E-banking in the country (Zeleke, 2016). It also provides many varieties of alternative channels from which some are not totally found in other banks in the country (Dashen Bank S.C, 2017a). It is also one of commercial banks which have large customer base and geographical coverage in the country. Hence, including this bank in this research is very reasonable to address the comprehensiveness and geographical inclusiveness.

Wegagen bank is the second private bank to introduce E-banking in the country. It is also mentioned for having internationally known brand (Tieto) payment switch that used to integrate many kinds of electronic payments (Worku, 2010; Zeleke, 2016, p.14). The bank is also one of highly profitable banks with large customer base and wide geographical coverage with more than 300 branches (Wegagen Bank S.C, 2017a). Moreover, the researcher works in this bank as a senior E-banking technical support officer which creates conducive environment to acquire any required data and support from experts working on the area.

Zemen bank intends to make all its customers ATM card holder (Zemen Bank S.C, 2016) and comparatively it has a record of large ATM and Mobile banking transactions related to its total account holders than other commercial banks. As this bank is known for few branches-based service, it is highly dependent on alternative E-banking channels. Aggressively working on E-banking adoptions is a matter of existence for this bank since it couldn't address its customers' demand with few number of branch services. Due to this mere fact, the bank has paid much attention for introducing more enhanced innovation-based services and technologies (Zeleke, 2016). Therefore, it is rational to select this bank in this research to examine behavior of customers of such kind of unique bank along with others.

In general, considering these mentioned banks in this study for the above described reasons is reasonable for identifying factors of customers' E-banking adoption in Ethiopia. Other banks do not have any specialty that enforces to directly include them in this research. However, due to similar nature of the business, findings of this research are likely to represent other commercial banks' customers which are not directly included in this study.

Sampling design to select customers from the four banks:

Studying the whole population in a survey research that encompasses a large group of study is not economical and manageable. Sampling is very useful to conduct such survey researches for its efficient use of resources (Kothari, 2004, p. 55). For this research, participants have been selected using a mix of different sampling techniques from the mentioned four banks. First, considering the four banks as four main strata, stratified sampling technique has been used to select approximately equal number of participants from the four banks. Second, another stratum is defined based on geographic location which consisted of five unique districts considered by all banks named as North district, East district, South district, West district and Central district. Considering these pre-defined districts as unique strata, proportional samples have been taken from each stratum to address the inclusiveness issue from all five districts across the country.

Then, Mekelle, Dire Dawa, Hawassa, Jimma and Addis Ababa cities are considered corresponding to the above five district locations purposefully as these cities are placements for district's head offices and main branches that have the largest customer size. This decision was very helpful to collect the data with relatively short period of time and less cost without compromising the data quality. Finally, convenience sampling technique has been applied to select individual participants from randomly selected branches of such district's main locations. Convenience sampling has been used for selecting customers based on the ease of access while they visit branches.

Sample size and distribution:

Sampling requires careful determination of sample size because it is based on the characteristics of this sample that we make inferences about the population. In general, increased sample size is more likely to increase statistical significance (Hinkin, 1995). However, it is important to maintain the balance between the size impact with manageable complexity. Chin (1998) and Hair et al. (2012) recommend a minimal sample size must be 10 times larger than either the block with larger number of formative indicators or the endogenous variable with the largest number of exogenous variables impacting it considering maximum of the two options. In this research model, there is one block of formative indicator with maximum number of 8 indicators and an endogenous variable (which is BI) impacted by 7 exogenous variables. Multiplying the maximum of the two, which is 8 by 10 gives the minimum required sample size equal to 80. Though PLS can be applied on small sample sizes, many authors recommend taking larger sample sizes for better results (Goodhue, Lewis, & Thompson, 2006).

On the other hand, Schwab's "thumb rule of 10" (as cited in Hinkin, 1995) suggested an item-to-response ratio should be at least 1:10 for each set of scales to be factor analyzed. Considering the above arguments, Schwab's rule has been found applicable for this study to determine the minimum sample size requirement. Since the research construct adapted from Venkatesh et al. (2012) has 28 basic items for independent variables, it requires a minimum of 280 respondents. Considering additional 15% to increase statistical significance and around 10% contingency for unsuccessful responses, total of 355 sample size was determined for evenly distribution among the five district locations. On the other hand, this ratio was distributed evenly for the four banks that made around 18 questionnaires to be distributed for each four banks in each five districts. However, due to Zemen bank's basic nature of serving for very few customers and lack of branch in West district, some slight adjustments were made to compensate the shortage of getting the required number of respondents by supplement additional questionnaires from other three banks.

Data collection procedure

Based on the above sample size and distribution plan, the actual primary data has been collected from each district starting from March 12 up to March 30, 2018 for about three weeks. While it took three days for each four main districts, data collection from Addis Ababa was taken for about five days. In all areas the data was collected primarily on the spot by the researcher with voluntary assistants of Wegagen bank district IT staffs and assigned persons of each bank personnel.

The first set of data was collected from North region Mekelle city district. Though 70 questionnaires were distributed and collected immediately, 6 questionnaires were incomplete that makes the response rate 91.4%. Similarly, by making continuous flights to East region (Dire Dawa district), South region (Hawassa district) and West region (Jimma district); 62,65 and 63 valid questionnaires were collected with 88.6%, 95.9% and 90% successful response rate respectively.

Finally, 75 questionnaires were distributed in Addis Ababa in different sub-districts and 67 valid questionnaires were collected with 89.3% successful response rate. These in general makes the successful rate of valid responses reached to an acceptable rate of 90.4%.

3.4. Data Analysis Tools and Techniques

The collected data should be well organized and analyzed to test the proposed hypothesis using statistical techniques. These techniques should be carefully selected based on the type of data collected and carried out in the context of measures derived from a theory (Lowery & Gaskin, 2014).

The process of data analysis has been started from coding the raw data into computer by converting from manually filled questionnaire papers. For this purpose, Microsoft (MS) Office products' MS Access and MS Excel were suitable. Initially, MS Access 2016 was used to code the collected data into computer for further processing. MS Access has been selected for its database capability of storing and retrieving data easily. Data entry is much easy and controlled with predefined formats and validity rules in MS Access database than using large Excel tables. MS Excel 2016 was used to correct data types, naming rules and representation values to make the record fit for further analysis. Finally, the complete dataset was saved in comma delimited (csv) file format as it is suitable for SmartPLS software and in Excel (.xlsx) file format as it is suitable for SPSS (Statistical Package for Social Sciences) software.

This well organized and stored data pass through in-depth analysis to find answers for the research problems. Descriptive analysis has been conducted to analyze the demographic data of respondents using SPSS which is suitable and user-friendly tool for determining basic frequency based statistical measures. It is one of the most widely used software package for data analysis in social and behavioral sciences (Dawson, 2002).

Structural Equation Modeling (SEM) using Partial Least Squares (PLS) has been used for path coefficient modeling due to its capability of testing the effects of several interaction items (Lowery & Gaskin, 2014; Venkatesh et al., 2012). SEM is a statistical technique for testing and estimating causal relationships between variables based on statistical data and qualitative causal assumptions while PLS is a component-based approach for testing structural equation models (Henseler, Ringle, & Sinkovics, 2009; Urbach & Ahlemann, 2010). According to Henseler et al. (2009), PLS has become a choice of varrious dicipilines that include management of information systems, e-business, organizational and consumer behaviors.

According to Venkatesh et al (2003), PLS was applied to examine the reliability and validity measures along with other construct measures. Hypothesis testing using PLS involves considering the likelihood of type I and type II errors, which relate to whether the data supports accepting or rejecting the hypothesis. Moreover, its capability of handling formative indicators, independency of data normalization and fitting for small sample size are the qualities of PLS to be preferred in testing complex multivariate causal relationships (Hoehle, 2011; Im et al., 2011; Venkatesh et al., 2012).

SmartPLS software has been used to test the model using PLS-SEM technique. It is selected for its softness and specific design features to ease the analysis of interactions (Venkatesh et al., 2012). While SmartPLS latest version (v3) is available in the market with enhanced features, it doesn't have free version for academic purpose unlike the previous version (v2). Though the trial and student versions of this latest version are available, they support data samples only less than 100. Hence, SmartPLS Version: 2.0.M3 was used for path coefficient modeling since it requires only registration with valid e-mail address to get its license from SmartPLS support team.

CHAPTER FOUR

IV. Data Analysis and Discussion

4.1 Overview

This chapter discussed the overall process of data analysis including data preparation (pre-processing), data processing and analyzing results. The statistical analysis presented in the first part is descriptive that quantifies respondents' demographic and topic related characteristics. In the main analysis part, both structural and measurement model results have been presented and discussed. To perform main data analysis, four different datasets were formed based on the respondents' response for questions under instruction II on the questionnaire. These are: ATM users' dataset where number of samples (n) = 317, Mobile banking users' dataset where n=162, Internet banking users' dataset where n=41 and the pooled dataset where n=520 (the sum of the three sub-datasets).

The first three sub-datasets were formed based on the positive responses for questions that asked the respondent whether he/she uses the specific E-banking channel or not. For instance, ATM banking users' dataset is formed by all questionnaires which has positive responses for the question "*Do you have used ATM banking?*". Likewise, Mobile banking users' dataset and Internet banking users' dataset are formed by the questionnaires which have positive responses for similar questions presented like the above. The pooled dataset was formed by combining datasets from the above three E-banking channel users' datasets (ATM banking users' dataset, Mobile banking users' dataset and Internet banking users' dataset) to have one large dataset.

Therefore, the main data analysis has been done in two ways. Initially, the analysis was done on three individual datasets for each E-banking channel users datasets. Finally, the analysis was conducted on a pooled dataset.

Data Preparation

During data preparation, the data which have been collected from a cross-sectional survey using structured close-ended questionnaires were coded in to computer using MS Access 2016. MS Access was preferred for easily inserting and retrieving of data using forms and queries, applying validation rules and exporting outputs to other statistical tools' file formats. In doing this pre-processing, incomplete questionnaires and questionnaires with invalid responses were rejected. Moreover, questionnaires with missing values for more than four items have been rejected. As Hair et al. (2014, p. 68) suggested, the amount of missing value should not be more than 15%. After this filtration, 321 responses out of 355 distributed questionnaires were considered valid for further data processing that makes 90.4% valid response rate.

This data preparation phase ended up with exporting the dataset into excel (.xlsx) file format. Then a central mean is calculated over the whole items to use it in place of missing values. Though both SPSS and SmartPLS have mechanisms to handle missing values, they ignore these observations from including in other significant analysis. Hence, according to Wong (2013) suggestion, finding a common value to replace all 34 missed values was operationalized in this research. The final complete dataset then saved in csv file format so that it will be possible to analyze using SmartPLS software.

4.2 Descriptive Statistics

4.2.1 Demographic characteristics

The respondent's demographic detail consists of six characteristics that includes gender, age, an average monthly income, education level, respondent's current city and the bank name in which he/she is registered as a customer. While the first four characteristics were directly responded by the respondent, the other two characteristics were filled by the researcher considering the place and the actual bank visited during data collection.

All the four personal characteristics were represented in the questionnaire as multiple-choice item in which the respondent marked only one of the given answers that describes him/her best. While the response items were presented in text format for respondent's easy understanding, all were converted to numerical values during data coding since only numbers are treated well by SmartPLS data analysis tool.

4.2.1.1 *Respondents per their gender*

Gender values were represented by 0 and 1 for "Male" and "Female" values respectively. As shown in ***Table 2***, about two folds (64%) of the respondents were males while the rest were females.

Table 2: Respondents frequency per gender

Gender	Frequency	Percent
Male	206	64.2
Female	115	35.8
Total	321	100.0

4.2.1.2 *Respondents per their age*

Respondents' age values were classified in to four groups that ranges in number of years as [below 26], [26 to 35], [36 to 45] and [above 45] and coded as 0, 1, 2, and 3 respectively. As shown in ***Table 3***, respondents whose age ranges from 26 to 35 years accounts for the largest percent (55%). Moreover, the cumulative percent of respondents whose age was less than 36 years were accounted for more than 83% that can be categorized as the youngest group.

Table 3: Respondents frequency per age

Age (in years)	Frequency	Percent
below 26	89	27.7
26-35	178	55.5
36-45	39	12.1
above 45	15	4.7
Total	321	100.0

4.2.1.3 *Respondents per their average monthly income*

Average monthly income was the third demographic profile that shows the respondent's an average monthly monetary earning. It was also categorized in four groups based on the country's employees' taxation category by merging two consecutive levels between the lowest and the highest rates for simplicity. Hence, the group is labeled as monthly average income [below Birr[5] 1,651], [from Birr 1,651 up to 5,250], [from Birr 5,251 up to 10,900] and [above Birr 10,900]. Like the above coding scheme, average monthly income values coded as 0, 1, 2, and 3 respectively from the lowest to the highest.

As it is shown in ***Table 4,*** most (46%) respondents earn an average monthly income ranged from Birr 5,251 up to 10,900 that can be categorized as middle incomers. Cumulatively, those who earn above Birr 5,251 takes 65% of the total respondents which shows majority of the respondents were can be categorized as middle or high incomers.

Table 4: Respondents frequency per an average monthly income

Average Monthly Income (in Birr)	Frequency	Percent
below 1,651	25	7.8
1,651-5,250	87	27.1
5,251-10,900	148	46.1
above 10,900	61	19.0
Total	321	100.0

4.2.1.4 *Respondents per their education level*

Education level was the fourth characteristics that indicates the respondent latest academic level categorized as [Elementary], [Secondary], [Diploma/TVET], [1st Degree], [2nd Degree] and [above 2nd Degree levels]. It was coded in the system from 0 to 5 from the lowest to the highest level respectively. As ***Table 5*** shows most (76%) of the respondents acquired either 1st or above degrees.

[5] Birr is Ethiopian national currency. 1 Birr is approximately equivalent to 0.037 USD as of May 2018.

Table 5: Respondents frequency per education level

Education Level	Frequency	Percent
Elementary	22	6.9
Secondary	18	5.6
Diploma/TVET	34	10.6
1st Degree	212	66.0
2nd Degree	34	10.6
above	1	.3
Total	321	100.0

4.2.1.5 *Respondents per their bank and residential city*

The respondents might be characterized by their living area and the bank in which they have a business relationship. For this reason, adding the two items in demographic profiles and reporting their frequency relationship is rational.

As ***Table 6*** shows distribution of respondents across the four banks selected for this study was nearly uniform except for Zemen bank which had contributed relatively small percent (13%). This was because the bank also had relatively small number of customers in the actual situation. Moreover, it was difficult to get number of customers in the branch at a time. Very few customers visit the bank at a time and they were not willing to take time and respond for questionnaires.

Table 6: Respondents distribution per selected banks for the study

	Male	Female	Total/ Bank	Percent
CBE	66	38	104	32
Dashen	57	30	87	27
Wegagen	54	36	90	28
Zemen	29	11	40	13

Similarly, the distribution of respondents across the region/city covered in the study was almost the same in which each five cities took nearly equal (20%) of the total valid sample as shown in ***Table 7***.

Table 7: Respondents distribution per selected cities for the study

	Male	**Female**	**Total/ City**	**Percent**
Addis Ababa	41	26	67	21
Dire Dawa	43	19	62	19
Hawassa	40	25	65	20
Jimma	38	25	63	20
Mekelle	44	20	64	20

4.2.1.6 *Respondents per the type of E-banking channel they used*

Frequency distribution of respondents with respect to their gender value and their experience of using different E-banking channels can be further illustrated as shown in ***Table 8*** and ***Figure 10*** respectively. ***Table 8*** visualizes the number of specific E-banking channel users per gender values and most importantly how much percent of each gender uses that specific product out of the total of the same gender registered as valid respondent.

Accordingly, from total valid male respondents almost all (98%) uses ATM banking, while nearly half (55%) use Mobile banking and only 16% use Internet banking. Likewise, all (100%) valid female respondents use ATM banking, while below half (43%) use Mobile banking and only few (7%) use Internet banking. This indicate that males are more likely users of Mobile and Internet banking than females.

Table 8: Respondents percentage per E-banking channel they used

	Male users	**Female users**	**Total**	**Males' percent** out of total Males	**Females' percent** out of total Females
ATM	202	115	317	98	100
Mobile	113	49	162	55	43
Internet	33	8	41	16	7

In ***Figure 10,*** Venn diagrams has been used to show the number of respondents who participate in each unique and joint product. Accordingly, 159 respondents have an experience of using only ATMs while 117 respondents use both ATM and Mobile banking. Number of respondents who use only Mobile banking were only 1%, while there was no user who use only Internet banking without using other two channels.

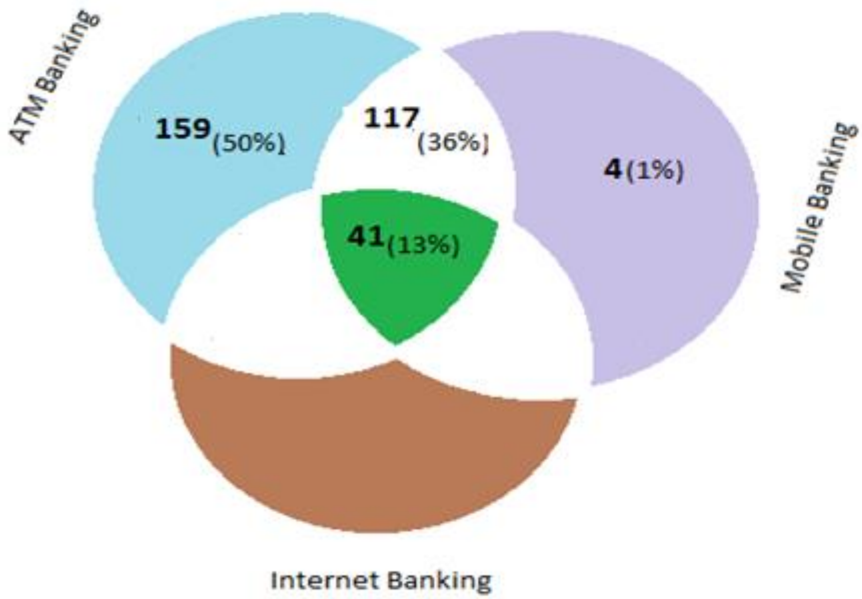

Figure 10: Respondents distribution per the type of E-banking they used

Moreover, the diagram revealed that only 41 (13%) respondents use all the three channels. It might be expected to get less number of users when one considers many products than single, or few number of products. That is why the number of users who uses all three channels is less than the number of users who uses two channels and much less than from the number of users who uses only one channel.

In addition to that, the diagram showed that all users who use Internet banking also uses the other two channels. Likewise, almost all Mobile banking users were also ATM banking users which generally indicated that the intention to use one system is likely to be depend on the experience of the user in similar systems aligned with the discussion of Venkatesh et al. (2012).

4.3 Structural and Measurement Models

4.3.1 Overview

SEM is a second-generation statistical technique best suited for testing and estimating causal relationships based on statistical data and qualitative causal assumptions (Urbach & Ahlemann, 2010). Lowery and Gaskin (2014) also emphasize the strength of SEM for modeling more specifically for complex models that include latent variables (LVs) which are not directly observed. Though covariant-based SEM (CB-SEM) are more familiar, PLS-SEM models are an alternative to structural equation models based on a component-based approach using a type of principle components analysis to construct LVs (Wong, 2013). Unlike the traditional CB-SEM, which uses a type of common factor analysis to create LVs, PLS-SEM is a variance-based in which constructs are considered as components where covariation may have been explained in terms of relationships among indicators (Garson, 2016).

A complete SEM characterized by two main sub-components (models) called structural (inner) model and measurement (outer) model. The structural model consists of relationship between endogenous (dependent) and exogenous (independent) LVs. Endogenous variables are dependent variables that have at least one path leading arrow pointing inwards. Exogenous variable are independent variables that have path leading arrows pointing outwards. The measurement models are defined for each LV to incorporate the relationship between the empirically observable indicator variables and the LVs (Wong, 2013; Urbach & Ahlemann, 2010).

Figure 11 illustrates such basic components supported by examples from this research. The yellow rectangular boxes represent Indicators of LVs. These are directly observable items in the research questionnaire. Each LV were represented by 3 or 4 indicators except the 'Use' behavior variable which is measured by 7 or 8 items depend on the channel. Blue circles represent LVs which are PE, EE, SI, FC, HM, PV, HT, BI and Use behavior in this study. (*only some part of the variables is presented in the diagram for illustration purpose*)

In this study, BI and 'Use' are endogenous variables while PE, EE, SI, FC, HM, PV and HT are exogenous variables. Symbols indicated in Greek letters **λ** and **β** are path coefficient numerical values that quantify the relationship between indicator and LV, and between two LVs respectively.

There are also numerical values inside the circles that shows by how much the endogenous variable varies for a unit change in the exogenous variable.

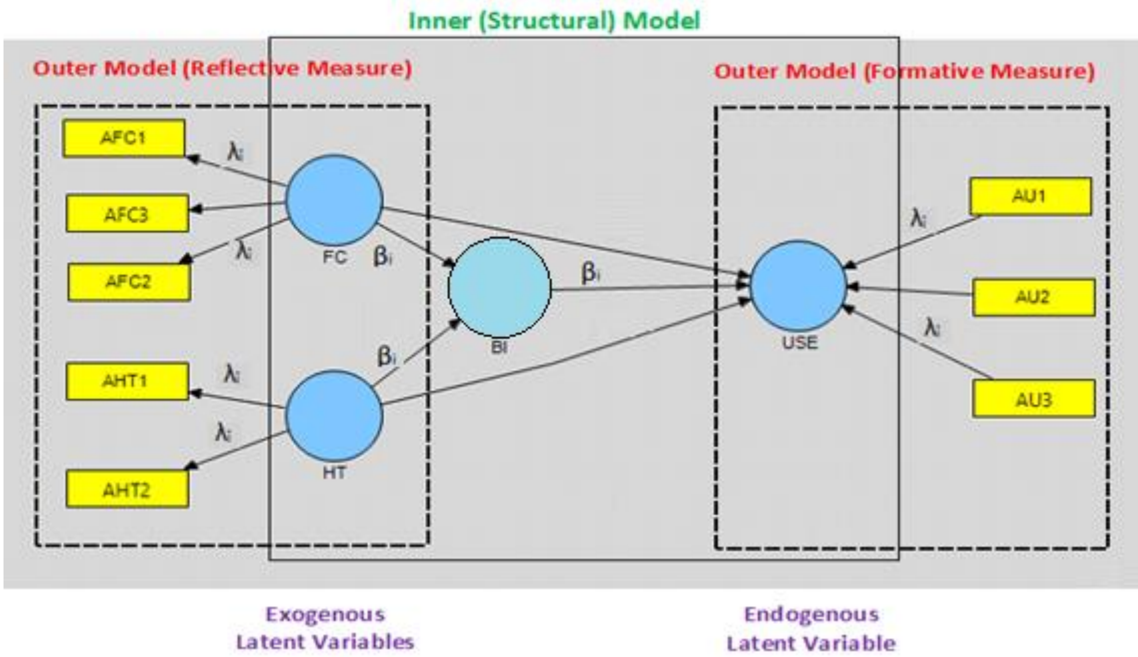

Figure 11: Inner Vs Outer models of SEM diagram

Adapted from Urbach and Ahlemann (2010)

Moreover, SEM consists of two types of measurement scales called formative and reflective measures. Formative measures are indicators that cause the LV and are not interchangeable among themselves. A reflective indicator is an observed variable that is assumed to be an effect (consequent) of a LV. In this research all indicators except those that used to indicate the Use intention are reflective indicators (Arenas-Gaitan et al., 2015; Venkatesh et al.2012). In later sub-sections of this chapter, findings of these measurements from tests conducted using PLS algorithm will be discussed.

Model validation is the actual process of systematically evaluating whether the hypotheses expressed by the structural model are supported by the data or not. Though PLS doesn't provide unique goodness-of-fit criterion, different criteria could be applied in two basic assessments of measurement model and the structural model (Henseler et al., 2009).

In this research model validation approaches are applied by following two different previously made researches. These are, approach of model validation for adoption of two different technologies in two different countries (Im et al., 2011) and approach of model validation for adoption of the same technology in different task-groups (Hoehle, 2011). Hence, model validation analysis has been done initially for each three E-banking channels datasets and then for the compiled pooled datasets over the three channels. Moreover, techniques and guidelines presented in two articles (Urbach & Ahlemann, 2010; Wong, 2013) and Garson's (2013) hand book on PLS-SEM have been used for an appropriate application of model validation.

4.3.2 Structural and Measurement Model: ATM banking users' dataset

4.3.2.1 *Measurement Models for reflective indicators*

Following the guideline developed by Wong (2013) on the test of measurement models, indicator reliability, internal consistency reliability, convergent validity and discriminant validity with application of standard decision rules are reported for reflective indicators while outer weights, convergent validity and collinearity of indicators are reported for formative indicators. Internal consistency reliability and discriminant validity were not assessed for formative indicators since it was meaningless for formative indicators where they were not expected to have high correlation. All the values reported are found from the report of SmartPLS after running the PLS algorithm with initial setting of: Path weighting scheme, Data metric mean= 0, Var=1, Maximum iterations= 5000, with 1.0E-5 stop criterion and initial weight of 1.0.

Internal Consistency Reliability (ICR):

Cronbach's alpha (α) is commonly used in social and behavioral sciences to measure ICRs that ranges alpha values from 0 (completely unreliable) to 1 (completely reliable). However, it is blamed to provide a conservative measurement in PLS since it assumes all indicators are equally reliable. In contrast, PLS prioritizes indicators according to their reliability, resulting in a more reliable measure called composite reliability (Henseler et al., 2009; Urbach & Ahlemann, 2010). Hence, ICR is basically measuresred using composite reliability in this study. According to Henseler et al. (2009), Urbach & Ahlemann (2010), Venkatesh et al. (2012) and Wong (2013), ICR values larger than .7 are desirable to assure strong internal consistency reliability. As ***Table 9*** shows both composite reliability and Cronbach's α values were larger than .7 (except for FC whose α= .64) that confirms significant ICRs.

Table 9: Composite reliability and Cronbach's α measures of the reflective model

	Composite Reliability	Cronbach's Alpha (α)
BI	0.90	0.83
EE	0.89	0.84
FC	0.78	**0.64**
HM	0.90	0.84
HT	0.87	0.81
PE	0.90	0.86
PV	0.93	0.89
SI	0.87	0.79

BI= behavioral intention, EE=effort expectancy, FC=facilitating condition, HM=hedonic motivation, HT=habit, PE=performance expectancy, PV=price value, SI=social influence

Indicator Reliability:

According to Urbach and Ahlemann (2010) description, Indicator reliability measures to what extent a variable or set of variables is consistent regarding what it intends to measure. In other words, it measures how much of the indicators variance is explained by the corresponding LV. In PLS approach, reflective indicators loading should be inspected for determining of the appropriateness of the indicator as it is essentially representing the correlation between the indicator and the LV (Chin, 1998). The reliability of one construct is independent of the other and calculated separately. In general, the larger the lodgings indicate the more reliable that LV. However, the preferred level is above .7 which is the level at which about half the variance in the indicator is explained by its factor and is also the level at which explained variance must be greater than error variance (Chin, 1998; Garson, 2016; Henseler et al., 2009; Wong, 2013).

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Table 10:Reliability and Validity measures with Factor loadings for reflective indicators

LV	Indicator	Indicator Reliability Outer Loadings (λ)	Composite Reliability (ICR)	Convergent Validity (AVE)	Discriminant validity Square roots of AVE
PE	APE1	0.83	0.90	0.70	0.84
	APE2	0.86			
	APE3	0.88			
	APE4	0.78			
EE	AEE1	0.84	0.89	0.68	0.82
	AEE2	0.90			
	AEE3	0.87			
	AEE4	**0.68***			
SI	ASI1	0.90	0.87	0.69	0.83
	ASI2	0.75			
	ASI3	0.84			
FC	AFC1	**0.65***	0.78	**0.48****	0.69
	AFC2	0.73			
	AFC3	0.80			
	AFC4	**0.56***			
HM	AHM1	0.89	0.90	0.75	0.87
	AHM2	0.92			
	AHM3	0.79			
PV	APV1	0.90	0.93	0.82	0.91
	APV2	0.92			
	APV3	0.90			
HT	AHT1	0.84	0.87	0.64	0.80
	AHT2	0.70			
	AHT3	0.82			
	AHT4	0.83			
BI	ABI1	0.85	0.90	0.74	0.86
	ABI2	0.89			
	ABI3	0.85			

*Shows low loading factor below the preferred value (.7), ** shows low AVE below the threshold (i.e. <.5)

Note: after AFC4 is removed, **λ** for FC1 improved to .68 and AVE for FC changed to .56 that significantly improved indicator reliability and convergent validity.

As it is shown in ***Table 10***, the outer loadings for all reflective indicators is much far from the preferred level except for fourth item of EE, and the first and fourth item of FC whose loadings are .68, .65 and .56 respectively. However, Henseler et al. (2009) suggest that items with lower loadings should be removed if the loading factors are smaller than .4 and eliminating that item goes to a substantial increase of composite reliability. Neither of the two requirements were true to remove these items. Hence, all the reflective model indicators were considered valid for indicator reliability.

Convergent Validity (AVE)

The two most common construct validity measures are convergent validity and discriminant validity (Wong, 2013). According to Urbach and Ahlemann (2010), convergent validity involves the degree to which individual items reflecting a construct converge in comparison to items measuring different constructs. A commonly applied criterion of convergent validity is the Average Variance Extracted (AVE) which reflects the average communality for each latent factor in a reflective model. Chin (1998) as well as Fornell and Larcker (1981) (as cited in Garson, 2016) suggested that AVE values should be greater than .5 that confirms at least half the variance of indicators are explained by the respective factor. ***Table 10*** shows that all values of AVEs were greater than the threshold value except for FC whose AVE equals .48. In such cases, Urbach and Ahlemann (2010) recommend dropping certain items from the measurement model and/or reallocate items to the structural model's LVs.

One of the likely causes for lacking convergent validity in the above case was the two lower values of item loadings for item number AFC1 (.65) and AFC4 (.56). Hence, repeated tests have been conducted by removing one item at a time. Finally, significant change (about 17% increment on AVE value of FC was occurred when item AFC4 was removed without impacting others. Hence, the fourth item (item AFC4) has been removed from further analysis. After this specific indicator removal, all AVE values become above the threshold (.5) that confirms convergent validity over all reflective constructs.

Discriminant Validity

Discriminant validity is another means of assuring constructs validity. While convergent validity involves the degree to which individual items reflecting a construct converge in comparison to items measuring different constructs, discriminant validity tests whether the items do not unintentionally measure something else (Urbach & Ahlemann, 2010). There are two common approaches to determine discriminant validity in PLS-SEM. The first one is application of AVE in such a way that if the square root of AVE is larger than the correlation between any pair of corresponding LVs, discriminant validity is confirmed (Fornell & Larcker 1981, as cited in Wong, 2013). ***Table 11*** demonstrates that the square roots of AVEs (bold on the diagonal) are larger than all the correlation values that confirms discriminant validity.

Table 11: AVE, Correlations and Square root of AVE's

	AVE	BI	EE	FC	HM	HT	PE	PV	SI	Use
BI	0.74	**0.86**								
EE	0.68	0.37	**0.82**							
FC	0.56	0.45	0.56	**0.75**						
HM	0.75	0.51	0.28	0.42	**0.87**					
HT	0.64	0.43	0.14	0.15	0.33	**0.80**				
PE	0.70	0.54	0.52	0.41	0.44	0.28	**0.84**			
PV	0.82	0.40	0.34	0.38	0.34	0.15	0.36	**0.91**		
SI	0.69	0.29	0.30	0.26	0.36	0.27	0.35	0.28	**0.83**	
Use	0.00	0.25	0.18	0.07	0.11	0.33	0.19	0.13	0.16	**NA**

**Bold on the diagonal are square roots of AVEs while off diagonals are correlations*

The second method to measure discriminant validity suggested by Chin (1998) is using cross-loadings. Cross-loadings are obtained by correlating the component scores of each LV with all other items. To assure discriminant validity, the loading of each indicator should be higher for its designated construct than or any of the other constructs and each of the constructs loads highest with its own items. This can be identified by taking the cross-loading output from SmartPLS into the Excel sheet and using the conditional formatting to highlight all cell values greater than .6 (considering the lowest indicator reliability equals .68).

As it is shown in ***Table 12***, all highlighted (also on bold for emphasis) cells are those on the diagonal that indicates the loading of each indicator was higher for its designated construct than or any of the other constructs and each of the constructs loaded highest with its own items which confirms discriminant validity was well achieved.

Table 12: Loadings and Cross-loadings for the reflective model

	BI	EE	FC	HM	HT	PE	PV	SI
ABI1	**0.85**	0.38	0.45	0.51	0.31	0.55	0.43	0.29
ABI2	**0.89**	0.27	0.38	0.38	0.43	0.40	0.33	0.22
ABI3	**0.85**	0.29	0.33	0.41	0.38	0.43	0.26	0.23
AEE1	0.31	**0.84**	0.46	0.13	0.04	0.44	0.26	0.15
AEE2	0.29	**0.90**	0.47	0.19	0.10	0.42	0.30	0.21
AEE3	0.30	**0.87**	0.49	0.22	0.15	0.41	0.31	0.23
AEE4	0.30	**0.68**	0.40	0.39	0.16	0.42	0.27	0.42
AFC1	0.28	0.29	**0.68**	0.32	0.17	0.23	0.29	0.15
AFC2	0.37	0.57	**0.76**	0.30	0.06	0.39	0.31	0.20
AFC3	0.36	0.35	**0.80**	0.33	0.13	0.29	0.26	0.22
AHM1	0.49	0.29	0.43	**0.89**	0.30	0.45	0.33	0.31
AHM2	0.46	0.22	0.35	**0.92**	0.27	0.38	0.28	0.31
AHM3	0.35	0.21	0.30	**0.79**	0.30	0.30	0.28	0.32
AHT1	0.42	0.16	0.19	0.37	**0.84**	0.28	0.18	0.22
AHT2	0.15	0.07	0.04	0.20	**0.70**	0.10	0.01	0.15
AHT3	0.33	0.08	0.10	0.17	**0.82**	0.22	0.09	0.21
AHT4	0.39	0.10	0.12	0.28	**0.83**	0.24	0.14	0.27
APE1	0.48	0.40	0.36	0.31	0.17	**0.83**	0.33	0.25
APE2	0.44	0.48	0.31	0.36	0.23	**0.86**	0.28	0.32
APE3	0.50	0.49	0.44	0.40	0.27	**0.88**	0.33	0.23
APE4	0.37	0.35	0.24	0.44	0.27	**0.78**	0.26	0.39
APV1	0.40	0.31	0.33	0.33	0.16	0.37	**0.90**	0.24
APV2	0.33	0.30	0.31	0.26	0.10	0.27	**0.92**	0.24
APV3	0.35	0.32	0.38	0.33	0.13	0.34	**0.90**	0.27
ASI1	0.31	0.32	0.26	0.33	0.26	0.37	0.26	**0.90**
ASI2	0.16	0.18	0.15	0.23	0.16	0.19	0.14	**0.75**
ASI3	0.22	0.22	0.22	0.31	0.25	0.27	0.26	**0.84**

Note: Perfect high loading in the diagonal indicates how significant discriminant validity exist

4.3.2.2 *Measurement Model for Formative constructs*

The validation of formative measurement models was different than reflective measurement models in which reliability becomes irrelevant and convergent validity assessments were not meaningful. Instead, analysis of outer weights, construct validity and collinearity of indicators were considered important to measure formative constructs (Henseler et al., 2009; Wong, 2013).

Outer model weights and Significance

Outer weights are loading factors for formative constructs so as outer loadings are for reflective constructs. Wong (2013) suggest testing the significance of formative indicators' outer weight by using bootstrapping in which at a minimum, an indicator's outer weight should have a t-value greater than1.96 for .05 significance. If it is less than 1.96 and the corresponding outer loading of the same indicator is also below 1.96, removing the indicator is recommended for a better solution.

Accordingly, bootstrapping was run for initial set of 5000 samples, as recommend by Wong (2013). As ***Table 13*** shows t-values except for formative indicator AU2 and AU3, were not significant at $p < .05$. However, their corresponding outer loadings (values in brackets) were all significant except for the fourth and seventh formative indicators (AU4 and AU7). Moreover, in formative model dropping an item requires substantial theoretical justification beyond the statistical measures (Garson, 2016; Henseler et al., 2009; Urbach & Ahlemann, 2010). Hence, none of these weak formative indicators were not excluded from further analysis.

Table 13: Outer model weight and T-value

	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	T-Statistics
AU1 -> USE	0.02	0.04	0.23	0.09 (2.80)
AU2 -> USE	0.50	0.44	0.22	*2.30 (3.88)
AU3 -> USE	0.68	0.62	0.15	**4.43 (5.08)
AU4 -> USE	-0.25	-0.23	0.17	1.46 (0.41)
AU5 -> USE	0.51	0.46	0.32	1.61 (2.66)
AU6 -> USE	0.09	0.09	0.36	0.24 (2.28)
AU7 -> USE	-0.40	-0.35	0.25	1.60 (0.27)

*$p<0.05$, **$p<0.001$

Construct Validity

Construct validity assessed the inter-construct correlations that can be assessed by using discriminant validity. MacKenzie et al. (as cited in Urbach & Ahlemann, 2010) suggest that correlations between formative and all other constructs of less than .7 indicate sufficient discriminant validity for formative model. From the ***Table 11*** above, the correlation between the formative LV (Use) and all other constructs ranges from .07 to .33 that confirms construct validity was well achieved. Lowery and Gaskin (2014) also suggested that variance inflation factor (VIF) below 3.3 as shown in ***Table 14*** indicate sufficient construct validity for formative indicators.

Multicollinearity

The degree of multicollinearity among formative indicators is another approach to check indicators validity. It can be assessed by using VIF or tolerance that indicates how much of an indicator's variance is explained by the other indicators of the same construct (Urbach & Ahlemann, 2010). According to Wong (2013), if VIF values are lower than 5 and their tolerance values are higher than 0.2, it indicates that there is no collinearity problem. Henseler et al. (2009) also sugested that VIF greater than 10 indicates destructive collinearity. Since SmartPLS v. 2.0 doesn't report VIF directly, SPSS v.23 was used to generate VIF and Tolerance report. As ***Table 14*** shown, all VIF values were lower than 5 and their corresponding tolerance values were above 0.2 which was consistent with (Venkatesh et al., (2012) that implies no collinearity problem existed in formative indicators. Moreover, similar VIF tests have been done to check collinearity among endogenous and exogenous constructs in which no issue of multicollinearity has been observed.

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Table 14: Collinearity (VIF/Tolerance) for formative indicators

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	5.32	0.29			
	AU1	-0.03	0.05	-0.04	0.59	1.70
	AU2	0.05	0.05	0.08	0.54	1.87
	AU3	0.14	0.05	0.16	0.59	1.71
	AU4	-0.05	0.07	-0.05	0.63	1.60
	AU5	0.08	0.08	0.11	0.78	1.28
	AU6	0.07	0.08	0.10	0.56	1.78
	AU7	-0.14	0.07	-0.16	0.75	1.33

Dependent Variable: AB1

4.3.2.3 *Structural Model Assessment*

Assessing the structural model is a focus of any path modelling in PLS-SEM approach. The structural model is also identified as the inner model which consists of exogenous and endogenous LVs. Wong (2013) recommend a structural model assessment to include explanation of target endogenous variables variance, inner model path coefficients size and dimension and checking for structural path significance by bootstrapping. In general, structural model analysis should be examined to evaluate how the data fit with the proposed structural model and validate hypothesized relationships. For this purpose; coefficient of determination (R^2), the value of adjusted R^2, effect size measurement (f^2) and predictive relevance (Q^2) has been calculated for in-depth analysis.

In PLS path modeling, the first essential criterion for structural equation model is the assessment of R^2 (Garson, 2016; Urbach & Ahlemann, 2010; Wong, 2013). R^2 measures the relationship of a LV's explained variance to its total variance (Urbach & Ahlemann, 2010). That means, it indicates that how much the variance in the endogenous variable is explained by the exogenous variables in the model that directly pointed towards it. Though there is no "cut-off" rule to determine the coefficients explanatory power, Chin (1998) considers values of approximately .67 as substantial, .33 as an average, and .19 and lower as weak coefficients.

As the inner model depicted in ***Figure 12***, the explained variance for the two endogenous LVs behavioral intention (BI) and Use behavior (Use) were .481 and .122. This indicate that 48% and 12% of variance in BI and Use were explained by the exogenous LVs in the model. More precisely, the finding shows that, PE, EE, SI, FC, HM, PV and HT together moderately explain 48% the variance in BI while BI, FC and HT together weakly explain 12% the variance in Use behavior.

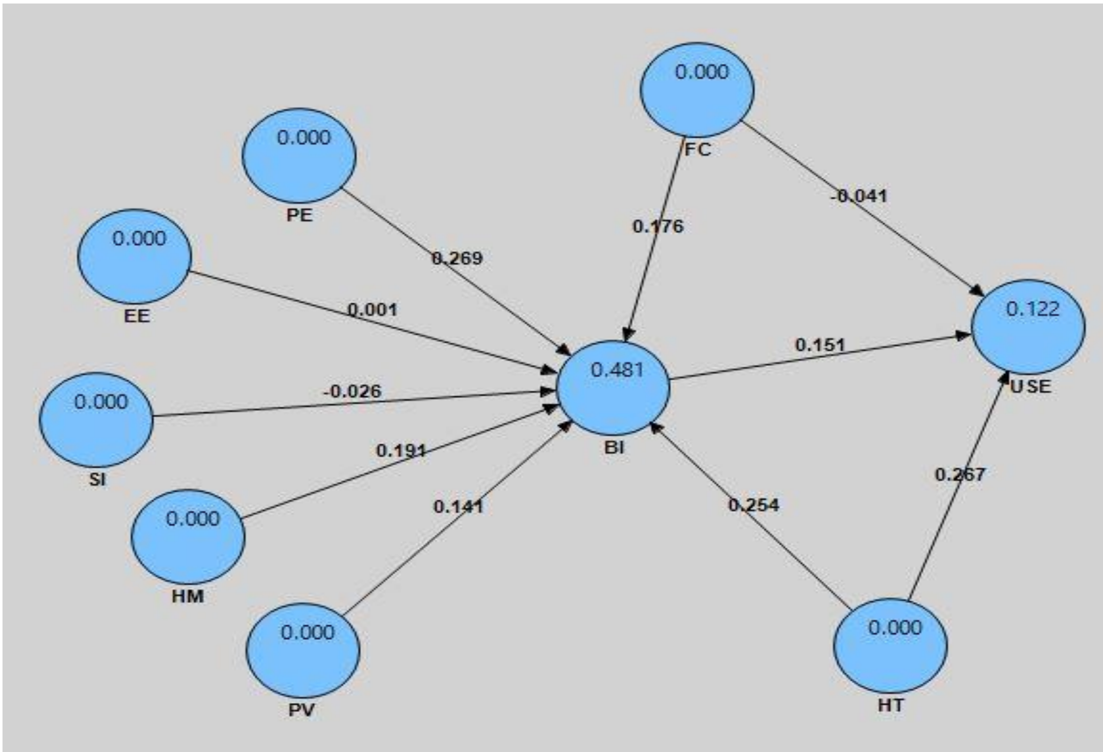

Figure 12: The structural (inner) model on the ATM users' dataset

The evaluation of the path coefficients was the next important analysis to validate the theoretically assumed relationship between LVs. Individual path coefficients of the PLS structural model can be interpreted as standardized beta coefficients of ordinary least squares regressions and it was mandatory to check the path coefficient's algebraic sign, magnitude, and significance for complete empirical validation (Henseler et al., 2009; Lowery & Gaskin, 2014). Similar algebric sign with a priori postulated algebraic signs provide a partial empirical validation of the theoretically assumed positive relationships between LVs. If it is in contrary, the priori assumed hypothesis is not supported. As it is shown in ***Figure 12*** the path coefficient between SI and BI, and between FC and 'Use' LVs were negative that marked two hypotheses H3 and H4.2 to be rejected.

The absolute magnitude of the path coefficient indicates the relationship strength in which Henseler et al. (2009) argued that path coefficients should exceed .1 to account for a certain impact within the model. Furthermore, the path coefficients should be significant at least at .05 which can be measured by using t-values in bootstrapping technique (Urbach & Ahlemann, 2010). Accordingly, the path coefficient .001between SI and BI was not strong enough to support the second hypothesis H2. Moreover, H8 has been found rejected due to its weak significance. All other hypotheses were supported for *p*<.05 significances. ***Table 15*** shows the detail path coefficient and t-values for all relations between LVs.

Table 15: Path coefficients and T-values for ATM banking users' dataset

	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	Path coefficients	T-Statistics (|O/STERR|)	Impact on hypothesis
PE -> BI	0.27	0.27	0.07	***0.27	3.99	Confirmed
HT -> BI	0.25	0.26	0.06	***0.25	4.27	Confirmed
HM-> BI	0.19	0.18	0.07	**0.19	2.78	Confirmed
FC -> BI	0.18	0.18	0.07	**0.18	2.68	Confirmed
PV -> BI	0.14	0.14	0.06	*0.14	2.39	Confirmed
EE -> BI	0.00	0.01	0.07	0.00	0.02	Disconfirmed
SI -> BI	-0.03	-0.03	0.05	-0.03	0.49	Disconfirmed
HT -> USE	0.27	0.28	0.07	***0.27	3.63	Confirmed
BI -> USE	0.15	0.16	0.09	0.15	1.62	Disconfirmed
FC -> USE	-0.04	-0.04	0.09	-0.04	0.49	Disconfirmed

*p<0.05, **p<0.01, ***p<0.001

As ***Figure 12*** and ***Table 15*** shows five hypothetical relationships between the exogenous PE, HT, HM, FC and PV LVs and the endogenous variable BI are supported with path coefficient of β greater than .1, higher t-values greater than 1.96 and significant at p< .01 except for PV significant at p< .05. The magnitude strength of PE is the strongest determinant factor of BI that showed if a user perceived the degree to which using a technology will provide benefits in performing certain activities, he/she will likely to behaviorally intended and adopt the given technology. This result is in accordance with previously made researches that found PE as the strongest determinant of BI in adopting different technologies (Huang & Kao, 2015; Merga, 2017; Venkatesh et al., 2012).

In contrary EE which is found as strong determinant of BI in previous researches (Huang & Kao, 2015; Venkatesh et al., 2012), was not supported in the ATM banking users' dataset in Ethiopian context. It implies that the effort required to perform financial transactions using ATMs didn't significantly affects the user to adopt the technology. Ain et al. (2015) has got similar result on studing the influence of learning value on learning management system use. Im et al. (2011) also has got similar weak relation between EE and BI in their study on Korean respondents. One likely reason for this result was that the majority (77%) of the respondents were holder of either the first degree or above that might make the effort required to use ATMs insignificant.

Another deviated finding here was that the result between SI and BI. SI in countries like Ethiopia where collectivism is dominant, was expected to highly influence on behavioral intention of adopting technologies (Im et al., 2011). However, the path coefficient SI on BI was negative and had a small t-value that made it insignificant. This was again due to the fact that majority (77%) of respondents were passed through tertiary level education that makes their decision of using technologies more based on rational justification of its benefit than social influence of others. This finding aligned with Alalwan et al. (2017), Merga (2017) and Khechine and Lakhal (2018) adoption studies.

In regarding to a theoretical relationship between the three independent (BI, FC and HT) and one dependent (Use) variables, only HT has been confirmed as a determinant factor with nearly $\beta = .3$, $t = 3.6$ and significant at $p < 0.001$. However, unlike most previous findings (Huang & Kao, 2015; Venkatesh et al., 2003; Venkatesh et al., 2012) that showed BI as a strongest predictor of Use behavior, in this ATM banking users' dataset, it was not confirmed due to very weak t-value (poor significant). This can be justified as in some cultures people might tend behavioral intended easily but takes time to commit the actual action. Venkatesh et al. (2012) also argue that the strength of HT automaticity surpasses the influence of BI to perform the actual action through time. Hence, once a user started to use ATM banking and perceived the technology as it has provided some benefits in performing certain activities, its likely to continue usage without planed intention.

The other surprised finding in this empirical test is the negative relation between the FC and Use behavior. However, few other studies (Arenas-Gaitan et al., 2015; Pynoo, et al., 2011) have found similar results that indicate the weak influence of FC on the actual Use behavior. In consumer context the term FC can be explained as consumer's perception of availability of all required resources, infrastructures and support to perform a behavior (Venkatesh et al., 2012). In ATM banking service, the two most important indicators were availability of ATMs in nearby with supportive infrastructure and the availability of support from others when there is a demand. These two items were not the determinant issues on use behavior of these sampled datasets for two likely reasons. First the availability of ATMs in the surveyed areas were not the issue either due to the banks aggressive expansion of ATMs in different locations or the interoperability of ATMs of all local banks through the national switch made the issue of availability of ATMs insignificant to determine the USE behavior. The second reason was that since majority of the respondents were educated in tertiary levels they have found the interaction with the ATMs easy and didn't require frequent support that matters their Use behavior. However, FC is significant factor to determine the behavioral intention of using ATMs until the users become familiar to use these technologies.

Adjusted R^2, Effect size (f^2) and Q-square effect(Q^2)

Garson (2016) noted that R^2 is likely to be increased for addition of exogenous variable even though the new variable has insignificant correlation with the endogenous variable. To penalize for such bias, adjusted R^2 can be determined using the following formula:

$$\textbf{Adjusted } \mathbf{R^2 = 1 - \{[(1 - R^2) * (n\text{-}1)]/[n\text{-}k\text{-}1]\}}$$

Where R^2 is the unadjusted R^2, n is sample size, and k is the number of exogenous factors used to predict a given endogenous factor. Accordingly, adjusted R^2 for BI and Use endogenous variables were found to be .47 and .10 respectively for insignificant (<2%) change on the original R^2 values These indicate that addition of new exogenous variable didn't bring substantial change on the already found R^2s.

Cohen's f^2 (as cited in Urbach & Ahlemann, 2010) also used to evaluate the effect size of each path in the structural equation model. f^2 measures the change in R^2 when an exogenous LV is removed from the model. That used to indicate whether an independent LV has a substantial impact on a dependent LV or not. Chin (1998) explained the effect size as the increase in R^2 of the LV to which the path is connected, relative to the LV's proportion of unexplained variance. Garson's (2016) formula **[$f^2 = (R^2_{origonal} - R^2_{omitted})/(1\text{-}R^2_{origional})$]** has been used to determine f^2 impact for each significant LVs and small to medium range effect size has been found. f^2 values of .02, .15, and .35 are termed as small, medium and large effects respectively (Henseler et al., 2009; Chin, 1998; Venkatesh et al., 2012).

The final model-fit assessment for the structural model involves the model's capability to predict, also called predictive relevance, the results on the largest population (Henseler et al., 2009). The most common measure of predictive relevance is Stone-Geisser's Q^2 which was named after its authors (Stone, 1974 and Geisser, 1974 as cited in Garson, 2016).

Predictive relevance can be assessed by using a technique called blindfolding in SmartPLS. By convention, Q^2 greater than 0 indicates the model is predictive of the given endogenous variable under investigation. In contrary, it is irrelevant to predict the given endogenous variable if Q^2 is less than or equal to 0 (Garson, 2016). Accordingly, by running blindfolding algorithm with an arbitrary setting of omission distance 7 as suggested by Chin (1998), Q^2 has been found closer to .35 which indicates high degree of predictive relevance regarding the endogenous LV, BI (Chin, 1998, Garson 2016). Since the procedure was applicable only for reflective endogenous variables, relevance indicator for "Use" variable was not computed (Garson, 2016; Henseler et al., 2009; Urbach & Ahlemann, 2010).

4.3.3 Structural and Measurement Model: Mobile banking users' dataset

The following sample dataset has been taken from the survey questionnaire filtered by customers positive response towards Mobile-banking usage. From total of 321 responded questionnaires almost half (162) respondents were identified as they used Mobile banking. This sample size was enough to test the model on Mobile banking users' dataset (Chin, 1998).

The descriptive statistic summarized in ***Table 16*** showed that 70% of the Mobile banking users respondents were males while the rest were females. Moreover, from the total approached male respondents, above half (55%) of them used Mobile banking. Similarly, 59% of the Mobile bank users' respondents were aged between 26 and 35 years. Again, about half of the total similar aged groups were Mobile banking users. Per average monthly income, almost 75% respondents earn above Birr 5,250 that can be categorized as middle and high incomers. While there was no significant variance in distribution per city, almost all (86%) of the respondents for Mobile banking users' dataset were above Diploma/TVET holders.

Table 16: Summarized demographic data for Mobile banking users' respondents

		Frequency	Percent	Percent per total similar groups
Gender	Male	113	70	55
	Female	49	30	42
Age	below 26	42	26	47
	26-35	95	59	53
	36-45	21	13	54
	above 45	4	3	27
Monthly Average Income	below 1,651	9	6	36
	1,651-5,250	33	20	38
	5,251-10,900	81	50	55
	above 10,900	39	24	64
Education Level	Elementary	7	4	32
	Secondary	7	4	39
	Diploma/TVET	8	5	24
	1st Degree	115	71	54
	2nd Degree	25	15	74
Residential City	Addis Ababa	33	20	49
	Dire Dawa	33	20	53
	Hawassa	32	20	49
	Jimma	33	20	52
	Mekelle	31	19	48

The overall approach of data analysis for the measurement and structural model on the ATM banking users' dataset has been followed for Mobile banking users' dataset except removing some redundant explanations.

4.3.3.1*Measurement Model for reflective indicators*

ICR and Indicator Reliability:

ICR of the Mobile banking users dataset has been measured by both the PLS composite reliability and Cronbach's alpha (α) despite its conservativity in PLS-SEM approach. As it is shown in ***Table 17***, both composite reliability and α values were larger than .7 that assures strong internal consistency (Henseler et al., 2009; Urbach & Ahlemann, 2010; Venkatesh et al., 2012; Wong, 2013).

Table 17: Composite Reliability and Cronbach's α measures of the reflective model

	Composite Reliability	**Cronbach's Alpha**
PE	0.93	0.90
EE	0.94	0.92
SI	0.92	0.87
HM	0.93	0.88
FC	0.85	0.77
HT	0.91	0.88
PV	0.97	0.96
BI	0.93	0.88

BI= behavioral intention, EE=effort expectancy, FC=facilitating condition, HM=hedonic motivation, HT=habit, PE=performance expectancy, PV=price value, SI=social influence

Indicator reliability also applied as reliability measure of the instrument on the Mobile banking users' dataset that was expected to be above .7 (Chin, 1998; Garson, 2016; Henseler et al., 2009; Wong, 2013). As it is shown in ***Table 18***, all values of indicator loadings showed the applicability of indicator reliability with slight difference in the fourth item of FC (MFC4).

Convergent and Discriminant Validity

Convergent and discriminant validity were measured to check the sample dataset validity to confirm convergence of individual items reflecting a construct in comparison to items measuring different constructs and to confirm the items didn't unintentionally measure something else (Urbach & Ahlemann, 2010). Both were measured in PLS based on the AVE values. All AVE values meet the minimum requirement of .5 (Chin, 1998) that validates convergent validity (see ***Table 18***).

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Table 18: Reliability and Validity measures with Factor loadings for reflective indicators

LV	Indicator	Indicator Reliability Outer Loadings (λ)	Composite Reliability (ICR)	Convergent Validity (AVE)	Discriminant validity Square roots of AVE
PE	APE1	0.86	0.93	0.78	0.88
	APE2	0.91			
	APE3	0.90			
	APE4	0.86			
EE	AEE1	0.90	0.94	0.81	0.90
	AEE2	0.93			
	AEE3	0.93			
	AEE4	0.83			
SI	ASI1	0.89	0.92	0.79	0.89
	ASI2	0.85			
	ASI3	0.92			
FC	AFC1	0.84	0.85	0.81	0.90
	AFC2	0.80			
	AFC3	0.74			
	AFC4	0.68*			
HM	AHM1	0.91	0.93	0.59	0.77
	AHM2	0.93			
	AHM3	0.86			
PV	APV1	0.96	0.97	0.92	0.96
	APV2	0.96			
	APV3	0.96			
HT	AHT1	0.86	0.91	0.73	0.85
	AHT2	0.79			
	AHT3	0.87			
	AHT4	0.88			
BI	ABI1	0.90	0.93	0.81	0.90
	ABI2	0.91			
	ABI3	0.88			

*Shows low loading factor below the preferred value (0.7),

Discriminant validity has been shown in ***Table 19*** by comparing the square root of AVE values with the correlation between any pair of corresponding LVs as it was mentioned by Former and

Lacker (as cited in Wong, 2016) to be larger than these values. This requirement also met by the data to confirm well established discriminant validity.

Table 19: AVE, Correlations and Square root of AVE's

	AVE	PE	EE	SI	HM	FC	HT	PV	BI	Use
PE	0.78	**0.88**								
EE	0.81	0.53	**0.90**							
SI	0.79	0.54	0.36	**0.89**						
HM	0.81	0.52	0.46	0.54	**0.90**					
FC	0.59	0.48	0.68	0.45	0.55	**0.77**				
HT	0.73	0.43	0.33	0.34	0.49	0.37	**0.85**			
PV	0.92	0.4	0.45	0.26	0.44	0.42	0.4	**0.96**		
BI	0.81	0.6	0.4	0.38	0.55	0.43	0.55	0.44	**0.90**	
Use	0.00	0.36	0.35	0.25	0.24	0.41	0.41	0.34	0.34	**NA**

**Bold on the diagonal are square roots of AVEs, off diagonals are correlations*

Cross-loading also has been checked using Excel conditional formatting to highlight all cell values greater than .7 (considering the lowest indicator reliability equals .70). As it is shown in ***Table 20***, all the highlighted (bold values) fit to the perfect diagonal that indicates the loading of each indicator was higher for its designated construct than or any of the other constructs and each of the constructs loads highest with its own items which confirms discriminant validity was well achieved.

Table 20: Loadings and Cross-loadings for the reflective model

	EE	FC	HM	HT	PE	PV	SI	BI
MEE1	**0.90**	0.58	0.35	0.29	0.46	0.39	0.30	0.33
MEE2	**0.93**	0.68	0.40	0.34	0.52	0.41	0.30	0.34
MEE3	**0.93**	0.62	0.41	0.27	0.48	0.43	0.31	0.39
MEE4	**0.83**	0.55	0.47	0.28	0.42	0.40	0.37	0.37
MFC1	0.58	**0.84**	0.42	0.30	0.36	0.38	0.33	0.38
MFC2	0.65	**0.80**	0.52	0.27	0.51	0.38	0.41	0.41
MFC3	0.39	**0.74**	0.43	0.32	0.29	0.23	0.33	0.28
MFC4	0.42	**0.68**	0.30	0.23	0.30	0.26	0.34	0.21
MHM1	0.42	0.55	**0.91**	0.40	0.45	0.36	0.51	0.57
MHM2	0.50	0.51	**0.93**	0.49	0.51	0.47	0.49	0.48
MHM3	0.30	0.40	**0.86**	0.43	0.44	0.37	0.45	0.43
MHT1	0.36	0.34	0.50	**0.86**	0.43	0.43	0.33	0.54
MHT2	0.20	0.27	0.36	**0.79**	0.27	0.21	0.25	0.30
MHT3	0.23	0.27	0.36	**0.87**	0.39	0.36	0.30	0.52
MHT4	0.31	0.35	0.42	**0.88**	0.36	0.34	0.26	0.47
MPE1	0.51	0.41	0.43	0.32	**0.86**	0.45	0.46	0.54
MPE2	0.52	0.49	0.41	0.44	**0.91**	0.35	0.47	0.54
MPE3	0.43	0.42	0.46	0.36	**0.90**	0.31	0.49	0.54
MPE4	0.39	0.39	0.54	0.41	**0.86**	0.29	0.47	0.49
MPV1	0.45	0.41	0.42	0.38	0.37	**0.96**	0.24	0.42
MPV2	0.45	0.39	0.42	0.36	0.39	**0.96**	0.26	0.39
MPV3	0.41	0.40	0.44	0.42	0.39	**0.96**	0.25	0.45
MSI1	0.35	0.44	0.50	0.31	0.49	0.28	**0.89**	0.36
MSI2	0.23	0.31	0.42	0.28	0.43	0.21	**0.85**	0.32
MSI3	0.37	0.45	0.52	0.30	0.51	0.20	**0.92**	0.33
MBI1	0.40	0.41	0.47	0.48	0.59	0.43	0.36	**0.90**
MBI2	0.33	0.36	0.48	0.52	0.55	0.40	0.32	**0.91**
MBI3	0.34	0.39	0.55	0.49	0.47	0.34	0.35	**0.88**

Note: Perfect high loading in the diagonal indicates how significant discriminant validity exist

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4.3.3.2 *Measurement Model for formative indicators*

Outer model weights and Significance

The outer model weight for eight formative indicators of Mobile banking users' dataset can be found from PLS output. These outer weights are expected to have a minimum of 1.96 t-value to be significant at $p < .05$ (Wong, 2016). Bootstrapping with 162 cases and 5000 re-sampling has been run to find results as shown below in ***Table 21***. The t-value for formative indicators of Mobile banking users' dataset indicate weak significance that forces to double check corresponding loading values. However, almost all the loading values were above the threshold value (1.96) that imply removing indicators with low outer weight not necessary as it is difficult to justify their removal theoretically (Garson, 2016; Henseler et al., 2009; Urbach & Ahlemann, 2010).

Table 21: Outer model weights and corresponding T-values

	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	T-Statistics
MU1 -> Use	0.56	0.38	0.39	*1.45(3.15)
MU2 -> Use	-0.05	0.02	0.36	0.13(2.09)
MU3 -> Use	0.08	0.05	0.30	0.25(2.06)
MU4 -> Use	0.42	0.31	0.48	*0.87(3.60)
MU5 -> Use	0.17	0.16	0.45	0.37(2.89)
MU6 -> Use	0.00	0.01	0.40	0.01(2.13)
MU7 -> Use	-0.23	-0.17	0.43	0.52(1.18)
MU8 -> Use	0.34	0.24	0.37	*0.93(2.07)

*p<0.5; values in brackets indicate corresponding loading values

Construct validity and multicollinearity issues on the formative indicators of Mobile banking users' dataset has been assessed using VIF (Urbach & Ahlemann, 2010). Lowery and Gaskin (2014) suggested VIF values below 3.3 indicate sufficient construct validity. Likewise, Wong (2013) also agree on the idea that VIF values lower than 5 and corresponding tolerance values greater than .2 confirms no collinearity issue. Accordingly, VIF values shown in ***Table 22*** indicated that construct validity was well achieved and multicollinearity was not a problem in Mobile banking user's dataset. Further assessment of VIF for the inner model also showed that all VIF values are less than 5 that indicates multicollinearity is not an issue for the inner model constructs too. Moreover, from the ***Table 19*** above, the correlation between the formative LV (Use) and all other constructs ranges from .24 to .41 that confirms construct validity is well achieved by meeting the requirement of these values to be less than .7 (MacKenzie et al., 2005 as cited in Urbach & Ahlemann, 2010).

Table 22: Collinearity (VIF/Tolerance) for formative indicators

Model		Unstandardized Coefficients		Standardized Coefficients	Collinearity Statistics	
		B	Std. Error	Beta	Tolerance	VIF
1	(Constant)	4.75	.28			
	MU1	0.22	0.07	0.32	0.60	1.66
	MU2	-0.06	0.05	-0.12	0.59	1.69
	MU3	-0.03	0.05	-0.06	0.68	1.47
	MU4	0.04	0.06	0.08	0.45	2.21
	MU5	0.09	0.06	0.17	0.39	2.59
	MU6	-0.05	0.06	-0.10	0.43	2.33
	MU7	-0.03	0.06	-0.06	0.44	2.25
	MU8	0.09	0.05	0.18	0.65	1.54

Dependent Variable: AB1

4.3.3.3 *Structural Model Assessment*

R^2 and Path coefficients

Coefficient of determination (R^2) measures how well the variance in endogenous LV is explained by the variance in the exogenous LVs. As we can see from the structural model PLS output in ***Figure 13***, the explained variance for the two endogenous LVs BI and Use behavior were nearly .51 and .25. This indicates that 51% variance in BI was explained by the exogenous PE, EE, SI, FC, HM, PV and HT variables in the model while 25% variance in Use behavior was explained by BI, FC and HT variables. As Chin (1998) explained, both endogenous variables were explained moderately by the other exogenous variables in the model. It was also noticed that, the result of these determinant coefficient had increment for Mobile banking users' dataset than the ATM banking users' dataset.

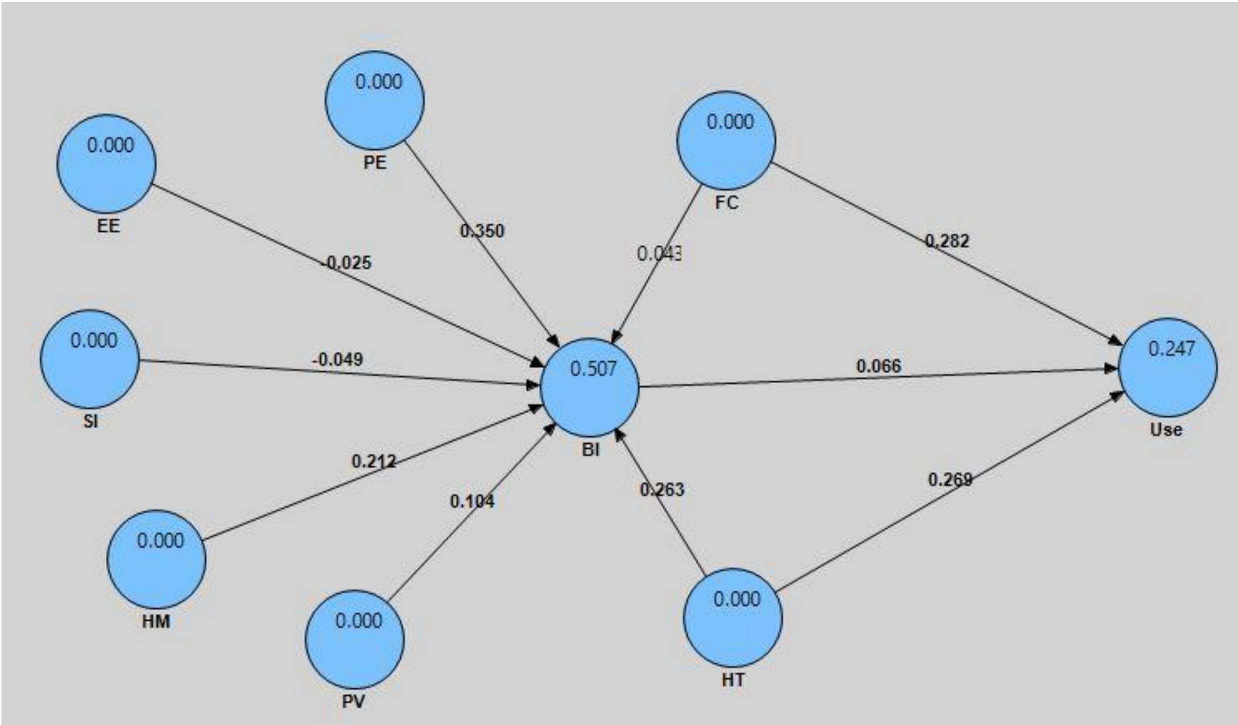

Figure 13: The structural (inner) model for Mobile banking users' dataset

The β coefficients on the directed lines as shown in ***Figure 13***, tell us the magnitude and direction of the relationships between the LVs. The negative coefficients between EE and BI and between SI and BI indicate that the positive assumption between these variables were not valid (Henseler et al., 2009). Hence, the two hypotheses: H2 = *EE has a positive impact on customers' BI of E-banking adoption in Ethiopia* and H3= *SI has a positive impact on customers' BI of E-banking adoption in Ethiopia* were rejected for Mobile banking users' dataset. The path coefficient for PV to determine BI was also neither strong in magnitude nor had significant t-value greater than 1.96 that leads to reject the corresponding hypothesis H6 = *PV has a positive impact on customers' BI of E-banking adoption in Ethiopia* in the Mobile banking users' dataset. Moreover, the path coefficient between BI and Use behavior and between FC and BI were below the threshold .1 (Henseler et al., 2009) that couldn't support the corresponding hypotheses H4.1= *FC has a positive impact on customers' BI of E-banking adoption in Ethiopia* and H8 = *BI has a positive impact on customers' E-banking adoption (use)* in the Mobile banking users' dataset.

The other remaining factors were considered as determining factors of the two endogenous LVs mainly due to their strong path coefficient β >.2 though they had weak significance (Chin, 1998). Hence, the path coefficients PE (β= .35, *t*=1.66), HT (β= .26, *t*= 1.32) and HM (β= .21, *t*=1.08) were considered as determinant factors of BI on the Mobile banking users' dataset. On the other hand, FC (β=.28, *t*=1.32) and HT (β= .27, *t*= 1.66) were considerable factors to determine the Use behavior. (see ***Table 23*** for the detail)

Table 23: Path coefficients and T-values for Mobile banking users' dataset

	Original Sample (O)	**Sample Mean (M)**	**Standard Error (STERR)**	**Path coefficients**	**T-Statistics (|O/STERR|)**	**Impact on hypothesis**
BI -> Use	0.09	0.13	0.21	0.07	0.45	Disconfirmed
EE -> BI	-0.03	0.01	0.22	-0.03	0.12	Disconfirmed
FC -> BI	0.04	0.08	0.23	0.04	0.20	Disconfirmed
FC -> Use	0.28	0.29	0.21	*0.28	1.32	Confirmed
HM -> BI	0.21	0.18	0.20	*0.21	1.08	Confirmed
HT -> BI	0.26	0.24	0.16	**0.26	1.66	Confirmed
HT -> Use	0.25	0.32	0.19	0.27	1.29	Confirmed
PE -> BI	0.35	0.36	0.21	**0.36	1.66	Confirmed
PV -> BI	0.10	0.11	0.17	*0.11	0.62	Disconfirmed
SI -> BI	-0.05	-0.07	0.16	-0.05	0.31	Disconfirmed

*p<0.5, **p<0.1

The path coefficient analysis showed that PE is still the most determinant variable of BI like it was true in the ATM banking user's dataset. Moreover, with similar justification for the case of EE in ATM banking users' dataset, it was not yet found as strong determinant factor of BI in Mobile banking users' dataset. HT was still relatively strong determinant for both BI and Use behaviors that confirms one's a user start to use the system and found it useful, it is likely to continue using the technology. SI, the other weak variable to represent BI of Mobile banking users', showed the influence of others to enable using a given technology was very weak. This was again due to the fact that majority (88% of Mobile banking users) were at least first-degree holders who made a decision of using technology based on the rational justification for its benefit rather than others' influence. Similar result regarding the relationship between BI and the actual Use behavior also noticed on Mobile banking users' dataset that confirmed BI to adopt a given technology didn't necessarily implied the actual usage behavior. This result shared the previous justification that in some cultural contexts, people might have good behavioral intention but fail to perform the actual action in that case behavioral intention will suffer from the power to enforce the actual usage.

In contrast to finding in the ATM banking users' dataset, FC affects only user's actual Use behavior to adopt Mobile banking than the user's behavioral intention towards using Mobile banking. This finding is in line with Baptista and Oliveira (2015) who found FC as significant factor to determine the actual Use behavior than the BI. This result was justifiable that FCs have more impact to those who already tried to use the technology than those who were not intended yet. Moreover, resources required to use Mobile banking were primarily the Mobile handset and a bank account. These things were already fulfilled on the user side that didn't require any further resources from the bank like ATM card and ATM machines. But, facilitating conditions like mobile network, internet, and call support from the banks' side can be considered as important conditions to enhance the actual Mobile banking usage.

Adjusted R^2, Effect size (f^2) and Q-square effect(Q^2)

Adjusted R^2 has been calculated according to Garson's (2016) guide to see the impact for addition of exogenous variable even though the new variable has insignificant correlation with the endogenous variable. Accordingly, adjusted R^2 for BI and Use endogenous variables were found to be .49 and .23 respectively for insignificant 1% and 2% change on the original R^2 values respectively.

Cohen's f^2 also used to evaluate the effect size of each path in the structural equation model by examining its change on R^2 when an exogenous LV is removed from the model. using Garson's (2016) formula [$f^2 = (R^2_{origonal} - R^2_{omitted})/(1-R^2_{origional})$], values ranged from 0 to .13 has been found that indicated small to slightly moderate impacts (Henseler et al., 2009; Chin, 1998; Venkatesh et al., 2012).

Finally, the model's predictive relevance was assessed by using Stone-Geisser's Q^2 in which value greater than 0 indicates the model is predictive of the given endogenous variable under investigation (Garson, 2016). Accordingly, by running blindfolding algorithm with an arbitrary setting of omission distance 7, Q^2 has been found high (.36) degree of predictive relevance regarding the endogenous LV BI (Chin, 1998; Garson, 2016; Henseler et al., 2009; Urbach & Ahlemann, 2010).

4.3.4 Structural and Measurement Model: Internet banking users' dataset

Total valid number of observation for this dataset was 41. This sample dataset was relatively smaller than the previous two sampled datasets. This was mainly because this technology was still in infancies stage in Ethiopia and finding large number of respondents from this group were too difficult. However, according to Goodhue et al. (2006), "thumb rule of 5" was acceptable by many researches though it might affect the prediction power. The thumb rule of 5 requires sample size of 5 times the highest number of formative indicators. Accordingly, it was required to have a minimum of 40 samples that match with the collected samples. Hence, proceeding path modelling analysis for this dataset was justified.

As it is summarized in ***Table 24*** below, 80% of the Internet banking users' respondents were males while the rest were females. Moreover, from the total approached male respondents, only 16% of them used Internet banking. Similarly, 71% of the Internet banking users' respondents were aged between 26 and 35 years old. Again, only 16% of the total similar aged groups were Internet banking users. Per average monthly income, Majority (83%) of respondents earn above Birr 5,250 that can be categorized as middle or high incomers. While there was no significant variance in distribution per city, almost all (93%) of the respondents for Internet banking users' dataset were above Diploma/TVET holders.

The overall approach of data analysis for the measurement and structural model on the previous two channels users' dataset has been followed for Internet banking users' dataset except some minor modifications.

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Table 24: Summarized demographic data for Internet banking users' respondents

		Frequency	Percent	Percent per total similar groups
Gender	Male	33	80	16
	Female	8	20	7
Age	below 26	7	17	8
	26-35	29	71	16
	36-45	5	12	13
Average Monthly Income	below 1,651	1	2	4
	1,651-5,250	6	15	7
	5,251-10,900	20	49	14
	above 10,900	14	34	23
Education Level	Diploma/TVET	3	7	9
	1st Degree	27	66	13
	2nd Degree	11	27	32
Residential City	Addis Ababa	8	20	12
	Dire Dawa	9	22	15
	Hawassa	8	20	12
	Jimma	8	20	13
	Mekelle	8	20	13

4.3.4.1 *Measurement Model for reflective indicators*

The two measures of reliabilities that commonly applied in PLS have been conducted to the Internet banking users' dataset too. ICR has been measured by both the PLS composite reliability and Cronbach's alpha despite its conservativity in PLS-SEM. As it is shown in ***Table 25***, both composite reliability and Cronbach's α values were larger than .7 that assures strong internal consistency (Henseler et al., 2009; Urbach & Ahlemann, 2010; Venkatesh et al., 2012; Wong, 2013).

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Table 25: Composite Reliability and Cronbach's alpha measures of the reflective model

	Composite Reliability	Cronbach's Alpha
BI	0.96	0.94
EE	0.95	0.93
FC	0.93	0.90
HM	0.97	0.95
HT	0.94	0.92
PE	0.98	0.97
PV	0.97	0.96
SI	0.96	0.94

BI= behavioral intention, EE=effort expectancy, FC=facilitating condition, HM=hedonic motivation, HT=habit, PE=performance expectancy, PV=price value, SI=social influence

The PLS output for indicator reliability also revealed that the minimum threshold .7 (Chin, 1998; Garson, 2016; Wong, 2013) has been met for all outer loadings as shown in ***Table 26*** below.

Convergent and Discriminant Validity

To confirm convergence of individual items reflecting a construct in comparison to items measuring different constructs, convergent validity was assessed. As ***Table 26*** shows, all AVE results of the LVs have been found above the threshold .5 (Chin, 1998) that convince the existence of convergent validity.

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Table 26: Reliability and Validity measures with factor loadings for reflective indicators

LV	Indicator	Indicator Reliability (λ)	Composite Reliability (ICR)	Convergent Validity (AVE)	Discriminant validity Square roots of AVE
PE	APE1	0.88	0.98	0.91	0.95
	APE2	0.99			
	APE3	0.98			
	APE4	0.97			
EE	AEE1	0.86	0.95	0.83	0.91
	AEE2	0.96			
	AEE3	0.95			
	AEE4	0.87			
SI	ASI1	0.93	0.96	0.90	0.95
	ASI2	0.95			
	ASI3	0.93			
FC	AFC1	0.93	0.93	0.77	0.88
	AFC2	0.89			
	AFC3	0.86			
	AFC4	0.83			
HM	AHM1	0.95	0.97	0.90	0.95
	AHM2	0.98			
	AHM3	0.92			
PV	APV1	0.94	0.97	0.93	0.96
	APV2	0.99			
	APV3	0.96			
HT	AHT1	0.90	0.94	0.80	0.90
	AHT2	0.82			
	AHT3	0.92			
	AHT4	0.93			
BI	ABI1	0.93	0.96	0.89	0.94
	ABI2	0.95			
	ABI3	0.94			

Discriminant validity was also assessed using AVE values in such a way that confirming all correlation values between any pair of corresponding LVs were below the square roots of AVE values in accordance to Former and Lacker (as cited in Wong, 2016). (See ***Table 27*** for the detail).

Table 27: AVE, Correlations and Square root of AVE's

	AVE	BI	EE	FC	HM	HT	PE	PV	SI	USE
BI	0.89	**0.94**								
EE	0.83	0.68	**0.91**							
FC	0.77	0.75	0.69	**0.88**						
HM	0.90	0.74	0.62	0.71	**0.95**					
HT	0.80	0.71	0.39	0.58	0.66	**0.90**				
PE	0.91	0.77	0.68	0.79	0.77	0.72	**0.95**			
PV	0.93	0.60	0.59	0.46	0.69	0.67	0.73	**0.96**		
SI	0.90	0.40	0.44	0.41	0.54	0.56	0.58	0.60	**0.95**	
USE		-0.12	-0.28	-0.15	-0.07	0.41	-0.03	0.11	0.24	**NA**

**Bold on the diagonal are square roots of AVEs, off diagonals are correlations*

Cross-loading also has been checked using Excel conditional formatting to highlight all cell values greater than .8 (considering the lowest indicator reliability equals .8). As it is shown in ***Table 28***, all the highlighted (bold values) cells fit to the perfect diagonal that indicated the loading of each indicator was higher for its designated construct than or any of the other constructs and each of the constructs loaded highest with its own items which confirms discriminant validity was well achieved (Chin, 1998).

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Table 28: Loadings and Cross-loadings for the reflective model

	BI	EE	FC	HM	HT	PE	PV	SI
IBI1	**0.93**	0.65	0.75	0.63	0.59	0.67	0.48	0.35
IBI2	**0.95**	0.66	0.66	0.70	0.69	0.64	0.59	0.32
IBI3	**0.94**	0.63	0.72	0.77	0.73	0.85	0.62	0.45
IEE1	0.51	**0.86**	0.69	0.51	0.31	0.59	0.45	0.32
IEE2	0.66	**0.96**	0.70	0.62	0.41	0.70	0.61	0.42
IEE3	0.69	**0.95**	0.65	0.61	0.36	0.64	0.63	0.43
IEE4	0.62	**0.87**	0.50	0.52	0.32	0.53	0.45	0.43
IFC1	0.64	0.70	**0.93**	0.68	0.48	0.72	0.45	0.41
IFC2	0.76	0.72	**0.89**	0.63	0.45	0.71	0.31	0.31
IFC3	0.64	0.54	**0.86**	0.56	0.56	0.60	0.42	0.29
IFC4	0.56	0.42	**0.83**	0.61	0.60	0.74	0.47	0.44
IHM1	0.75	0.60	0.68	**0.95**	0.64	0.74	0.60	0.50
IHM2	0.74	0.63	0.70	**0.98**	0.66	0.77	0.69	0.49
IHM3	0.62	0.54	0.63	**0.92**	0.58	0.67	0.68	0.57
IHT1	0.68	0.46	0.65	0.72	**0.90**	0.76	0.69	0.51
IHT2	0.44	0.23	0.51	0.48	**0.82**	0.50	0.45	0.53
IHT3	0.71	0.36	0.50	0.55	**0.92**	0.68	0.64	0.51
IHT4	0.68	0.31	0.45	0.60	**0.93**	0.63	0.60	0.49
IPE1	0.66	0.55	0.71	0.60	0.62	**0.88**	0.64	0.44
IPE2	0.75	0.68	0.78	0.76	0.71	**0.99**	0.71	0.57
IPE3	0.77	0.66	0.76	0.78	0.72	**0.98**	0.72	0.58
IPE4	0.75	0.69	0.76	0.79	0.69	**0.97**	0.71	0.60
IPV1	0.53	0.51	0.37	0.59	0.54	0.63	**0.94**	0.49
IPV2	0.62	0.60	0.45	0.68	0.67	0.73	**0.99**	0.61
IPV3	0.59	0.60	0.49	0.71	0.71	0.73	**0.96**	0.64
ISI1	0.30	0.34	0.38	0.43	0.47	0.48	0.51	**0.93**
ISI2	0.35	0.42	0.38	0.49	0.56	0.54	0.54	**0.95**
ISI3	0.45	0.47	0.39	0.59	0.55	0.60	0.64	**0.96**

Note: Perfect high loading in the diagonal indicates how significant discriminant validity exist

4.3.4.2 *Measurement Model for formative indicators*

Outer model weights and Significance

The outer model weights are measures of the formative indicators importance to explain a formative LV. These outer weights are expected to have a minimum of 1.96 t-value to be significant at p < .05 (Wong, 2016). By using a bootstrapping technique with 39 cases *(two observations were removed due to high outlier impact that prevents the bootstrap from running properly*) for re-sampling, the following results has been found as shown below in ***Table 29***.

Table 29: Outer model weights and corresponding T-values

	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	T-Statistics
IU1 -> USE	1.14	1.27	0.95	*1.20 (8.6)
IU2 -> USE	0.11	-0.08	1.05	0.10(6.9)
IU3 -> USE	-0.49	-0.48	0.24	**2.07(3.3)
IU4 -> USE	-1.18	-1.06	1.06	*1.11(3.7)
IU5 -> USE	1.14	1.00	1.06	*1.08(3.9)
IU6 -> USE	0.51	0.49	0.22	**2.28(3.0)
IU7 -> USE	-0.26	-0.26	**0.22**	*1.17(2.3)
IU8 -> USE	-0.02	0.01	0.20	**0.12(1.1)**

*p<0.5, **p<0.05; values in brackets indicate corresponding loading values

The t-value for formative indicators of Internet banking users' dataset indicate weak significance that forces to double check corresponding loading values (which are values in bracket). However, almost all the loading values except for the eighth (IU8) indicator, were above the threshold value 1.96 that imply keeping all indicators in the model. It is already mentioned above that removing formative indicators based on the statistics result was not recommended (Garson, 2016; Henseler et al., 2009).

This specific sample dataset also assessed for construct validity using VIF. Lowery and Gaskin (2014) suggest that VIF for formative factors should be less than 10. As it is shown in ***Table 30***, all formative indicators were less than 10 that meet the above requirement. Moreover, from the ***Table 27*** above, the correlation between the formative LV (Use) and all other constructs were ranged from -.28 up to .41 that met the requirement of these values to be less than .7 (MacKenzie et al., 2005 as cited in Urbach & Ahlemann, 2010).

Table 30 also showed that most formative indicators have VIF value lower than 5 and Tolerance value greater than .2 that indicated collinearity was not a main issue (Wong, 2013). Further assessment of VIF for the inner model also showed that all VIF values were less than 5 that indicates multicollinearity was not also an issue for the inner model.

Table 30: Collinearity (VIF/Tolerance) for formative indicators

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3.30	0.60			
	IU1	0.559	0.28	0.69	0.15	6.75
	IU2	0.254	0.30	0.30	0.14	7.02
	IU3	-0.249	0.15	-0.36	0.37	2.74
	IU4	-0.52	0.32	-0.65	0.11	9.21
	IU5	0.418	0.27	0.55	0.14	7.21
	IU6	0.154	0.16	0.22	0.37	2.70
	IU7	-0.205	0.17	-0.29	0.33	3.07
	IU8	-0.001	0.16	0.00	0.41	2.44

Dependent Variable: AB1

4.3.4.3*Structural Model Assessment*

R^2 and Path coefficients

The causal relationship between the endogenous and exogenous LVs was assessed using R^2 to see how well the model fits to the Internet banking users' dataset. As it is shown in ***Figure 14***, the model fits more for the Internet users' dataset in which the variance for both BI and Use behavior were explained well than in the two previous models. While the variance in BI was strongly (77%) explained by the seven exogenous variables, the variance in the actual Use behavior was explained by 54%. As Chin (1998) categorized, both endogenous variables can be said substantially explained by the other exogenous variables in the model.

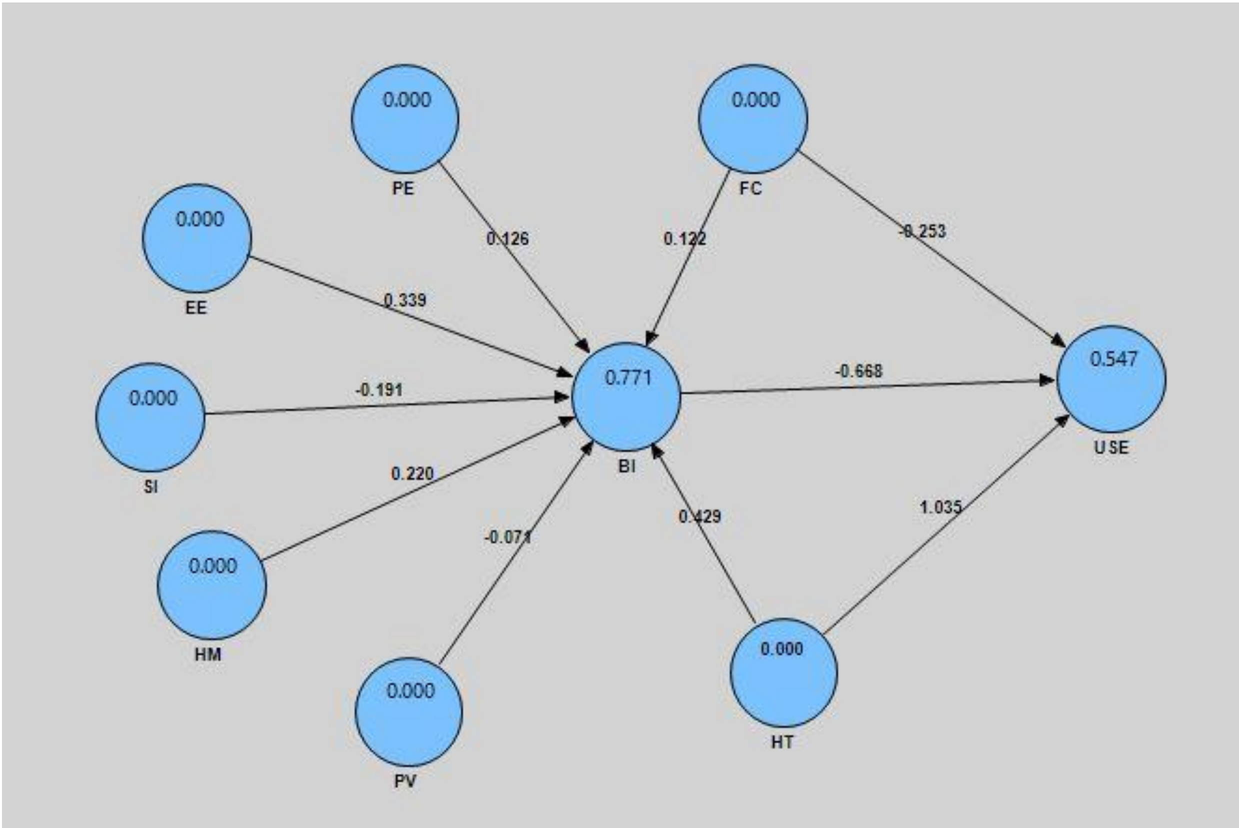


Figure 14: The structural (inner) model for Internet banking users' dataset

Figure 14 also clearly showed the path coefficients (β) values for all the paths between the LVs. As Henseler et al. (2009) agreed, the path coefficients with negative values didn't support the initial theoretical assumption. Hence, the relationships between the exogenous variables (SI and PV) and the endogenous variable (BI) were not supported. Moreover, the causal relation between FC and Use and between BI and Use behaviors were not supported. Hence, Hypotheses H3, H4.2, H6 and H8 were rejected according to the model in the Internet banking users' dataset. Though PE had positive β coefficient value, it was not either above .2 or significant at $p < .05$ to confirm the corresponding hypothesis.

The remaining exogenous variables were considered as determinant factors for the endogenous variables BI and Use behavior to one or more of the following reasons. HT (β= .43, t= 2.84) is considered as the strongest determinant factor of BI on the Internet banking users' dataset for qualifying both parameters (Urbach & Ahlemann, 2010). EE is the next strong determinant factor with β= .34 significant at $p < .1$. On the other hand, HM with β= 0.22 and HT with β= 1.00 were considered as determinant factor of BI and Use behavior respectively for their strong coefficient as it was justified by Chin (1998).

Table 31: Path coefficients and T-values for Internet banking users' dataset

	Original Sample (O)	**Sample Mean (M)**	**Standard Error (STERR)**	**Path coefficients**	**T-Statistics (|O/STERR|)**	**Impact on hypothesis**
SI -> BI	-0.19	-0.19	0.13	-0.19	1.45	Disconfirmed
EE -> BI	0.34	0.35	0.19	*0.34	1.77	Confirmed
PE -> BI	0.14	0.21	0.20	0.13	0.70	Disconfirmed
FC -> BI	0.11	0.00	0.20	0.13	0.53	Disconfirmed
FC -> USE	0.12	0.15	0.18	-0.25	0.67	Disconfirmed
BI -> USE	0.35	0.36	0.21	*-0.67	1.69	Disconfirmed
PV -> BI	-0.08	-0.07	0.18	-0.07	0.45	Disconfirmed
HM -> BI	0.22	0.21	0.21	0.22	1.05	Confirmed
HT -> BI	0.43	0.44	0.15	**0.43	2.84	Confirmed
HT -> USE	0.26	0.27	0.18	1.00	1.44	Confirmed

**p<0.1, **p<0.01

Unlike the previous two cases where PE is the strongest factor to determine much of the variance on BI, in the Internet banking user's dataset, HT and EE becomes the most substantial factor. HT is one of the substantial factors in determining the variance on BI in all three channel cases that strengthen the idea how day to day practices influence not only behavioral intentions but also the actual actions. However, EE, unlike in the previous cases, become the substantial factor with β = .34 and significance level of 95%. This was because Internet banking needed prior knowledge and experience of using Internet for different services. The numerical presentation on the demography data also supports this idea that most (93%) of Internet banking users were above Diploma/TVET holders that shows how their education background become a factor for others to do not use Internet banking.

HM gets more weight than on the previous cases since Internet services require more attractiveness and enjoyableness which arouse the hedonic motives. FC still have weak influence on determining the change on BI and actual Use behaviors that indicated how the users were continue to adopt a technology once they have got it useful and attractive indifference of the available FCs. Moreover, as mentioned above, the tertiary level educational background of these respondents enabled them to perform their financial transactions through the Internet without difficulty and additional support. Hence, FC has got weak significance to influence the BI of Internet banking users.

The unfamiliar result of the causal relationship between BI and the actual Use behavior is also the same in the case of Internet banking users' like the previous two channels users. More conversely, here negative path coefficient occurred that shows how the BI is far from influencing the actual Use behavior. The result further strengthens the idea that in the context of Ethiopia, behavioral intention not necessarily influences the actual action.

Adjusted R^2, Effect size (f^2) and Q-square effect(Q^2)

Similar in-depth analysis of model fit has been checked through Adjusted R^2, effect size (f^2) and Q^2. Accordingly, Garson's (2016) formula has been applied to find adjusted R^2 for BI and Use endogenous variables and new R^2 values of 0.766 and 0.536 were found respectively for insignificant 1% change on the original R^2.

Cohen's f2 also used to evaluate the effect size of each path in the structural equation model by examining its change on R^2 when an exogenous LV is removed from the model. Using Garson's (2016) formula [$f^2 = (R^2_{origonal} – R^2_{omitted})/(1-R^2_{origional})$] to determine f^2, values ranged from .01 to .22 has been found that indicates small to slightly moderate impacts (Henseler et al., 2009; Chin, 1998; Venkatesh et al., 2012).

Finally, the model's predictive relevance was assessed by using Stone-Geisser's Q^2 in which value greater than 0 indicates the model is predictive of the given endogenous variable under investigation (Garson, 2016). Accordingly, by running blindfolding algorithm with an arbitrary setting of omission distance 7, Q^2 has been found high (0.65) degree of predictive relevance regarding the endogenous LV BI. Since the procedure is applicable only for reflective endogenous variables, relevance indicator for "Use" variable is not computed (Chin, 1998; Garson, 2016; Henseler et al., 2009; Urbach & Ahlemann, 2010).

4.3.5 Structural and Measurement Model: Across the pooled datasets

As it is described before, the questionnaire was designed in a suitable way to collect data from three (ATM, Mobile and Internet) E-banking channel users. The respondent might use only one channel, two channels or all three channels. As ***Figure 10*** revealed, out of the total 321 respondents, 317 respondents were answered section II of the questionnaire which was prepared to get response from ATM banking Users. Likewise, Section III, which was designed for Mobile banking user, has been responded by 162 users, while Section IV, which was designed for Internet banking users, has been responded by 41 users. Since the same instrument was applied to collect data by changing only the E-banking channel type as ATM, Mobile and Internet, the data can be pooled together to study the model fitness on the whole dataset so that comprehensive judgment can be done on E-banking adoption. Hence, the total number of samples (n) become 520 for the pooled datasets which is the sum of 317 responses on ATM banking, 162 responses on Mobile banking and 41 responses on Internet banking. This approach is adopted from (Venkatesh et al., 2003) in which they made two setup of data collection environments (one in Entertainment other in Telcom services) in two conditions of (one voluntary and other mandatory environments) and finally they pooled up in to the sum of four different observations. Hoehle (2011) also applied similar technique on his dissertation study of consumer intentions to use electronic banking channels focusing on the role of task-channel fit.

In compiling the responses from each E-banking channel users' dataset in to one single dataset, some activities were required to make the compiled dataset ready for PLS-SEM tests. The first action was selecting all common formative indicators from each samples dataset of E-banking channels users' dataset. This is required because the number of formative indicators for the three cases were not the same. While there were 7 formative indicators for ATM banking users' dataset, there were 8 formative indicators for the other two channels users' datasets. Moreover, there were 3 items which were not commonly found on all three datasets. Hence, the 4^{th} item (U4) from the ATM banking users' dataset and the 7^{th} and 8^{th} items from both Mobile banking and Internet banking datasets were excluded from the pooled datasets since they were not found in ATM banking users' formative indicators. Moreover, these items had poor significance value ($t < 1.6$) during the test for each channel cases and had the least Mean value (closer to 2.5) comparing to other indicators in the same category. After removal, some items were required to be sorted again for uniform alignment across the all three datasets.

Regarding the PLS algorithm settings for path modeling and bootstrapping techniques, the following conditions were met for all measurements done during testing of the pooled datasets. The PLS algorithm was running with path weighting scheme, data metric with Mean0, Var 1, Maximum iterations of 5000, with initial weights 1.0 and 1.0E-5 abort criterion. Likewise, the bootstrapping algorithm was running for factor weighting scheme with no sign changes, 520 cases and 5000 re-samples setting. All settings and procedures were done in accordance of the guideline by Garson (2016).

4.3.5.1 *Reflective measurement model across the pooled datasets*

ICR and Indicator Reliability:

The reliability and validity tests for the three datasets have been successfully done as reported earlier. However, for confirmatory purpose, internal consistency reliability and indicator reliabilities have been checked in the pooled datasets. Likewise, two validities and one multicollinearity tests have been checked for the pooled datasets.

Accordingly, the ICR has been measured through both Composite reliability and Cronbach's alpha techniques as shown in ***Table 32***. As a result, substantial ICR which is above .7 (Venkatesh et al., 2012; Wong, 2013) has been found in both tests despite the fact that Cronbach's α was expected to be more conservative in PLS-SEM (Henseler et al., 2009; Urbach & Ahlemann, 2010).

Table 32: Composite Reliability and Cronbach's α measures of the reflective model

	Composite Reliability	Cronbach's Alpha
BI	0.90	0.84
EE	0.92	0.88
FC	0.82	0.71
HM	0.91	0.86
HT	0.89	0.83
PE	0.92	0.88
PV	0.94	0.91
SI	0.89	0.81

Indicator reliability, as it measures to what extent a variable or set of variables is consistent regarding what it intends to measure, should be above .7 to indicate at least half the variance in the indicator is explained by its factor (Chin, 1998; Garson, 2016; Henseler et al., 2009; Wong, 2013). Moreover, these authors suggested that outer loading (also called indicator loading) can be used in PLS to assess the indicator reliability. As shown in ***Table 33***, all loading values for indicator reliability were above the threshold .7 except for two (FC1and FC4) indicators. Additional trials have been made by removing one of these items at a time and removing FC4 has been found to improve the loading value of FC1 to become above .7 and the corresponding AVE value to become .6 while do not affect other values. Hence, the lowest loading value indicator (FC4) has been removed from further analysis.

Convergent Validity and Discriminant Validity

Convergent and discriminant validity measures were the two most common methods applied in PLS-SEM researches in which they can be measured using AVE values (Wong, 2013; Urbach & Ahlemann. 2010). According to Chin (1998), AVE values reflect the average communality for each LV in a reflective model. These values were expected to be greater than .5 to confirm at least half the variance of the indicators were explained by the respective LV. In the above ***Table 33***, all AVE values were above the threshold that guarantees convergent validity in the pooled datasets.

Table 33: Reliability and Validity measures with Factor loadings for reflective indicators

LV	Indicator	Indicator Reliability Outer Loadings (λ)	Composite Reliability (ICR)	Convergent Validity (AVE)	Discriminant validity Square roots of AVE
PE	PE1	0.79	0.92	0.73	0.85
	PE2	0.89			
	PE3	0.90			
	PE4	0.84			
EE	EE1	0.88	0.92	0.75	0.86
	EE2	0.92			
	EE3	0.91			
	EE4	0.74			
SI	SI1	0.88	0.89	0.72	0.85
	SI2	0.79			
	SI3	0.88			
FC	FC1	**0.69***	0.82	0.54**	0.73
	FC2	0.78			
	FC3	0.79			
	FC4	**0.66***			
HM	HM1	0.89	0.91	0.78	0.88
	HM2	0.92			
	HM3	0.83			
PV	PV1	0.91	0.94	0.85	0.92
	PV2	0.93			
	PV3	0.92			
HT	HT1	0.83	0.89	0.67	0.82
	HT2	0.75			
	HT3	0.82			
	HT4	0.86			
BI	BI1	0.84	0.90	0.75	0.87
	BI2	0.89			
	BI3	0.87			

*Shows low loading factor below the preferred value (0.7)

** AVE value for FC has been changed to 0.6 after removing FC4

Discriminant validity is the other dimension of constructs validity which assures the closeness of the indicators to the intended construct so that unintentional measure of something else is not happened (Urbach & Ahlemann, 2010). The first technique to assess discriminant validity in PLS is through the square roots of corresponding AVE values for each construct. This technique also called Fornell & Larcker technique (as cited in Wong, 2013) which determine the discriminant validity by comparing the square roots of AVE values with the correlation values between any pair of corresponding LVs as shown in ***Table 34*** . To be said that discriminant validity is substantial, the square root of AVE values should be larger than all the corresponding correlation values (Wong, 2013; Garson, 2016).

Table 34: AVE, Correlations and Square root of AVE's

	AVE	BI	EE	FC	HM	HT	PE	PV	SI	Use
BI	0.75	**0.87**								
EE	0.75	0.43	**0.86**							
FC	0.60	0.50	0.65	**0.78**						
HM	0.78	0.55	0.44	0.54	**0.88**					
HT	0.67	0.49	0.26	0.27	0.42	**0.82**				
PE	0.73	0.57	0.58	0.49	0.52	0.38	**0.85**			
PV	0.85	0.45	0.43	0.43	0.42	0.28	0.41	**0.92**		
SI	0.72	0.34	0.37	0.38	0.44	0.33	0.45	0.30	**0.85**	
Use	0.00	0.24	0.29	0.22	0.19	0.37	0.29	0.22	0.21	**NA**

**Bold on the diagonal are square roots of AVEs, off diagonals are correlations*

The second technique to measure discriminant validity is using cross-loadings (Chin, 1998). Cross-loadings in PLS are direct outputs that correlate the component scores of each LV with all other items. To assure discriminant validity, the loading of each indicator should be higher for its designated construct than any of the other constructs and each of the constructs should be loaded highest with its own indicators. This can be identified by taking the cross-loading output from SmartPLS into the Excel sheet and using the conditional formatting to highlight all cell values greater than a minimum loading value (which is .73 in this case).

Table 35: Loadings and Cross-loadings for the reflective model

	BI	EE	FC	HM	HT	PE	PV	SI
BI1	**0.84**	0.43	0.49	0.52	0.38	0.55	0.46	0.31
BI2	**0.89**	0.33	0.42	0.44	0.47	0.47	0.38	0.28
BI3	**0.87**	0.34	0.39	0.47	0.43	0.46	0.33	0.28
EE1	0.40	**0.88**	0.58	0.35	0.21	0.53	0.38	0.27
EE2	0.35	**0.92**	0.59	0.35	0.23	0.51	0.36	0.29
EE3	0.38	**0.91**	0.58	0.37	0.23	0.50	0.39	0.30
EE4	0.35	**0.74**	0.48	0.45	0.23	0.46	0.34	0.43
FC1	0.35	0.40	**0.73**	0.38	0.23	0.29	0.36	0.26
FC2	0.43	0.67	**0.82**	0.46	0.19	0.49	0.37	0.32
FC3	0.37	0.41	**0.78**	0.40	0.22	0.34	0.27	0.29
HM1	0.53	0.43	0.54	**0.89**	0.36	0.50	0.37	0.39
HM2	0.50	0.41	0.48	**0.92**	0.38	0.48	0.39	0.40
HM3	0.41	0.31	0.39	**0.83**	0.37	0.40	0.36	0.39
HT1	0.45	0.27	0.25	0.42	**0.83**	0.37	0.31	0.28
HT2	0.23	0.16	0.16	0.28	**0.75**	0.21	0.12	0.23
HT3	0.42	0.19	0.22	0.29	**0.82**	0.31	0.22	0.26
HT4	0.45	0.22	0.23	0.36	**0.86**	0.32	0.24	0.30
PE1	0.46	0.43	0.36	0.33	0.23	**0.79**	0.37	0.33
PE2	0.50	0.56	0.43	0.44	0.35	**0.89**	0.34	0.40
PE3	0.54	0.55	0.51	0.49	0.35	**0.90**	0.37	0.36
PE4	0.44	0.44	0.37	0.52	0.37	**0.84**	0.32	0.44
PV1	0.45	0.41	0.43	0.43	0.26	0.40	**0.91**	0.27
PV2	0.37	0.38	0.36	0.35	0.23	0.35	**0.93**	0.27
PV3	0.41	0.38	0.40	0.39	0.28	0.38	**0.92**	0.29
SI1	0.34	0.38	0.35	0.41	0.30	0.44	0.28	**0.88**
SI2	0.22	0.22	0.24	0.30	0.23	0.30	0.20	**0.79**
SI3	0.28	0.32	0.35	0.41	0.30	0.38	0.28	**0.88**

Note: *Perfect high loading in the diagonal indicates how significant discriminant validity exist*

As it is shown in ***Table 35***, all highlighted (also bolded for emphasis) cells were those on the diagonal that indicate the loading of each indicator was higher for its designated construct than any of the other constructs and each of the constructs loaded highest with its own items which confirmed discriminant validity was well achieved.

4.3.5.2 *Formative measurement model across the pooled datasets*

Different authors have argued that formative indicators should be differently treated for outer model measurement in which the ordinary reliability becomes irrelevant and convergent validity is not meaningful (Henseler et al., 2009; Wong, 2013). The most common outer model measurements include the assessment of outer weights with their significance, construct validity and multicollinearity (Garson, 2016; Henseler et al., 2009; Venkatesh et al., 2012; Wong, 2013).

Often, bootstrapping was considered to assess formative indicators' outer weight significance in which an acceptable *t*-value of 1.96 indicate a significance level of 95%. If that is not the case, it is important to check the corresponding outer loading significance before removing a formative indicator. Wong (2013) and Henseler et al. (2009) also emphasized that formative indicators collectively represent all the relevant dimensions of the LV so that omitting one indicator could omit one unique part of the measurement model that brings change in the meaning of the LV.

Accordingly, bootstrapping was run with the initial setting defined earlier in this section (see section 4.3.5) and the following outputs were found as shown in ***Table 36*** that indicates most outer weights were significant at $p < .05$.

Table 36: Outer model weights and corresponding T-value

	Original Sample (O)	**Sample Mean (M)**	**Standard Error (STERR)**	**T-Statistics**
U1 -> USE	0.44	0.43	0.14	**3.29(7.9)
U2 -> USE	0.07	0.07	0.14	0.50(5.8)
U3 -> USE	0.68	0.66	0.08	***8.86(9.1)
U4 -> USE	0.45	0.44	0.20	**2.29(5.8)
U5 -> USE	0.05	0.05	0.23	0.234(4.7)
U6 -> USE	-0.22	-0.22	0.17	*1.28(2.7)

*p<0.5, **p<0.05, ***p<0.001

Though the *t*-values for indicators U2 and U5 were not significant, their corresponding high outer loading makes them important to be kept in the model. The complete list of t-statistics for all corresponding reflective indicators also showed that all indicators, except the above two, were significant at $p < .05$ for substantial *t*-values of above 1.96.

Construct validity is one common measurement model in which discriminant validity is assessed in the outer formative model. This validity measure can be applied through VIF as Lowery and Gaskin (2014) suggested and VIF values below 3.3 indicate sufficient construct validity for formative indicators. From ***Table 37*** below, VIF values were clearly seen to be below 3.3 except for one indicator (U5) that shows construct validity is well established. The other method to assess construct validity is through evaluating formative indicators discriminant validity in which MacKenzie et al. (as cited in Urbach & Ahlemann, 2010) suggested that correlations between formative and all other constructs should be below .7 to indicate sufficient discriminant validity. This is also applied in this empirical test where ***Table 34*** shows all correlation values between the formative and all other constructs is below .7 and ranged from .19 to .37.

Table 37: Collinearity (VIF/Tolerance) for formative indicators

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	1.8E-05	0.04		0.00	1.00		
	U1	0.15	0.05	0.15	2.76	0.01	0.62	1.61
	U2	-0.06	0.06	-0.06	-0.97	0.33	0.58	1.73
	U3	0.16	0.04	0.16	3.72	0.00	0.98	1.02
	U4	0.21	0.07	0.21	2.92	0.00	0.35	2.86
	U5	-0.02	0.08	-0.02	-0.21	0.84	0.28	3.62
	U6	-0.20	0.06	-0.20	-3.12	0.00	0.44	2.27

Dependent Variable: BI1

In formative model, indicators were not expected to correlate each other and so it is very important to check multicollinearity. Multicollinearity used to measure how much of an indicator's variance is explained by other indicators of the same construct (Urbach & Ahlemann, 2010). Wong (2013) noted how VIF measures can be applied to measure multicollinearity in which no multicollinearity problem occurred if values of VIF are all below 5 and Tolerance values are above .2. SPSS v.23 generated report to determine the VIF result on the pooled datasets presented in ***Table 37***. It showed that all VIF values were below 5 and corresponding tolerance values were above .2. While the VIF values ranged from 1.02 to 3.62, tolerance values were ranged from .28 to .98. These results were consistent with Venkatesh et al. (2012) which indicated no collinearity problems existed.

Moreover, similar VIF tests have been done on this pooled dataset to check collinearity among endogenous and exogenous constructs as shown ***Table 38*** and ***Table 39*** in which all VIF values are less than 3 that indicates no multicollinearity problem.

*Table 38: Collinearity (VIF/Tolerance) for inner model**

Model 1	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-2.27E-06	.031		.00	1.00		
EE	-0.02	0.05	-0.02	-0.46	0.65	0.48	2.08
FC	0.14	0.05	0.14	3.14	0.00	0.48	2.08
HM	0.20	0.04	0.20	4.73	0.00	0.55	1.81
HT	0.24	0.04	0.24	6.77	0.00	0.77	1.29
PE	0.27	0.04	0.27	6.33	0.00	0.53	1.89
PV	0.14	0.04	0.14	3.90	0.00	0.72	1.40
SI	-0.04	0.04	-0.04	-1.20	0.23	0.71	1.40

*Dependent Variable: BI

*Table 39: Collinearity (VIF/Tolerance) for inner model***

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	-5.854E-07	.040		.00	1.00		
BI	0.02	0.05	0.02	0.40	0.69	0.63	1.59
FC	0.13	0.05	0.13	2.90	0.00	0.76	1.32
HT	0.32	0.05	0.32	6.89	0.00	0.76	1.32

**Dependent Variable: USE

4.3.5.3 *Structural Model Assessment on the pooled datasets*

Determination coefficient (R^2)

The structural (inner) model basically consists of exogenous and endogenous LVs. ***Figure 15*** is presented below to comprehensively show both the outer and inner model together. Circles in the diagram are parts of the inner model that represents main LVs. Rectangular blocks are part of the outer model that represent observable indicators. (Garson, 2016; Wong, 2013).

The path modeling overall predictability and goodness-fit are primarily assessed through the coefficient of determination (R^2) values. As it is shown in the diagram (***Figure 15***), R^2 for behavioral intention (BI) is .500 while it is .151 for the other endogenous LV "Use behavior". This means 50% of variance in BI is explained by the seven exogenous factors included in the model. According to Chin (1998), this rate is categorized under "moderate" range. Similarly, the three factors (FC, BI and HT) explain 15% of the variance in the Use behavior which can be categorized as "weak" coefficient of determination.

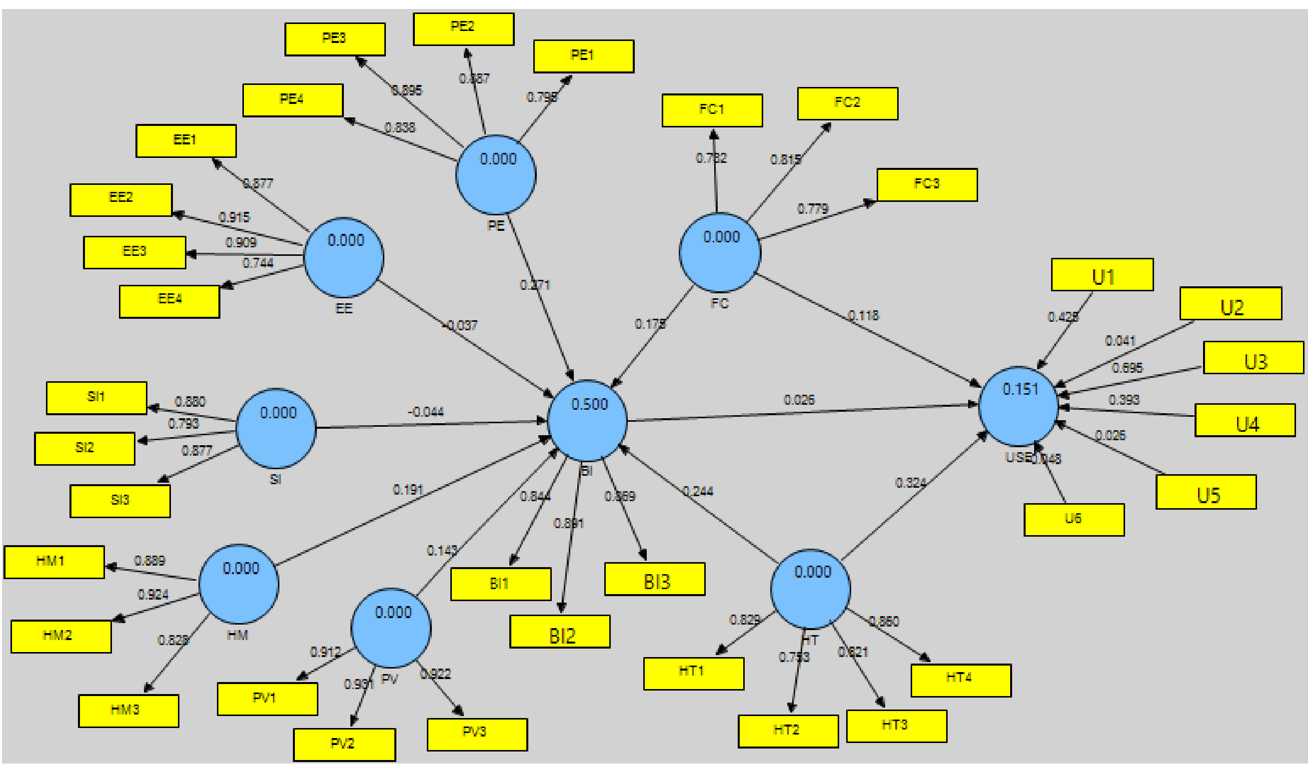


Figure 15: Structural and measurement model for the complete pooled datasets

Though the model is found weak in explaining the variance in Use behavior, there are evidences other researchers who found similar results. For instance, the original UTAUT model R^2 values for usage behavior were ranged from 36% to 52% (Venkatesh et al., 2003). Khechine and Lakhal (2018) have also found only around 12% explained variance for the Use behavior on their technology adoption study. Reported meta analyses on health informatics also revealed that from 19% to 38% variance in health behaviors explained by BI (CHIRr, 2013). One possible reason for weak explained variance of Use behavior in this study might be in line with Khechine and Lakhal (2018) justification that blame the measurement instrument of the Use behavior which is self-reported by the respondents unlike the original Venkatesh et al. (2003) who used system logs.

Path coefficient assessment

Path coefficients of structural model can be interpreted as standardized beta (β) coefficients of ordinary least squares regressions to indicate the causal relationship direction and its strength. While the algebraic signs indicate the agreement between the initial theoretical assumption and the actual empirical result, the coefficient magnitude indicates how well the relation is strong. The strength varied from -1 to 1 in where an absolute value closer to 1 indicates high strength while the value closer to 0 indicates weak relation. Moreover, the significance level of these β coefficients is very important to confirm the hypothetical relation. An accepted *t*-value equal to 1.96 is required to have significant result at $p < .05$ (Garson, 2016; Henseler et al., 2009; Lowery & Gaskin; 2014, Wong, 2013).

A summary of path coefficients along with *t*-value are presented in ***Table 40*** to show whether the initial assumed relations are confirmed or not. Accordingly, the assumed causal relationships and corresponding findings are discussed in brief below.

Table 40: Path coefficients and T-values on the pooled datasets

Hypothesis		**Original Sample (O)**	**Sample Mean (M)**	**Standard Error (STERR)**	**Path coefficients**	**T-Statistics (|O/STERR|)**	**Impact on hypothesis**
H1	PE -> BI	0.27	0.27	0.06	***0.27	4.89	**Confirmed**
H2	EE -> BI	-0.04	-0.03	0.06	-0.04	0.65	**Disconfirmed**
H3	SI -> BI	-0.04	-0.04	0.04	-0.04	1.05	**Disconfirmed**
H4.1	FC -> BI	0.18	0.18	0.05	**0.18	3.20	**Confirmed**
H4.2	FC -> USE	0.12	0.12	0.05	*0.12	2.29	**Confirmed**
H5	HM -> BI	0.19	0.19	0.05	***0.19	3.55	**Confirmed**
H6	PV -> BI	0.14	0.14	0.04	**0.14	3.28	**Confirmed**
H7.1	HT -> BI	0.24	0.24	0.05	***0.24	5.41	**Confirmed**
H7.2	HT -> USE	0.31	0.31	0.05	***0.32	6.18	**Confirmed**
H8	BI -> USE	0.05	0.05	0.06	0.03	0.76	**Disconfirmed**

*p<0.05, **p<0.01, ***p<0.001

H1: PE -> BI

The first hypothesis: 'Performance Expectancy has a positive impact on customer's behavioral intention of E-banking adoption in Ethiopia' has been supported on the pooled datasets for β= .27 significant at p< .001. Venkatesh et al. (2012) associates PE with utilitarian value that can be measured in terms of other measures like performance speed, productivity and usefulness. This indicates that if someone perceived a new technology as useful to perform some activity more quickly and productively, it will arouse BI to use that technology. The significant relationship found between PE and BI on the compiled pooled datasets also indicates that customers' behavioral intention towards E-banking adoption in Ethiopian context is highly influenced by customers' PE of E-banking technology. The result is in accordance of the initial UTAUT (Venkatesh et al., 2003), UTAUT2 (Venkatesh et al., 2012) and findings of empirical tests on Phablets adoption (Huang & Kao, 2015), international comparison of technology adoption (Im et al., 2011) and a local research conducted on Mobile banking adoption (Merga, 2017).

H2: EE -> BI

The second hypothesis: 'Effort Expectancy has a positive impact on customer's behavioral intention of E-banking adoption in Ethiopia' has not been supported on the pooled datasets. The relation is characterized by negative β coefficient and insignificant *p* value that confirms rejection of the hypothesis. Though the result opposes the initial assumption of UTAUT, Ain et al. (2016) has got similar findings that rejected the positive hypothetical relationship between EE and BI.

The basic ground of this hypothetical relationship was the degree of ease associated with the use of a system is significant factor to adopt a new system (Thompson et al., 1991; Venkatesh et al., 2003; Venkatesh et al., 2012). However, the likely reason to reject this hypothesis in this dataset is not the theoretical assumption, instead most (76%) of respondents, as shown in ***Table 5***, were either 1^{st} or 2^{nd} degree holders who didn't find the use of E-banking technologies difficult. Im et al. (2011) also explained such kinds of result might happened if the society is willing to take time and effort to learn a new technology.

H3: SI -> BI

The third hypothetical relationship is between SI and BI stated as 'Social influence has a positive impact on customers' behavioral intention of E-banking adoption in Ethiopia'. It basis the assumption of customers' degree of perceiving important others believe that they must use a given technology influences their BI to adopt new technology (Venkatesh et al., 2012). Other researchers (Ajzen, 1991; Thompson et al., 1991) also support the idea of strong social influence on BI.

However, the empirical evidence of negative β coefficient and insignificant *p* value found from testing the model on the pooled complete dataset showed non-supported relation between SI and BI. The result is similar with that of Merga (2017) who studied the impact of SI on BI of Mobile banking adoption in CBE. Alalwan et al. (2017) also found similar result that indicates the influence of others on technology adoption could be insignificant. The result was also supported by Khechine & Lakhal (2018) who found the effect of SI on BI as insignificant. According to their explanation, the youngest group use the opportunity of voulenteriness context to escape other's influence ho were in flavour to use new technologies.

One possible justification for this result might be the academic background of respondents as majority of them belong to the tertiary level educational background. As a result, they might basis rational justification of using a system based on its usefulness rather than based on others' influence to adopt new technologies. Im et al., (2011) also compared this relationship in US and Korean users and found similar result on the US users. They justified that US users were making rational decisions while Korean were more influenced by social norms.

H4.1: FC -> BI and **H4.2: FC -> USE**

The two hypothetical relationships between FC and the two endogenous LVs BI and USE behavior were supported for $\beta = .18$, $p < .01$ and $\beta = .12$, $p < .05$ respectively. This relationship can be stated as: Facilitating condition has a direct positive impact on both the customer's behavioral intention and the actual Use behaviors of E-banking adoption in Ethiopian context. This indicates that, facilitating conditions play significant role in supporting customer's behavioral intention towards E-banking adoption and the actual usage experience.

These results are in accordance with Venkatesh et al. (2003), Venkatesh et al. (2012), Huang and Kao (2015). In contrast, Merga (2017) has got FC as insignificant factor to influence customer's behavioral intention of Mobile banking adoption in the study conducted on customers of CBE.

H5: HM -> BI

HM is about the essence of individual's psychological and emotive experiences of fun or pleasure derived from using a technology (Brown and Venkatesh, 2005 as cited in Venkatesh et al., 2012). Though HM was not included in the first UTAUT, Venkatesh et al., (2012) strongly argued HM as important determinant of technology acceptance and use behaviors.

The empirical result found on path modeling analysis has shown that the hypothesis HM has a positive impact on customers' BI of E-banking adoption in Ethiopia is supported on the pooled datasets across the study for $\beta = .19$ and $p < .001$. This can be interpreted as customers of E-banking technologies in Ethiopia were significantly affected by the pleasing or exciting pleasures they found from using these technologies. These results were in line with that of Huang and Kao (2015), who found HM as crucial factor for Phablet adoption and Alalwan et al. (2017) who found strong positive relation between BI and HM in their study of Jordanian bank customers mobile banking adoption.

H6: PV -> BI

One of the unique constructs of UTAUT2 by Venkatesh et al., (2012) from the original UTAUT by Venkatesh et al., (2003) is the addition of price value as determinant factor of BI in consumers' context. Using E-banking technologies involves some costs of registration and annual card fee for ATM cards, service charge fees, and data service carrier costs for Mobile and Internet services. The hypothetical relationship between PV and BI in based on the fact that consumers adopt a technology when they perceived the benefits of using a technology is greater than all the monetary cost associated with using the technology.

Similar to the result of previous research findings (Alwan et al., 2017; Huang & Kao, 2015; Merga, 2017), PV has been determinant factor of BI on the compiled dataset with $\beta = .14$ and significant at $p < .01$. This result indicates that the degree of assumed benefit over monetary costs to use E-banking technologies plays significant role in determining customers' behavioral intention to adopt such technologies among the studied population.

H7.1: HT -> BI and **H7.2: HT -> USE**

The other very substantial relationship found is between HT and the two endogenous LVs. Habit is the new factor added on UTAUT by Venkatesh et al., (2012) for making the previous theory more fit to the consumer context. It is expressed as a self-reported perception of experience as related to passage of time from the initial use a target technology. The theorized assumption of Habit has a positive impact on customers' behavioral intention of E-banking adoption in Ethiopia and Habit has a direct positive impact on customers' E-banking adoption (USE) in Ethiopia were supported for $\beta = .24$ and $\beta = .32$ respectively with significant $p < .001$in both cases.

This empirical proof confirmed that once customers behaviorally intended to use E-banking technologies and found it useful to support day to day activity, their experience become habitual to adopt the technology well. Sugar (1967) (as cited in Thompson et al., 1991) also found HT as the strongest predictor of college students' cigarette smoking behavior. Similar findings also found by Huang and Kao (2015) on studying the impact of HT on behavioral intention to adopt Phablet technologies. Kim and Malhotra (as cited in Venkatesh et al., 2012) also found prior experience on use as a strong driving force for future action (use) of similar technology.

H8: BI -> USE

Behavioral intention, which is described as subjective probability of a person to perform some behavior (Fishbein & Ajzen, 1975), was assumed to have strong motivational factor that influences a certain behavior. However, this research finding on the compiled pooled datasets revealed that the assumption is not supported among the studied population of the current study. The relationship between BI and the actual Usa behavior was characterized by β= .03 and weak significant *p* value. Though many researchers have found strong positive relation between BI and the actual Use behaviors, few other researchers also found unsupported relation. For instance, Baptista and Oliveira (2015) found the effect of BI on use behavior as insignificant on Mozambique adult populations. Khechine and Lakhal (2018) showed that BI influence Use behavior only if it is moderated by autonomy. Webb and Sheeran, (2006) also indicated that intentions have less impact on behavior when users lack control over the actual behavior in cases where there are conducive environments for habit formation.

Possible explanation for such deviated finding could be the same as that of Im et al. (2011) on that studied adoption difference on two culturally different countries (US and Korea). On their study, they found that the impact of BI on Use behavior was different across the two countries samples where US users were found likely to use the system if they have intention to use it unlike Korean users. In addition to that, these authors suggested further examination of the relationship between culture and technology adoption for better understanding. Baptista and Oliveira (2015) also mentioned social reactions as potential causes to reduce the BI influence on the actual behavior. Hence, social culture can be mentioned as a cause for weak relation between BI and Use behaviors.

On related justifications, some researchers have shown that habit has strong direct effect on technology use over and above the effect of behavioral intention on the actual use behavior. Experiments in these researches also revealed the impact of behavioral intention on the technology use could be reduced and less important through time when habit increases (Limayem et al., 2007 as cited in Venkatesh et al., 2012). As we see above, the impact of habit on behavioral intention and direct use behavior is substantially strong that can influence the impact of behavioral intention on technology use. Hence, we can interpret the result as customers' behavioral intention of E-banking adoption doesn't predict the likeliness of the intended action in Ethiopian context. Instead, other factors like habitual practices make them frequent performer that can lead to complete adoption of technologies.

Adjusted R^2, Effect size (f^2) and Q-square effect(Q^2)

Following similar procedures on previous tests, Adjusted R^2 has been calculated according to Garson's (2016) guide to see the impact for addition of exogenous variable even though the new variable has insignificant correlation with the endogenous variable. Accordingly, adjusted R^2 for BI and Use endogenous variables were found to be 0.49 and 0.15 respectively for insignificant change on the original R^2 values respectively.

Cohen's f^2 also used to evaluate the effect size of each path in the structural equation model by examining its change on R^2 when an exogenous LV is removed from the model. Applying the formula used by Garson (2016), resulted in the effect size (f^2) values ranged from .00 to .08 as shown in ***Table 41***. These ranged values of f^2 were categorized as small to slightly moderate effects (Henseler et al., 2009; Chin, 1998; Venkatesh et al., 2012).

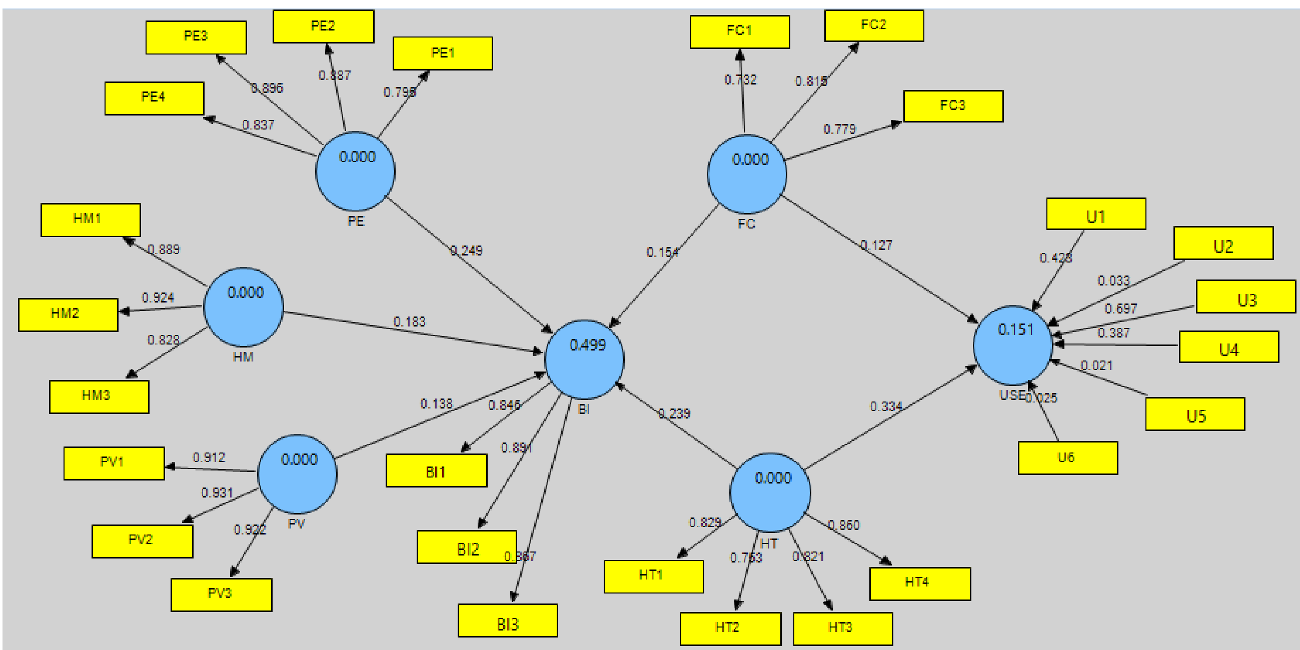
Table 41: Effect Size for individual exogenous LVs change on endogenous LVs

Omitted	**Original R^2 values**		**New R^2 values**		**Effect size (f^2) on:**	
exogenous LV	BI	Use	BI	Use	BI	Use
FC	0.50	0.15	0.49	0.14	0.03	0.01
PE	0.50	0.15	0.46	0.15	0.08	0.00
EE	0.50	0.15	0.50	0.15	0.00	0.00
SI	0.50	0.15	0.50	0.15	0.00	0.00
HM	0.50	0.15	0.48	0.15	0.04	0.00
PV	0.50	0.15	0.49	0.15	0.03	0.00
HT	0.50	0.15	0.46	0.08	0.08	0.08

Finally, the model's predictive relevance was assessed by using Stone-Geisser's Q^2 in which value greater than 0 indicates the model is predictive (Garson, 2016). Accordingly, by running blindfolding algorithm with an arbitrary setting of omission distance 7, Q^2 has been found .36 for BI that indicates high degree of predictive relevance. Since the procedure is applicable only for reflective endogenous variables, relevance indicator for the formative “Use” variable is not computed (Chin, 1998; Garson, 2016; Henseler et al., 2009; Urbach & Ahlemann, 2010).

Refined Path modeling for the conceptual model of the study

Further path modeling assessment has been made to revise the initial conceptual model of the study by removing all non-supported relations. Accordingly, the new model has been tested using PLS algorithm after the unsupported relations between EE and BI, SI and BI, and between BI and Use behavior were removed. As it is shown in ***Figure 16*** the refined path model consists of only supported relations with positive β coefficients and significant $p< .05$. Hence, the new model had five exogenous variables (PE, FC, HM, PV, HT) and two endogenous variables (BI and Use behavior) along with seven confirmed significant positive relations.



Note: all p values become improved ($p< .01$)after removing rejected relations.

Figure 16: Revised model structure based on findings on the pooled datasets

4.3.6 Summaries of findings and discussions

The path modeling has been tested in four different datasets: the ATM banking users' dataset, the Mobile banking users' dataset, the Internet banking users' dataset and the complete pooled datasets across the study. Though similar procedure and model has been used for all the four cases, the findings were not the same. What is maintained the same across all tests is the reliability and validity of the sample datasets. In this section, findings from all cases are summarized and interpreted accordingly.

Following the two basic model techniques (Measurement model and Structural model), repeated tests have been made to see how the proposed model fits to the sample dataset. For measurement model reliability tests, indicator reliability and ICR have been found acceptable results for all datasets except for very few cases as suggested by Garson (2016), Henseler et al. (2009) and Wong (2013). Convergent and Discriminant validity was also assessed to check how well the indicators were converged to their construct and at the same time not indicating something else. AVE values were dominantly used to check these validities and almost in all cases the results were satisfactory. In ATM dataset, FC was exhibited to have low (< .5) AVE value (Chin, 1998) that resulted in removing its fourth indicator (FC4) and improve the result. Discriminant validity was assessed and meet the requirement in all datasets by comparing the square roots of AVE values with the corresponding paired correlation values. Cross-loadings were also used to check whether the perfect diagonal has occurred that indicated high convergent and discriminant validity.

For formative models' measurements outer weights, construct validity and collinearity issues were assessed, and an acceptable result were found in almost all cases. Construct validity and Multicollinearity were measured using VIF and Tolerance values. As a result, construct validity of formative indicators was maintained for VIF values with less than the threshold 3.3 (Lowery & Gaskin, 2014) and collinearity was not the issue in any case due to the low VIF values (less than 5) and high tolerance values (more than .2) in most cases (Wong, 2013).

The structural model assessment was mainly done through R^2, F^2 and Q^2 measures. ***Table 42*** shows the compiled result for all four cases. As it is shown, the degree of explained variance (R^2) in Internet banking users' dataset is substantially strong for both endogenous variables than on other datasets. This indicates that the model was more fit to this dataset than others even though the number of observation is small. This is due to the capability of PLS for small sample size and some variables like hedonic motivation gets more weight in such technologies where the user interaction is high. Moreover, the predictive relevance (Q^2) is substantially high (.36) for this dataset that indicates the model is capable to predict unknown indicators of the reflective endogenous LV. The Cohen's effect size (f^2) has small to slightly moderate impact due to very small change in adjusted R^2 values (Chin, 1998; Garson, 2016; Urbach & Ahlemann, 2010).

Table 42: R^2, Adjusted R^2, F^2 and Q^2 for each dataset

	Original R^2		**Adjusted R^2**		**Cohen's f^2**		**Q^2**	
Sample dataset	**BI**	**Use**	**BI**	**Use**	**BI**	**Use**	**BI**	**Use***
ATM banking user's dataset	0.48	0.12	0.47	0.10	0.03 - 0.09	0.00 - 0.06	0.35	NA
Mobile banking users' dataset	0.51	0.25	0.50	0.23	0.00 - 0.10	0.00 - 0.07	0.36	NA
Internet banking users' dataset	0.77	0.55	0.77	0.54	0.01 - 0.28	0.00 - 0.22	0.66	NA
All pooled datasets	0.50	0.15	0.49	0.15	0.00 - 0.08	0.00 - 0.08	0.36	NA

**Use is formative indicator in which predictive relevance is not applicable*

On the other datasets, applied model measurements have shown almost similar results with the test on the pooled dataset. Regarding to the structural model assessment in the remaining datasets, coefficient of determination (R^2) is nearly 50% for explaining the variance in BI and 12% to 25 % of the variance in Use behavior. In all cases the actual Use behavior is explained in very small amount than BI. The model's predictive relevance on the other three datasets is nearly 0.36 that indicates high level of predictive relevance (Chin, 1998; Garson, 2016). The effect size ranges from small to moderate level which is similar result with that of Venkatesh et al. (2012).

The path coefficient analysis conducted in all sampled datasets has shown confirmation of the initial assumptions for some hypotheses while others were rejected. These findings in each dataset have been compiled together in ***Table 43*** for easy understanding and comparison. As it is shown in this table, H5, H7.1 and H7.2 were fully supported in all sample datasets. H1and H6 were also supported in all, except for Internet banking users' dataset. These showed that PE, HM, PV and HT have more significant influence on BI to adopt E-banking adoption in Ethiopian context than others. Moreover, HT has been found as the very influential factor in determining the actual Use behavior.

Table 43: Summary of path coefficients for each dataset

Hypothesis		ATM banking users' dataset		Mobile banking users' dataset		Internet banking users' dataset		Across the pooled datasets	
		β	**Result**	**β**	**Result**	**β**	**Result**	**β**	**Result**
H1	PE -> BI	***0.27	+	**0.35	+	0.13	-	***0.27	+
H2	EE -> BI	0.00	-	-0.03	-	*0.34	+	-0.04	-
H3	SI -> BI	-0.03	-	-0.05	-	-0.19	-	-0.04	-
H4.1	FC -> BI	**0.18	+	0.04	-	0.13	-	**0.18	+
H4.2	FC -> USE	-0.04	-	*0.28	+	-0.25	-	*0.12	+
H5	HM -> BI	**0.19	+	*0.21	+	*0.22	+	***0.19	+
H6	PV -> BI	*0.14	+	*0.36	+	-0.07	-	**0.14	+
H7.1	HT -> BI	***0.25	+	**0.27	+	**0.43	+	***0.24	+
H7.2	HT -> USE	***0.27	+	*0.27	+	1.00	+	***0.32	+
H8	BI -> USE	0.15	-	0.07	-	-0.67	-	0.03	-

*Strong significances: *p< .05, **p<.01, ***p<.001;*

Note: += Confirmed, - Disconfirmed

In contrast, H2, H3 and H8 were not confirmed in all sampled datasets (except H2 is supported in the Internet users' dataset) that indicate how EE and SI were weak to explain the change in BI and also how BI is a weak LV to explain the change in the actual Use behaviors of E-banking adoption in Ethiopian context. Though there were many agreements in regarding to the poor influence of SI on BI, Findings regarding to the impact of EE on BI and the impact of BI on the actual Use behavior were controversial and in contradictions with some previous findings that call for further investigations in Ethiopian context and similar adoption cases.

Further Analysis on Moderators' Effect

Testing for moderators' effect is not the intention of this paper, however, we extended the analysis to test the moderating effects of age and gender on our model to show the possibility of further modification of the UTAUT2 model in future researches. In UTAUT2, the relation between PV and BI was stronger for older women and the relation between HM and BI was stronger for younger men. On the other hand, the effect of HT on both BI and the actual Use behavior was stronger for older men (Venkatesh et al., 2012). However, some other researchers like Arenas-Gaitan et al. (2015) have not found significant evidence to consider gender as moderator variable on UTAUT2.

Henseler (2012) suggested that one of the non-parametric approach to test the moderator effect is by running an independent PLS test for different group. For this purpose, PLS Multigroup Analysis (PLS-MGA) technique has been used as Hair et al. (2014) recommended this approach as it is much suitable for testing categorical moderator variables. Since, gender is purely categorical, and age also represented as categorical variable using pre-defined age ranges, MGA approach has been used for testing such effects.

To apply PLS-MGA on gender as moderating variable, the pooled dataset has been split in to two groups for "male' and 'female' using SPSS case-based selection. Likewise, the pooled dataset also split in to two groups based on age groups as the first group holds those whose age were below 26 years and the second group holds those whose age value were above 35. Before doing the actual MGA, all measurement tests were conducted using the SmartPLS on separate dataset. These test results were acceptable as Hair et al. (2012) recommended that each dataset must be meet rule of thumb for sample size and meet the threshold values for reliability and validity tests.

Once the measurement tests granted, the standard inner model assessment and bootstrapping was applied to test moderation effects on each sub-group datasets. As a result, gender has been found as it has no significant moderating effect on supported positive relation of the refined model. However, age has a dim significant moderating effect for HM and PV in which HM has a slightly stronger effect on the younger group, PV has a slightly stronger effect on the older group. *(the detail result for such moderation effect analysis is presented in the index i.)*

Regarding to the new R^2 values, though the specific group R^2 values in general are larger than the results found before the dataset is split, but slight difference is exhibited among the two gender groups. As it is shown in ***Table 44***, R^2 for BI and Use behavior became 52% and 16% respectively for the male group, it was 44% and 15% respectively for the women group. However, these R^2 values had noticeable differences among the two age-based groups. As it is shown in ***Table 45***, R^2 for BI and Use behavior became 58% and 38% respectively for the older group, it was 48% and 15% respectively for the younger group.

Table 44: Change on R2 values for new group-based testing per gender

Dependent Variable	R^2 Values the whole group (before splitting per gender)	Male group	Females group
BI	0.50	0.52	0.44
Use behavior	0.15	0.16	0.15

Table 45: Change on R2 values for new group-based testing per age difference

Dependent Variable	R^2 Values the whole group (before splitting per gender)	Age group (Below 26 yrs)	Females group (above 35 yrs)
BI	0.50	0.58	0.48
Use behavior	0.15	0.38	0.15

CHAPTER FIVE

V. Conclusion and Recommendations

5.1 Overview of the research process

This research was aimed to further shed light on the E-banking adoption in Ethiopian context and overcome previously mentioned problems by conducting comprehensive study of E-banking adoption factors among different commercial bank customers located in different regions of the country. To achieve its main goals an intensive literature review has been done and a conceptual research model build that consists of seven exogenous and two endogenous LVs adopted from Venkatesh et al. (2012). A quantitative survey research was conducted to collect data from customers of E-banking technologies in four banks across the main cities of the country and empirically test the model using PLS-SEM technique.

5.2 Measurement and structural model evaluation

The overall model testing process has been done on four separate datasets: the ATM banking users' dataset (n=317), the mobile banking users' dataset (n=162), the Internet banking users' dataset (n=41) and the entire pooled datasets (n=520) which is the sum of each sub-dataset. In each dataset, indicator reliability and internal consistency reliability has been met .7 for reliability measures of reflective indicators. Moreover, convergent validity and discriminant validity were met .5 for reflective indicators as construct validity was addressed for formative indicators. Content validity for formative indicators was assured by including all the available services from intensive literatures reviewed. Moreover, no multicollinearity problem also faced during measurement evaluation of formative outer model.

Structural model assessment shows moderate level predicting power in which R^2 measures were found to be 48%, 51%, 77% and 50% respectively in the ATM banking users' dataset, the Mobile banking users' dataset, the Internet banking users' dataset and the pooled datasets, to explain the variance in BI by other exogenous variables. Likewise, R^2 measures for Use behavior were found to be 12%, 25%, 55% and 15% in each respective dataset that indicates the model weakly represented the variance in Use behavior except in the case of Internet banking users' dataset. The predictive relevance of the model was assessed by Q^2 in which moderate to strong predictive relevance is observed for all datasets.

The main data analysis has been considered on the entire pooled datasets that address the comprehensiveness issue. In this dataset, the model has a moderate level predictive power that explain 50% of the variance in BI and 15% of the variance in Use behavior. Moreover, the path coefficient analysis showed that, out of the ten assumed hypothetical relations, seven of them were confirmed while the rest were not. Two of these non-supported relations were some of the interesting finding of this study that includes the relation between EE and BI and the relation between BI and the actual Use behavior. The complete lists of supported hypotheses are:

H1: PE has a positive impact on customer's BI of E-banking adoption in Ethiopia.

H4.1: FC has a positive impact on customers' BI of E-banking adoption in Ethiopia.

H4.2: FC has a direct positive impact on customers' E-banking adoption (Use) in Ethiopia.

H5: HM has a positive impact on customers' BI of E-banking adoption in Ethiopia.

H6: PV has a positive impact on customers' BI of E-banking adoption in Ethiopia.

H7.1: HT has a positive impact on customers' BI of E-banking adoption in Ethiopia.

H7.2: HT has a direct positive impact on customer's E-banking adoption (Use) in Ethiopia.

In contrast, the complete lists of rejected hypotheses are:

H2: EE has a positive impact on customers' BI of E-banking adoption in Ethiopia.

H3: SI has a positive impact on customers' BI of E-banking adoption in Ethiopia.

H8: BI has a positive impact on customers' E-banking adoption (Use) in Ethiopia.

Based on their beta coefficient magnitude, these factors can be arranged from the highest to the lowest as: PE, HT, HM, PV, and FC on determining customers' BI of E-banking adoption, while HT and FC were determinant on the actual use behavior of E-banking technology in Ethiopian context.

Further analysis on comparing specific findings of each dataset demonstrate that somehow varied results have been found with some similarity pattern. Three hypotheses (H5, H7.1 and H7.2) that state the positive relationship between HM and HT with BI and HT with Use behavior were fully supported in all sample datasets. H1and H6 were also supported in all, except for Internet banking users' dataset that confirms a positive relationship between PE and PV with BI. These showed that PE, HM and PV and HT have more significant influence on BI to adopt E-banking technologies in Ethiopian context than others. Moreover, HT has been found as the very influential factor in determining the actual Use behavior.

In contrast, H2, H3 and H8 were not confirmed in all sampled datasets (except H2 is supported in the Internet users' dataset) that indicate that how these variables are weak to explain the change in BI and actual Use behavior of E-banking adoption in Ethiopian context.

5.3 Contribution of the research

5.3.1 Theoretical contribution

An important theoretical contribution of this research is testing the UTAUT2 theory in Ethiopian context that has a different cultural context. Though UTAUT2 was tested in different countries dominantly in Europe, US and Asia, it is not well tested in least developed countries like Ethiopia. Hence, this research extends the applicability of the original (Venkatesh et al., 2012) model in one more country which has diversified culture and society.

Another important feature of this research is that the research model was tested in comprehensive manner for E-banking technologies unlike the most dominant tests conducted only on specific technologies. This comprehensive study made an empirical test using PLS by sorting the cross-sectional data in different sampled datasets to see the impact on variety ways. Hence, it extends the applicability of the model in testing similar technology adoptions that belongs to same category.

The third contribution of this research originates from the controversial findings of the association between BI and USE behavior. Almost in all previously made researches, BI has been found as strong determinant factor of the actual use behavior. However, this relation couldn't be confirmed on all tests made in different datasets. This deviated finding might call researchers to examine further on the area to come up with better understanding of the relation between BI and the actual Use behavior in different cultural contexts.

5.3.2 Practical contribution

This research also has significant practical contribution for banks and financial institutions in Ethiopia. The most valuable contribution for practitioners from this research is the evidence of hypothetical relationships between different LVs. Referring the findings of the model test on the entire pooled datasets, the confirmed relations between five exogenous and two endogenous variables helps the practitioners to visualize theses relations in the domain for E-banking adoption.

The explicit empirical evidences found on each E-banking technology users' dataset helps the practitioner further to consider factors of the specific E-banking technology. For instance, in ATM banking technology, the significant determinant factors to influence the BI and the actual Use behaviors were PE, HT, HM, PV and FC from which PE is the strongest determinant factor of BI while HT takes the lions share in influencing the Use behavior. This enables practitioners to focus on specific factors depending on the specific product they offered to their customers.

The data is proportionally gathered for this research from four banks. Hence, practitioners from each bank can make further study by using this data to see specific nature of relations on their customers. This might help them to know whether their customers behave like others or have unique characteristics. Such kinds of studies are very useful for banks like Zemen bank which focuses on specific group of customers.

On the other hand, practitioners can use the well designed and tested instrument of this survey for future researches. Preparing and testing data gathering instrument is very time consuming and costly. Hence, they can benefit from adopting this instrument for similar in-depth researches.

5.4 Recommendations

5.4.1 Recommendations for practitioners

The findings of this research are very helpful in understanding the main factors of customers' E-banking adoption in Ethiopia context. The comprehensiveness nature of including the three most dominant E-banking technologies in the study is very useful as it enables practitioners to have broader picture of E-banking adoption situation in the country. Consequently, based on the research findings, the following are recommended for practitioners.

From the findings of the model test on the entire pooled datasets, the confirmed relations between five exogenous and two endogenous variables are the key outputs of this research for practitioners to take actions on the area. For instance, PE has been found the strongest determinant factor of BI for E-banking adoption. Hence, practitioners must focus on the benefit (usefulness) of E-banking technology than other factors. This can be achieved by adding more valued functionalities on the available E-banking services. Moreover, it needs to integrate financial activities with other service providers where most people are likely dependent for their daily life. This might include, but not limited to enabling paying bills for electric, water and telecommunication, and conducting payment fees for schools, government offices, entertainments and other trade organizations through these E-banking channels.

Habit is the next most important determining factor that has been found influential in determining the BI and actual use behaviors. It is confirmed that, once the customer started to use a system and finds it useful, it becomes a habitual action to use that system again and again. This implies that practitioners must find alternatives that will expose customers to try these E-banking technologies. Recommended actions on the above factor can be integrated with creating conducive environment for customers to exercise using E-banking channels. This can be realized by work with governmental and non-governmental organizations to enforce customers for using E-banking channels in specific services. Hence, once start to familiarize the technology using these forced conditions, it becomes a habitual action to uses these systems for any other related services.

Hedonic Motivation is the third important determining factor that has been found influential on determining the BI and actual use behaviors. This indicates that practitioners must focus on these technologies' desirable fun, happiness and pleasure characteristics that rouse the users' hedonic motivation. Improving the overall attractiveness of these technologies along with adding some entertaining features might help to address these requirements. More specifically, Mobile and Internet banking channels need to incorporate fun and pleasures that used to attract customers' attention and help to develop habits.

Price value and facilitating conditions are the fourth and fifth most important factors that influence customers' behavioral intention towards E-banking adoption. Hence, practitioners in the field should think about how they can increase their products price value. These can be done in two ways, one by increasing the functionalities and usefulness of the technologies over the associated costs to use the provided services. Second, decreasing associated registration or service charge fees will help to attract customers toward using the systems more frequently, which indirectly build the habit factor. On the other hand, banks should think on the way they set prices (service fees) for using E-banking channels versus getting the similar service from the physical branches.

The current trend also discourages to use E-banking channels by applying some registration and service fees without considering the fee for internet service provider. On contrast, there is no direct payment or service fee for similar services acquired from physical branches. These might push customers to go to banks physically instead of using E-banking channels. Hence, banks should either remove service fees from E-banking channels or set relatively higher service fees for similar services given in branches that require lot of administrative and professional costs.

Regarding facilitating conditions, most commonly the network and internet infrastructures for all E-banking technologies usage and the allocation of ATMs in more convenient and nearby places are very important to provide more comfortable conditions to E-banking users. Providing frequent follow-ups and on prompt support are the other key areas that all practitioners in the areas should attain. Telecom service, as it is the only infrastructure and service provider for the country, must work hard to address network and internet services which are the bad experiences of poor facilitating conditions for not only E-banking, but also for any other electronic services.

On the other hand, as their registry database indicated, banks have high number of registered customers for different E-banking services though very few are utilizing the provided service. This existing fact is in line with the research findings that indicates behavioral intention as not predicting well for the actual use performance. In some cultural contexts, people might tend to behaviorally aroused and registered to use a new system but that by itself is not enough for technological adoption. Instead, habit has been found as a driving force for the actual use performance in some context. Hence, instead of spending much to arouse behavioral intentions by advertisement, banks should find the way that enforce the customer to use the system and see how the system is useful to perform day to day activities.

From explicit empirical evidences found on each E-banking technology users' datasets, practitioners are recommended to take some measures with respective to specific products. For instance, in ATM banking technology, the significant determinant factors to influence the BI and the actual Use behaviors are PE, HT, HM, PV and FC from which PE is the strongest determinant factor of BI while HT takes the lions share in influencing the Use behavior. This indicate that practitioners must pay attention to the usefulness of ATM banking, their attractiveness, the price values and facilitating conditions like issuing debit cards on time with full functionality, allocating ATMs in nearby areas, following up the ATMs functionality and providing on prompt supports.

On the other hand, HM and HT are the common significant factor of E-banking adoption in the case of Mobile and Internet banking users' dataset. This indicates that practitioners must pay more attention to make such services more attractive to have a fun and pleasure impacts on customers. These might include, but not limited to, improving backgrounds, layouts, text formats and enabling them with some additional entertain capabilities. For both E-banking technologies and most importantly for Internet banking technologies.

5.4.2 Recommendations for future research

Utilization of researches on technology adoption is not yet addressed well in least developed countries like Ethiopia. Hence, more research is recommended to be conducted in the areas. More specifically, further researches in the following areas are recommended based on the limitations of this research.

The first recommendation of future research is to conduct the longitudinal research on the E-banking adoption. The findings in this research are based on the cross-sectional study that is conducted within specified area at a time. However, adoption behavior is highly influenced by time variation that requires conducting similar researches in time interval. Moreover, the findings in this study revealed that only weak variance in Use behavior is explained by the model that demands further studies to identify other factors that yields significant variance.

The other limitation of this study was its non-equal number of observation for different E-banking technologies datasets. It was mainly due to time constraint and the infancy stage of some of the E-banking technologies in the country. Hence, future researches can enhance the result by allotting more time to get an even number of respondents on each E-banking technology.

On the other hand, the original UTAUT2 incorporates additional moderates that includes age, gender and experience. The impact of these moderators is not addressed in this model. Hence, further research is recommended to test the model with these moderators in Ethiopian context.

The last, but not the least recommendation is to encourage technology adoption researches on other technologies. It is obvious that different technologies are being introduced in our day to day activities. However, their adoption level is not well tested to make significant enhancements. Hence, both academicians and practitioners are advised to conduct technology adoption studies in different fields and technologies.

References

Aderonke, A. A. (2010). An empirical investigation of the level of users' acceptance of e-banking in Nigeria. *Journal of Internet Banking and Commerce, 15*(1), 1-13.

Ain, N., Kaur, K., & Waheed, M. (2016). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development, 32*(5), 1306-1321. doi:10.1177/0266666915597546

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211.

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology and Health, 26*(9), 1113-1127. doi:10.1080/08870446.2011.613995

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 99–110.

Alawadhi, S., & Morris, A. (2008). Theu use of the UTAUT model in the adoption of E-govenment services in Kuwait. *Hawaii International Conference on System Sciences*, *41*, pp. 1-11.

Al-Smadi, M. O. (2012). Factors affecting adoption of electronic banking: An analysis of the perspectives of bank's customers. *International Journal of Business and Social Science, 3*(17), 293-309.

Arenas-Gaitan, J., Peral-Peral, B., & Ramon-Jeronimo, M. A. (2015). Elderly and Internet banking: An application of UTAUT2. *Journal of Internet Banking and Commerce, 20*(1), 1-23.

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior, 50*, 418-430.

BPC Banking. (2016). *News*. Retrieved December 25, 2017, from BPC Banking Technologies Group: http://www.bpcbt.com/news/press-releases/bpc-banking-technologies-delivers-payments-interoperability-first-time-ethiopia

Carr, V. H. (1999). Technology adoption and diffusion. *The Learning Center for Interactive Technology*.

CBE. (2017). *Epayment*. Retrieved December 21, 2017, from Commercial Bank of Ethiopia: http://www.combanketh.et/EPayment.aspx

CBE Communication. (2016, July). CBE informer. *6*(3). Retrieved December 21, 2017, from http://www.combanketh.et/AboutUs/Publications.aspx

Chin, W. (1998). The partial least squares approach to structural equation modeling. In W. Chin, & G. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295-336). Lawrence Erlbaum Associates.

CHIRr. (2013). *Behavioral Intention*. Retrieved May 26, 2018, from Consumers health informatics research resources: https://chirr.nlm.nih.gov/behavioral-intention.php

Cruz, P., Neto, L. B., Munoz-Gallego, P., & Laukkanen, T. (2010). Mobile banking rollout in emerging markets: Evidence from Brazil. *International Journal of Bank Marketing, 28*(5), 342-371.

Daniel, E. (1999). Provision of electronic banking in the UK and the Republic of Ireland. *International Journal of Bank Marketing, 17*(2), 72-83.

Dashen Bank S.C. (2017a). *Product and Services*. Retrieved December 22, 2017, from Dashen Bank S.C: https://dashenbanksc.com

Dashen Bank S.C. (2017b). *21st annual report for the year ended June 30, 2017.* Addis Ababa: Dashen Bank S.C. Retrieved December 17, 2017, from https://www.dashenbanksc.com

Datta, S. K. (2010). Accepance of e-banking among adult customers: An emperical investigation in India. *Journal of Internet Banking and Commerce, 15*, 1. Retrieved October 09, 2017, from http://www.icommercecentral.com/open-access/acceptance-of-ebanking-among-adult-customers-an-empirical-investigation-in-india-1-17.php?aid=38370

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of Information technology. *MIS Quarterly, 13*(3), 319-340.

Dawson, C. (2002). *Practical research methods: A user - friendly guide to mastering research.* United Kingdom.

DeYoung, R. (2001). The Internet's place in the banking industry. *Chicago Fed Letter*, 1-4. Retrieved from http://www.frbchi.org

Ethio telecom. (2017). *home,corporate news*. Retrieved December 27, 2017, from ethio telecom: http://www.ethiotelecom.et

Fenuga, O. (2010). The effect of electronic payment on customer service delivery. *International Journal of Economic Development Research & Investment, 1*.

Fikru, W. (2011). *Assessment of customers' attitudes and satisfaction levels with technology based self service: A case study on ATM user of Dashen Bank in Addis Ababa.* (master's thesis), Addis Ababa University, Marketing Management.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research.* Addison-Wesley: MA.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research.

Garson, G. D. (2016). *Partial least squares: Regression and structural equation models.* Statistical Associates Blue Book Series.

Gemechu, A. (2014). Factors affecting adoption of electronic banking system in Ethiopian banking industry. *Journal of Management Information System and E-commerce, 1*(1), 1-17.

Gifford, D. K., Stewart, L. C., Payne, A. C., & Treese, G. W. (1995). Payment switches for open networks. *Technologies for the Information Superhighway*, 26-31.

Gikandi, J. W., & Bloor, C. (2010). Adoption and effectiveness of electronic banking in Kenya. Electronic commerce research and applications. *9*(4), 277-282.

Girma, K. (2016). *Challenges and opportunities of electronic banking in Ethiopian banking Industry.* (master's thesis), Addis Ababa University, School of Business & Public Administration, Accounting and Finance.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213-236.

Goodhue, D., Lewis, W., & Thompson, R. (2006). PLS, small sample size, and statistical power in MIS research. *Hawaii International Conference on System Sciences*, *39*, pp. 1 - 10.

Hair, J. F., Hult, G. T., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM).* Sage.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*(3), 414-433.

Henseler, J. (2012). PLS-MGA: A non-parametric approach to partial least squares-based multi-group analysis. *Challenges at the Interface of Data Analysis, Computer Science, and Optimaization*, 495-501.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). the use of partial least squares path modelling in international marketing. *Advances in International Marketing, 20*, 277-319. doi:10.1108/S1474-7979(2009)0000020014

Hevner, A., & Chatterjee, S. (2010). Design science research in information systems. 9-22.

Hinkin, T. R. (1995). A review of scale development practices in the study of organizations. *Journal of Management, 21*(5), 967-988.

Hoehle, H. (2011). *Consumer intentions to use electronic banking channels: The role of Task-Channel Fit.* (phd's thesis), Victoria University of Wellington.

Huang, C.-Y., & Kao, Y.-S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of Phablets by DNP. *Mathematical Problems in Engineering*, 1-23. Retrieved from http://dx.doi.org/10.1155/2015/603747

Im, I., Hong, S., & Kang, M. S. (2011). An international comparison of technology adoption: Testing the UTAUT model. *Information & Management, 48*(1), 1-8.

Jahangir, N., & Begum, N. (2008). The role of perceived usefulness, perceived ease of use, security and privacy, and customer attitude to engender customer adaptation in the context of electronic banking. *African Journal of Business Management, 2*(1), 32-40. Retrieved from http://www.academicjournals.org/AJBM

Khechine, H., & Lakhal, S. (2018). Technology as a double-edged sword: From behavior prediction with UTAUT to students' outcomes considering personal characteristics. *Journal of Information Technology Education Research, 17*, 63-102.

Kindie, H. (2016). *Customers' perception towards Mobile banking security: The case of Commercial Bank of Ethiopia in Addis Ababa.* (master's thesis), Addis Ababa University, School of Information Sciences, Information SCience.

Kinfe, M. (2016). *Challenges and prospect of E-Banking in Ethiopia.* (master's thesis), Addis Ababa University, Accounting and Finance.

Kolodinsky, J. M., Hogarth, J. M., & Hilgert, M. A. (2004). The adoption of electronic banking technologies by US consumers. *International Journal of Bank Marketing, 22*(4), 238-259.

Kothari, C. R. (2004). *Research methdology: Methods and techniques* (Second ed.). India: New Age International.

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management, 14*(1), 21-38.

Liu, Z. Y. (2014). *An Analysis of Technology Acceptance Model: Exploring user acceptance and intension of taxi-hailing app in Shanghai.* University of Gothenburg, Computer Science and Engineering. Göteborg, Sweden: in the Programme Software Engineering and Management.

Lowery, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for Building and Testing Behavioral Causal Theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication, 57*(2), 123-146.

Maduku, D. K. (2014). Customers' adoption and use of e-banking services: the South African perspective. *Banks and Bank Systems, 9*(2), 78-88.

Marcopolis LLC. (2017). *Top Banks in Ethiopia*. Retrieved November 27, 2017, from http://www.marcopolis.net/top-banks-in-ethiopia.htm

Mattila, M., Karjaluoto, H., & Pento, T. (2003). Internet banking adoption among mature customers: early majority or laggards? *Journal of Services Marketing, 17*(5), 514-528.

Merga, D. (2017). *Identifying factors influencing customers' behavioral intention to the adoption of Mobile banking: The case of Commercial Bank of Ethiopia.* (masther's thesis), Addis Ababa University, School of Information Sciences, Information Science.

Muche, B. (2017). Influence of demographic factors on user's adoption of electronic banking in Ethiopia. *Journal of Internet Banking and Commerce, 22*(57), 1-17.

Natasha, M., Faiza, S., Maryum, A., & Atta, R. (2014). The factors effecting e-banking usage in Pakistan. *Journal of Management Information System and E-commerce, 1*(1), 57-94.

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: An extension of the technology acceptance model. *Internet Research, 14*(3), 224-235. doi:10.1108/10662240410542652

Podder, B. (2005). *Factors influencing the adoption and usage of internet banking: A New Zealand perspective.* (master's thesis), Auckland University of Technology, School of Computer & Information Sciences, Auckland.

PSS. (2017). *Services*. Retrieved December 25, 2017, from Premier Switch Solution S.C: http://www.pssethiopia.com

Pynoo, B., Devolder, P., Tondeur, J., Braak, J. v., Duyck, W., & Duyck, P. (2011). Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study. *Computers in Human Behavior, 27*(1), 568-575.

Rogers, E. M. (1983). *Diffusion of innovation* (3rd ed.). New York: The Free Press.

Sahin, I. (2006). Detailed review of Rogers' diffusion of innovations theory and educational technology-related studies based on Rogers' theory. *The Turkish Online Journal of Educational Technology, 5*(2).

Shah, M. H., Khan, S., & Xu, M. (2005). A survey of critical success factors in e-banking. *In European, Mediterranean & Middle Eastern Conference on Information Systems*, (pp. 7-8).

Sharma, R., & Mishra, R. (2014). A review of evolution of theories and models of technology adoption. *IMJ, 6*(2), 17-29.

Shittu, O. (2010). The impact of electronic banking in nigeria banking system.

Sohrabi, M., Yee, J. Y., & Nathan, R. J. (2013). Critical success factors for the adoption of e-banking in Malaysia. *International Arab Journal of e-Technology, 3*(2).

Statista. (2017). *Reports*. (Statista Inc.) Retrieved December 24, 2017, from Statista: The Statistics Portal: https://www.statista.com/statistics/274774/forecast-of-mobile-phone-users-worldwide/

Surendran, P. (2012). Technology Acceptance Model: A survey of literature. *International Journal of Business and Social Research (IJBSR), 2*(4), 175-178.

Tefera, E. (2017). *Adoption of E-commerce framework for Ethiopian banks.* (master's thesis), Addis Ababa University, School of Information Science.

Tesfaye, E. (2016). *Factors affecting intention to use e-banking at Bank of Abyssinia in the case of Addis Ababa branches.* (master's thesis), Addis Ababa University, College of Business and Economics, Department of Management.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly, 15*(1), 125-143. Retrieved from http://www.jstor.org/stable/249443

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology Theory and Application, 11*(2), 5-40.

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273-315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Webb, T. L., & Sheeran, P. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological Bulletin, 132*(2), 249-268.

Wegagen Bank S.C. (2015). *Wegagen Bank S.C 2014/15 annual report.* Addis Ababa: Wegagen Bank S.C. Retrieved December 15, 2017, from https://www.wegagenbanksc.com/index.php/pages/annual-report

Wegagen Bank S.C. (2017a). *Product-services*. Retrieved December 23, 2017, from Wegagen Bank S.C: https://www.wegagenbanksc.com/index.php/product-services

Wegagen E-banking Services Directorate. (2016). *E-banking Services Directorate annual report 2015/16.* Addis Ababa.

Wegagen E-banking Services Directorate. (2017). *E-Banking Services Directorate annual report 2016/17.* Addis Ababa: Wegagen Bank S.C.

Wong, K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin, 24*(1), 1-32.

Worku, G. (2010). Electronic banking in Ethiopia: Practices, opportunities and challenges. *Journal of Internet Banking and Commerce, 15*(2), 1-8. Retrieved September 12, 2017, from http://www.icommercecentral.com/open-access/electronicbanking-in-ethiopia-practices-opportunities-and-challenges-1-8.php?aid=38390

Yiheyis, A. (2015). *Evalluation of customers' satisfaction regarding PSS automated teller machine (ATM) banking service in Addis Ababa.* (master's thesis), Addis Ababa University, Accounting and Finance.

Yohannes, A. (2010). *Key factors that determine adoption of Internet banking in Ethiopia.* (master's thesis), Addis Ababa University, School of Business & Public Administration, Accounting and Finance.

Zahid, N., Mujtaba, A., & Riaz, A. (2010). Consumer acceptance of online banking. *European Journal of Economics, Finance and Administrative Sciences, 27*(1).

Zeleke, A. (2016). *Opportunities and challenges in the adoption of e-banking services: The case of Dashen Bank S.C.* (master's thesis), Addis Ababa University, Executive Masters of Business Administration (EMBA).

Zemen Bank S.C. (2016). *Annual report 2016.* Zemen Bank S.C. Retrieved November 27, 2017, from http://www.zemenbank.com/images/2016/11/Annual-Report-English-2016-email.pdf

Zemen Bank S.C. (2017a). *Annual report 2017.* Addis Ababa: Zemen Bank S.C. Retrieved December 24, 2017, from http://zemenbank.com/images/Annual-Report-English-2017.pdf

Zemen Bank S.C. (2017b). *Multi-channel banking*. Retrieved December 20, 2017, from Zemen Bank S.C: http://www.zemenbank.com

Appendices

Appendix i. Moderation effect tests using bootstrapping and Levene's test

A. Moderation effect tests using bootstrapping and Levene's test for Gender

	Male		Female		T-statistic	p-value	Result
	Sample Mean (M)	Standard Error (STERR)	Sample Mean (M)	Standard Error (STERR)			
FC -> BI	0.17	0.07	0.21	0.07	0.38	0.70	NS
FC -> USE	0.17	0.07	0.03	0.12	1.09	0.28	NS
HM -> BI	0.16	0.07	0.21	0.10	0.43	0.67	NS
HT -> BI	0.29	0.06	0.16	0.08	1.27	0.20	NS
HT -> USE	0.30	0.07	0.34	0.09	0.28	0.78	NS
PE -> BI	0.28	0.07	0.28	0.10	0.05	0.96	NS
PV -> BI	0.12	0.05	0.19	0.08	0.72	0.47	NS

B. Moderation effect tests using bootstrapping and Levene's test for Age

	Below 26 yrs		Above 35 yrs		T-statistic	p-value	Result
	Sample Mean (M)	Standard Error (STERR)	Sample Mean (M)	Standard Error (STERR)			
FC -> BI	0.19	0.09	0.28	0.12	0.62	0.53	NS
FC -> USE	0.08	0.14	0.27	0.10	0.86	0.39	NS
HM -> BI	0.19	0.09	-0.06	0.14	*1.61	0.11	NS
HT -> BI	0.25	0.08	0.17	0.09	0.62	0.54	NS
HT -> USE	0.39	0.10	0.54	0.08	1.00	0.32	NS
PE -> BI	0.24	0.09	0.20	0.14	0.27	0.79	NS
PV -> BI	0.09	0.08	0.36	0.14	*1.75	0.08	NS

* t > 1.6 that indicates weak significance

Note:

NS mean 'Not significant' as t-value is less than the threshold 1.96 as suggested by Wong (2013).

t-value is calculated using the following formula based on Levene's test as explained by Hair et al. (2014).

$$t = \frac{Path_{sample\_1} - Path_{sample\_2}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} * S.E.^2_{sample1} + \frac{(n-1)^2}{(m+n-2)} * S.E.^2_{sample2}}\right] * \left[\sqrt{\frac{1}{m} + \frac{1}{n}}\right]}$$

Path $_{sample\_1}$ and Path $_{sample\_2}$ are sample mean values, while S.E represent corresponding standard errors

n and m represent number of group1 and group 2 observations respectively where:

number of observation for Male's group is 348
number of observation for Females group is 172
number of observation for age below 26 yrs group is 137
number of observation for age above 35 yrs group is 84

Appendix ii. An official translation of original items in to Amharic language

The original items were adopted from Venkatesh et al. (2012) in English language. The following equivalent translation is the final version which was first made by an official translator then revised by language and business experts.

**** In place of E-banking, ATM/Mobile or Internet banking are used independently for each questionnaire's sections***

Performance Expectancy (በውጤታማነት ረገድ)		
PE1	I find E-banking useful in my daily life	የኢ-ባንኪንግ[5] ግልጋሎትን በዕለት ተዕለት እንቅስቃሴ ጠቃሚ ሆኖ አግኝቼዋለው
PE2	Using E-banking increases my chances of achieving things that are important to me	ኢ-ባንኪንግ መጠቀሜ ለኔ ጠቃሚ የሆኑ ነገሮችን እንዳሳካ እድል ፈጥሮልኛል
PE3	Using E-banking helps me accomplish things more quickly	ኢ-ባንኪንግ መጠቀሜ ነገሮችን በፍጥነት እንዳከናውን ረድቶኛል
PE4	Using E-banking increases my productivity	ኢ-ባንኪንግ መጠቀሜው ጤታማነቴን ጨምሮታል
Effort Expectancy (በጥረት ረገድ)		
EE1	Learning how to use E-banking is easy for me	የኢ-ባንኪንግ አጠቃቀምን መማር ለኔ ቀላል ነው
EE2	Interaction with E-banking is clear and understandable	የኢ-ባንኪንግ አጠቃቀም ግልፅ እና መረዳት የሚቻል ነው
EE3	I find E-banking easy to use	የኢ-ባንኪንግ አጠቃቀም ቀላል ሆኖ አግኝቼዋለው
EE4	It is easy for me to become skillful at using E-banking	የኢ-ባንኪንግ አጠቃቀም የላቀ ክህሎት እንዲኖረኝ ማድረግ ለኔ ቀላል ነው
Social Influence (የማህበረሰብ ተፅዕኖ)		
SI1	People who are important to me think that I should use E-banking	ለኔ ጠቃሚ የምላቸው ግለሰቦች ኢ-ባንኪንግ መጠቀም እንዳለብኝ ያስባሉ
SI2	People who influence my behavior think that I should use E-banking	ባህሪዬ ላይ ተፅዕኖ የሚያደርጉ ግለሰቦች ኢ-ባንኪንግ መጠቀም እንዳለብኝ ያስባሉ
SI3	People whose opinions that I value prefer that I use E-banking	አስተሳሰባቸውን የማከብራቸው ግለሰቦች የኢ-ባንኪንግን መጠቀም እንዳለብኝ ያስባሉ
Facilitating Condition (ምቹ ሁኔታዎች)		
FC1	I have the resources necessary to use E-banking	ኢ-ባንኪንግ ለመጠቀም የሚያስፈልጉ ነገሮች አሉኝ
FC2	I have the knowledge necessary to use E-banking	ኢ-ባንኪንግ ለመጠቀም የሚያስፈልግ እውቀት አለኝ
FC3	If I have got problems, I can get support from the bank	ችግሮች ሲያጋጥሙኝ ከባንኩ በቂ ድጋፍ አገኛለው
FC4	I can get help from others when I have difficulties using E-banking	ኢ-ባንኪንግ መጠቀም በሚያስቸግረኝ ጊዜ ከሌሎች ሰዎች እርዳታን ማግኘት እችላለው
Hedonic Motivation (አስደሳች ማነሳሻዎች)		
HM1	Using E-banking is fun	ኢ-ባንኪንግ መጠቀም አስደሳች ነው
HM2	Using E-banking is enjoyable	ኢ-ባንኪንግ መጠቀም ማራኪ ነው
HM3	Using E-banking is entertaining	ኢ-ባንኪንግ መጠቀም የሚያዝናና ነው

Price Value (የገንዘብ ዋጋ)		
PV1	E-banking is reasonably priced	የኢ-ባንኪንግ አገልግሎት ክፍያ ተመጣጣኝ ነው
PV2	E-banking is a good value for the money	ለኢ-ባንኪንግ የሚከፈለው ገንዘብ፣ ለሚሰጠው እሴት/ዋጋ ይመጥነዋል
PV3	At the current price, E-banking provides a good value	አሁን ባለው ክፍያ፣ ኢ-ባንኪንግ ተመጣጣኝ እሴት አለው
Habit (ልማድ)		
HT1	The use of E-banking has become a habit for me	ኢ-ባንኪንግ መጠቀም ልማድ ሆኖብኛል
HT2	I am addicted to using E-banking	ኢ-ባንኪንግን መጠቀም ሱስ ሆኖብኛል
HT3	I must use E-banking for daily financial activities	ኢ-ባንኪንግን ዕለት ተዕለት እንቅስቃሴዬ መጠቀም ግድ ሆኖብኛል
Behavioral Intentions (ባህሪያዊ ዝንባሌዎች)		
BI1	I intend to continue using E-banking in the future	ወደፊት ኢ-ባንኪንግን መጠቀሜን እቀጥላለሁኝ
BI2	I will always try to use E-banking in my daily life	ወደፊት ለዘወትር እንቅስቃሴዬ ሁልጊዜ ኢ-ባንኪንግን ለመጠቀም እሞክራለሁ
BI3	I plan to continue to use E-banking frequently	ኢ-ባንኪንግን በተደጋጋሚ መጠቀሜን ለመቀጠል ዕቅድ አለኝ
Adoption/Use (የመጠቀም ስርፀት)		
a) request remaining balance		ቀሪ ሂሳብ ማወቅ
b) request financial mini-statement		የሂሳብ አጭር መግለጫ መጠየቅ
c) withdraw cash		ገንዘብ ማውጣት
d) exchange foreign currency		የውጭ ምንዛሬን መቀየር
e) transfer money to own account		ወደ ራስ ሂሳብቁጥር ገንዘብ ማስተላለፍ
f) transfer money to another person's account		ወደ ሌላ ሰው የሂሳብቁጥር ገንዘብ ማስተላለፍ
g) transfer money to non-account holder		የሂሳብቁጥር ወደ ሌለው ግለሰብ ገንዘብ ማስተላለፍ
c) request foreign exchange information		የውጭ ምንዛሬ ለውጥ መረጃ መጠየቅ
g) pay bills (like bus / movie ticket, etc)		የተለያዩ ክፍያዎችን መፈፀም (ባስ/ፊልምትኬትወዘተ)
h) buy mobile air time (mobile card)		የሞባይል የአየር ሰዓት (የሞባይል ካርድ) መግዛት
h) request for other services like stop/initiate cheque, Card, etc.		የተለያዩ አገልግሎቶችን መጠየቅ (የቼክ ማቆሚያ እና ማስጀመሪያ፣ ካርድ ወዘተ)

Appendix iii. Letter of approval for conducting the survey

የኢትዮጵያ ንግድ ባንክ

COMMERCIAL BANK OF ETHIOPIA

Inter Departmental Memorandum

DATE ቀን	:	*March 5, 2018*
TO ለ	:	*TO WHOM IT MAY CONCERN*
FROM ከ	:	*Manager - Learning & Development*
SUBJET ጉዳይ	:	*Support for Term Paper*

As we are all aware of, CBE has been discharging its responsibility to contribute in the education of college/university students via apprenticeships, attachments and supporting graduating students during their term/research paper writing so as to enable them see real world cases before they graduate.

*In light of this, **Yemisrach Desta** graduating student of Addis Ababa University college of Natural Science-School of Information Science has selected our organization for his term paper on the topic of **"Customers' E - Banking adaption in Ethiopia"***

This is, therefore, to kindly request your good office to extend the usual co-operation in this regard without compromising confidential information.

With Regards,

Getu Bedilu

Manager Dire Dawa main

Data has been collected from our Branch

Commercial Bank of Ethiopia Jimma Branch

Mgr - Jimma main Branch

Mgr - Hirmata Branch

for your cooperation

23/3/2018

Manager Mekelle

please act accordingly

Ato Abiy

for your cooperation

08/03/2018

Data has been collected

ADDIS ABABA UNIVERSITY
College of Natural Science
School of Information
Science

To - Jimma Branch
Pls forward your cooperation

Manager for Branch Dashen Bank
20/03/2018

Date February 21 /2018
Ref:-SIS/ 08/2010

To: Administrative Assistant - Please handle it.

To:- Wegagen Bank Sc
Dashen bank Sc
Zemen bank Sc
Commercial Bank of Ethiopia (CBE)
Addis Ababa

Noted 20/3/18

The data has been collected

DASHEN AREA BANK

Dear Sir / Madam

BOLE MEDHANIALEM DASHEN AREA BANK

Student Yemisrach Desta (ID. No. GSE/0343/08) is a graduate student at the School of Information Science, Addis Ababa University. He is currently conducting a MSc thesis research under the title "Customers' E-Banking adoption in Ethiopia)".

I would like to thank you in advance for all the assistance that you would provide to the student.

DASHEN BANK S.Co. MAIN BRANCH

To - Mekelle
- Diredawa
- Awassa
- Jimma
- Main
- Airport
- Betcha
- Megenagna
- Piazza
- Blmedhanialem

With Regards,

Martha Yifiru (PhD)
Head, School of Information Science

Mgr. Hawlaw Hamwit
Please cooperate the student in the research process
20/03/18

Manager DEO
Please help

Data has been collected for our Branch

Please cooperate for the research

Tel. 1176 +251-(11)-122-91-91 Fax: 2122-91-92

አዲስ አበባ ዩኒቨርሲቲ
የተፈጥሮ ሳይንስ ኮሌጅ
የኢንፎርሜሽን ሳይንስ ት/ቤት

ADDIS ABABA UNIVERSITY
College of Natural Science
School of Information Science

Date February 21 /2018
Ref:-SIS/ 08/2010

To:- Wegagen Bank Sc
Dashen bank Sc
Zemen bank Sc
Commercial Bank of Ethiopia (CBE)
Addis Ababa

Dear Sir / Madam

Student Yemisrach Desta (ID No. GSE/0343/08) is a graduate student at the School of Information Science, Addis Ababa University. He is currently conducting a MSc thesis research under the title "Customers' E-Banking adaption in Ethiopia)".

I would like to thank you in advance for all the assistance that you would provide to the student.

With Regards,

Martha Yifiru (PhD)
Head, School of Information Science

To: All Districts
All Branches
Kindly cooperate with the Miss/Ato Yemisrach Desta who is our E-banking dpt. staff.
Thanks in Advance
Alexander G. Berhe
CIO, Wegagen Bank SC.
03/03/18

Gofa Branch
pls assist him on his requests for filling questionnaires.
23/03/18

Confirmation
data has been collected from Bole Medhanealem Branch

✉: 1176 ☎: +251-(11)-122-91-91 ☎:2122-91-92

Data has been collected
Megenagna Branch

WEGAGEN BANK S.C.
Megenagna Branch

WEGAGEN BANK S.C
BOLE MEDHANEALEM
BRANCH

ዘመን ባንክ
Zemen
BANK

INTER-DEPARTMENTAL MEMO

Date: **March 06, 2018**

To: **V.P – Customer Service**

From: **Director – Promotion and Public Relations**

SUBJECT: Approval to conduct survey on "Customer's E-Banking adoption in Ethiopia"

Ato Yemisrach Desta, who is a graduate student studying Master of Science in Information Science at Addis Ababa University, has requested Zemen Bank to distribute his Survey Questionnaire at the Banking Centers in order to conduct a research on "Customers' E-banking adoption in Ethiopia" per attached details.

Hence, the Promotion and Public Relation Department believes that the outcome of the research will aid the Bank to understand its customer's feedback on E-banking.

Therefore, this is to kindly request your approval to Ato Yemisrach Desta to conduct his research and distribute 20 Survey Questionnaires each at Main Branch, Mekelle, Dire Dawa and Hawassa Banking Center.

Osewno,
Please proceed with the
above request.
March 09, 18

Sincerely,

Cc: Director – PBB Department

* 10 Questionneries are filled
by our branch custmers and Yemisrach collect
from our branch.

Joseph Tito St.
P.O.Box 1212
Addis Ababa, Ethiopia
Tel: 0115 54 00 57
www.zemenbank.com

Local-Knowledge International Standards

- 17 Questionneres are filled at main Branch. 28/03/18

Zemen Bank S.C.
Main Branch

Appendix iv. Questionnaire in Amharic version

አዲስ አበባ ዩኒቨርሲቲ
የተፈጥሮ ሳይንስና ኮምፕዩቲሽን ኮሌጅ
ኢንፎርሜሽን ሳይንስ ትምህርትክፍል

ውድ ተሳታፊ፤

ይህ መጠይቅ በአዲስ አበባ ዩኒቨርሲቲ የኢንፎርሜሽን ሳይንስ ትምህርት ክፍል ለሚሰጠው የኢንፎርሜሽን ሳይንስ ማስትሬት ዲግሪ ማሟያ ጥናታዊ ፅሑፍ መረጃ ለመሰብሰብ የተዘጋጀ ነው፡፡ ጥናቱ **"የደንበኞች የኤሌክትሮኒክ ባንክ ቅበላ ስርፀት በ ኢትዮጵያ"** በሚል ርእስ የባንክ ደንበኞችን የኤሌክትሮኒክ ባንክ ቅበላ የሚወስኑ ነገሮችን ለመለየትና ተያይዞም የመፍትሄ ሃሳቦች ለመጠቆም የሚደረግ ሲሆን የእርስዎ ትክክለኛ ምላሽ ለጥናቱ መሳካት ከፍተኛ አስተዋፅዖ ያድርጋል፡፡

ጥያቄዎቹን በሙሉ ለመመለስ ከ20 ደቂቃ በላይ እንደማይወስድብዎና በተጨማሪም የሚሰጡት ምላሽ ሚስጥራዊነቱ ተጠበቆ ለጥናቱ ስራ ብቻ እንደሚውል ላረጋግጥልዎ እወዳለሁ፡፡

ለጥናቱ ያልዎት ተሳትፎ ሙሉ በሙሉ በፍቃደኝነት ላይ የተመሰረተ ሲሆን ለአጠቃላይ ትብብርዎ በቅድሚያ ምስጋና አቀርባለሁ።

በመጠይቁ ላይ ግልጽ ያልሆነልዎት ነገር ወይም ማንኛውም አስተያየት ካልዎት በሚከተለው አድራሻ ሊያሳውቁኝ ይችላሉ፡፡

የምስራችደስታ፣

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yemmu@yahoo.com

መመሪያ -1፡

1. በመጠይቁ ላይ ስምዎን መግለጽ አይጠበቅብዎትም
2. ስምምነትዎን ለማመልከት የ(✓)ምልክት በሳጥኖቹ ውስጥ ያድርጉ
3. በመጀመሪያ **<u>በክፍል-1</u>** ውስጥ ያሉትን ጥያቄዎች ይመልሱ። ከዛ ***<u>መመሪያ-2</u>*** ላይ ያለውን ይመልሱና በእሱ መሰረት ቀሪዎቹን ጥያቄዎች ይመልሱ።

<u>ክፍል 1፡ ግለ መረጃ</u>

ፆታ	ወንድ ☐	ሴት ☐	
እድሜ (በ አመት)	ከ 26 በታች ☐	ከ [36 – 45] ☐	
	ከ [26 – 35] ☐	ከ 45 በላይ ☐	
ወርሃዊ አማካኝ ገቢ (በብር)	ከ 1,651 በታች ☐	ከ [5,251-10,900] ☐	
	ከ [1,651-5,250] ☐	ከ 10,900 በላይ ☐	
የትምህርት ደረጃ	የመጀመሪያ ደረጃ ☐	ዲፕሎማ/ቲቪቲ ☐	ማስተርስ ☐
	ሁለተኛ ደረጃ ☐	ዲግሪ ☐	ከዛ በላይ ☐

መመሪያ -2፡

እባክዎ ከዚህ በታች ከተዘረዘሩት የ ኢባንኪንግ ዘርፎች ውስጥ እርስዎ የሚጠቀሙዋቸውን ለማወቅ በስተቀኝ ካሉት ሳጥኖች ውስጥ <u>"አዎ"</u> ወይም <u>"አይ"</u> በሚለው ላይ የ(✓) ምልክት በማድረግ ምርጫዎትን ያሳዩ፡፡

<u>መልስዎ "አዎ" ከሆነ በጎን ወደ ተመለከቱት ንዑስ ክፍሎች በመሄድ ዝርዝር ጥያቄዎችን ይመልሱ፡፡</u>

ኤቲኤም ባንክን ይጠቀማሉ?	አዎ ☐ ፤አይ☐	**"አዎ" ከሆነ ወደ ክፍል 2 ይሂዱ (ገፅ 2)**
ሞባይል ባንክን ይጠቀማሉ?	አዎ ☐ ፤አይ☐	**"አዎ" ከሆነ ወደ ክፍል 3 ይሂዱ (ገፅ 4)**
ኢንተርኔት ባንክን ይጠቀማሉ?	አዎ ☐ ፤አይ☐	**"አዎ" ከሆነ ወደ ክፍል 4 ይሂዱ (ገፅ 6)**

<u>ክፍል 2፡ ኤቲኤም ባንክን በተመለከተ የተዘጋጀ የንድፈ ሀሳብ መለኪያ</u>

በዚህ ክፍል ኤቲኤም ባንክን በተመለከተ በደንበኞች ባህሪ ላይ ተፅዕኖ ሊፈጥሩ የሚችሉ መንስኤዎች ተዘርዝረዋል፡፡ እርስዎም ለ እያንዳነዱ ሃሳብ በምን ያህል ደረጃ እንደሚስማሙ በስተቀኝ ካሉት ከ 1- 7 ከተፃፈባቸው ሳጥኖች ውስጥ በ አንዱ ላይ ብቻ **የ (✓)** ምልክት   በማድረግ ምላሽ ይስጡ፡፡

የስምምነት ደረጃዎች፡

(1)=በፍፁም አልስማማም (2)=አልስማማም   (3)=በትንሹ አልስማማም

(4)=ለመወሰን እቸገራለሁ (5)=በትንሹ እስማማለሁ (6)=እስማማለሁ (7)=በጣም እስማማለሁ

መለያ	**የንድፈ ሃሳበ መለኪዎች**	በፍፁም አልስማማም	አልስማማም	በትንሹ አልስማማም	ለመወሰን እቸገራለሁ	በትንሹ እስማማለሁ	እስማማለሁ	በጣም እስማማለሁ
በውጤታመነት ረገድ (**Performance Expectancy)**								
PE1	የኤቲኤም ግልጋሎትን በዕለት ተዕለት እንቅስቃሴ ጠቃሚ ሆኖ አግኝቼዋለው	1	2	3	4	5	6	7
PE2	ኤቲኤም መጠቀሜ ለኔ ጠቃሚ የሆኑ ነገሮችን እንዳሳካ እድል ፈጥሮልኛል	1	2	3	4	5	6	7
PE3	ኤቲኤም መጠቀሜ ነገሮችን በፍጥነት እንዳከናውን ረድቶኛል	1	2	3	4	5	6	7
PE4	ኤቲኤም መጠቀሜ ውጤታማነቴን ጨምሮታል	1	2	3	4	5	6	7
በጥረት ረገድ (**Effort Expectancy)**								
EE1	የኤቲኤም አጠቃቀምን መማር ለኔ ቀላል ነው	1	2	3	4	5	6	7
EE2	የኤቲኤም አጠቃቀም ግልፅ እና መረዳት የሚቻል ነው	1	2	3	4	5	6	7
EE3	የኤቲኤም አጠቃቀም ቀላል ሆኖ አግኝቼዋለው	1	2	3	4	5	6	7
EE4	የኤቲኤም አጠቃቀም የላቀ ክህሎት እንዲኖረኝ ማድረግ ለኔ ቀላል ነው	1	2	3	4	5	6	7
የማህበረሰብ ተፅዕኖ (**Social Influence)**								
SI1	ለኔ ጠቃሚ የምላቸው ግለሰቦች ኤቲኤም መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
SI2	ባህሪዬ ላይ ተፅዕኖ የሚያደርጉ ግለሰቦች ኤቲኤም መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
SI3	አስተሳሰባቸውን የማከብራቸው ግለሰቦች ኤቲኤም መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
ምቹ ሁኔታዎች (**Facilitating Conditions)**								
FC1	ኤቲኤም ለመጠቀም ምቹና ቅርብ በሆነ ቦታ አገኛለሁ	1	2	3	4	5	6	7
FC2	ኤቲኤም ለመጠቀም የሚያስፈልግ እውቀት አለኝ	1	2	3	4	5	6	7
FC3	ኤቲኤም ስጠቀም ለሚያጋጥሙኝ ችግሮች ከባንኩ በቂ ድጋፍ አገኛለው	1	2	3	4	5	6	7
FC4	ኤቲኤም መጠቀም በሚያስቸግረኝ ጊዜ ከሌሎች ሰዎች እርዳታን ማግኘት እችላለው	1	2	3	4	5	6	7
አስደሳች ማነሳሻዎች (**Hedonic Motivation)**								
HM1	ኤቲኤም መጠቀም አስደሳች ነው	1	2	3	4	5	6	7
HM2	ኤቲኤም መጠቀም ማራኪ ነው	1	2	3	4	5	6	7
HM3	ኤቲኤም መጠቀም የሚያዝናና ነው	1	2	3	4	5	6	7
የዋጋ እሴት(**Price Value)**								

PV1	የኤቲኤም አገልግሎት ክፍያ ተመጣጣኝ ነው	1	2	3	4	5	6	7
PV2	ለኤቲኤም የሚከፈለው ገንዘብ፣ ለሚሰጠው እሴት/ዋጋ ይመጥነዋል	1	2	3	4	5	6	7
PV3	አሁን ባለው ክፍያ፣ ኤቲኤም ተመጣጣኝ እሴት አለው	1	2	3	4	5	6	7
ልማድ (**Habit)**								
HT1	ኤቲኤም መጠቀም ልማድ ሆኖብኛል	1	2	3	4	5	6	7
HT2	ኤቲኤም መጠቀም ሱስ ሆኖብኛል	1	2	3	4	5	6	7
HT3	ኤቲኤም ለዕለት ተዕለት እንቅስቃሴዬ መጠቀም ግድ ሆኖብኛል	1	2	3	4	5	6	7
HT4	ኤቲኤም መጠቀም ከውስጤ ጋር ተዋህዷል	1	2	3	4	5	6	7
ባህሪያዊ ዝንባሌዎች (**Behavioral Intention)**								
BI1	ወደፊት ኤቲኤም መጠቀሜን እቀጥላለሁኝ	1	2	3	4	5	6	7
BI2	ወደፊት ለዘወትር እንቅስቃሴዬ ሁልጊዜ ኤቲኤምን ለመጠቀም እሞክራለው	1	2	3	4	5	6	7
BI3	ኤቲኤምን በተደጋጋሚ መጠቀሜን ለመቀጠል ዕቅድ አለኝ	1	2	3	4	5	6	7
የመጠቀም ስርፀት **(E-banking adoption/ USE)** ከዚህ በታች ያሉትን የኤቲኤም አገልግሎቶች በምን ያህል ድግግሞሽ እንደሚጠቀሙ በስተቀኝ ካሉት ከ 1- 7 ከተዘፈባቸው ሳጥኖች ውስጥ በ አንዱ ላይ ብቻ የ(✓) ምልክት በማድረግ ምርጫዎትን ያሳዩ		**ተጠቅሜ አላውቅም ≈ 0%**	**ከስንት አንዴ ≈ 10%**	**በጣም አልፎ አልፎ ≈ 30%**	**አንድ አንዴ ≈ 50%**	**በተደጋጋሚ ≈ 70%**	**ዘወትር ≈ 90%**	**ሁሌ ጊዜ ≈ 100%**
ሀ) ቀሪ ሂሳብዎን ማወቅ		1	2	3	4	5	6	7
ለ) የሂሳብ አጭር መግለጫ መጠየቅ		1	2	3	4	5	6	7
ሐ) ገንዘብ ማውጣት		1	2	3	4	5	6	7
መ) የውጭ ምንዛሬን መቀየር`		1	2	3	4	5	6	7
ሰ) ወደ ሌላ የራስ ሂሳብ ቁጥር ገንዘብ ማስተላለፍ		1	2	3	4	5	6	7
ረ) ወደ ሌላ ሰው የሂሳብ ቁጥር ገንዘብ ማስተላለፍ		1	2	3	4	5	6	7
ሸ) የሂሳብ ቁጥር ወደሌለው ግለሰብ ገንዘብ ማስተላለፍ		1	2	3	4	5	6	7

ክፍል 3፡ ሞባይል ባንክን በተመለከተ የተዘጋጀ የንድፈ ሀሳብ መለኪያ

በዚህ ክፍል ሞባይል ባንክን በተመለከተ በደንበኞች ባህሪ ላይ ተፅዕኖ ሊፈጥሩ የሚችሉ መንስኤዎች ተዘርዝረዋል፡፡ እርስዎም ለ እያንዳነዱ ሃሳብ በምን ያህል ደረጃ እንደሚስማሙ በስተቀኝ ካሉት ከ 1- 7 ከተፃፈባቸው ሳጥኖች ውስጥ በ አንዱ ላይ ብቻ **የ (✓)** ምልክት በማድረግ ምላሽ ይስጡ፡፡

የስምምነት ደረጃዎች፡

(1)=በፍፁም አልስማማም (2)=አልስማማም (3)=በትንሹ አልስማማም

(4)=ለመወሰን እቸገራለሁ (5)=በትንሹ እስማማለሁ (6)=እስማማለሁ (7)=በጣም እስማማለሁ

መለያ	**የንድፈ ሃሳበ መለኪያዎች**	በፍፁም አልስማማም	አልስማማም	በትንሹ አልስማማም	ለመወሰን እቸገራለሁ	በትንሹ እስማማለሁ	እስማማለሁ	በጣም እስማማለሁ
በውጤታመነት ረገድ (**Performance Expectancy)**								
PE1	የሞባይል ባንክ ግልጋሎትን በዕለት ተዕለት እንቅስቃሴ ጠቃሚ ሆኖ አግኝቼዋለው	1	2	3	4	5	6	7
PE2	ሞባይል ባንክ መጠቀሜ ለኔ ጠቃሚ የሆኑ ነገሮችን እንዳሳካ እድል ፈጥሮልኛል	1	2	3	4	5	6	7
PE3	ሞባይል ባንክ መጠቀሜ ነገሮችን በፍጥነት እንዳከናውን ረድቶኛል	1	2	3	4	5	6	7
PE4	ሞባይል ባንክ መጠቀሜ ውጤታማነቴን ጨምሮታል	1	2	3	4	5	6	7
በጥረት ረገድ (**Effort Expectancy)**								
EE1	የሞባይል ባንክ አጠቃቀምን መማር ለኔ ቀላል ነው	1	2	3	4	5	6	7
EE2	የሞባይል ባንክ አጠቃቀም ግልፅ እና መረዳት የሚቻል ነው	1	2	3	4	5	6	7
EE3	የሞባይል ባንክ አጠቃቀም ቀላል ሆኖ አግኝቼዋለው	1	2	3	4	5	6	7
EE4	የሞባይል ባንክ አጠቃቀም የላቀ ክህሎት እንዲኖረኝ ማድረግ ለኔ ቀላል ነው	1	2	3	4	5	6	7
የማህበረሰብ ተፅዕኖ (**Social Influence)**								
SI1	ለኔ ጠቃሚ የምላቸው ግለሰቦች ሞባይል ባንክን መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
SI2	ባህሪዬ ላይ ተፅዕኖ የሚያደርጉ ግለሰቦች ሞባይል ባንክን መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
SI3	አስተሳሰባቸውን የማከብራቸው ግለሰቦች ሞባይል ባንክን መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
ምቹ ሁኔታዎች (**Facilitating Conditions)**								
FC1	ሞባይል ባንክ ለመጠቀም የሚያስፈልጉ ነገሮች አሉኝ	1	2	3	4	5	6	7
FC2	ሞባይል ባንክ ለመጠቀም የሚያስፈልግ እውቀት አለኝ	1	2	3	4	5	6	7
FC3	ሞባይል ባንክ ስጠቀም ለሚያጋጥሙኝ ችግሮች ከባንኩ በቂ ድጋፍ አገኛለው	1	2	3	4	5	6	7
FC4	ሞባይል ባንክ መጠቀም በሚያስቸግረኝ ጊዜ ከሌሎች ሰዎች እርዳታን ማግኘት እችላለው	1	2	3	4	5	6	7
አስደሳች ማነሳሻዎች (**Hedonic Motivation)**								
HM1	ሞባይል ባንክ መጠቀም አስደሳች ነው	1	2	3	4	5	6	7
HM2	ሞባይል ባንክ መጠቀም ማራኪ ነው	1	2	3	4	5	6	7
HM3	ሞባይል ባንክ መጠቀም የሚያዝናና ነው	1	2	3	4	5	6	7

የዋጋ እሴት (**Price Value**)								
PV1	የሞባይል ባንክ አገልግሎት ክፍያ ተመጣጣኝ ነው	1	2	3	4	5	6	7
PV2	ለሞባይል ባንክ የሚከፈለው ገንዘብ፣ ለሚሰጠው እሴት/ዋጋ ይመጥነዋል	1	2	3	4	5	6	7
PV3	አሁን ባለው ክፍያ፣ ሞባይል ባንክ ተመጣጣኝ እሴት አለው	1	2	3	4	5	6	7
ልማድ (**Habit**)								
HT1	ሞባይል ባንክ መጠቀም ልማድ ሆኖብኛል	1	2	3	4	5	6	7
HT2	ሞባይል ባንክ መጠቀም ሱስ ሆኖብኛል	1	2	3	4	5	6	7
HT3	ሞባይል ባንክ ለዕለት ተዕለት እንቅስቃሴዬ መጠቀም ግድ ሆኖብኛል	1	2	3	4	5	6	7
HT4	ሞባይል ባንክ መጠቀም ከውስጤ ጋር ተዋህዷል	1	2	3	4	5	6	7
ባህሪያዊ ዝንባሌዎች (**Behavioral Intention**)								
BI1	ወደፊት ሞባይል ባንክን መጠቀሜን እቀጥላለሁኝ	1	2	3	4	5	6	7
BI2	ወደፊት ለዘወትር እንቅስቃሴዬ ሁልጊዜ ሞባይል ባንክን ለመጠቀም እሞክራለው	1	2	3	4	5	6	7
BI3	ሞባይል ባንክን በተደጋጋሚ መጠቀሜን ለመቀጠል ዕቅድ አለኝ	1	2	3	4	5	6	7

የመጠቀም ስርፀት **(E-banking adoption/ USE)** ከዚህ በታች ያሉትን የሞባይል ባንክ አገልግሎቶች በምን ያህል ድግግሞሽ እንደሚጠቀሙ በስተቀኝ ካሉት ከ 1- 7 ከተፃፈባቸው ሳጥኖች ውስጥ በ አንዱ ላይ ብቻ የ(✓) ምልክት በማድረግ ምርጫዎትን ያሳዩ	**ተጠቅሜ አላውቅም ≈ 0%**	**ከስንት አንዴ ≈ 10%**	**በጣም አልፎ አልፎ ≈ 30%**	**አንድ አንዴ ≈ 50%**	**በተደጋጋሚ ≈ 70%**	**ዘወትር ≈ 90%**	**ሁሌ ጊዜ ≈ 100%**
ሀ) ቀሪ ሂሳብዎን ማወቅ	1	2	3	4	5	6	7
ለ) የሂሳብ አጭር መግለጫ መጠየቅ	1	2	3	4	5	6	7
ሐ) የውጭ ምንዛሪ ለውጥ መረጃ መጠየቅ	1	2	3	4	5	6	7
መ) ወደ ሌላ የራስ ሂሳብ ቁጥር ገንዘብ ማስተላለፍ	1	2	3	4	5	6	7
ሰ) ወደ ሌላ ሰው የሂሳብ ቁጥር ገንዘብ ማስተላለፍ	1	2	3	4	5	6	7
ረ) የሂሳብ ቁጥር ወደሌለው ግለሰብ ገንዘብ ማስተላለፍ	1	2	3	4	5	6	7
ሽ) የተለያዩ ክፍያዎችን መፈፀም (የባስ ቲኬት፤የአየር ቲኬት፤ ፊልም… ወዘተ)	1	2	3	4	5	6	7
ቀ) የሞባይል የአየር ሰዓት (የሞባይል ካርድ) ለመግዛት	1	2	3	4	5	6	7

ክፍል 4፡ ኢንተርኔት ባንክን በተመለከተ የተዘጋጀ የንድፈ ሀሳብ መለኪያ

በዚህ ክፍል ኢንተርኔት ባንክን በተመለከተ በደንበኞች ባህሪ ላይ ተፅዕኖ ሊፈጥሩ የሚችሉ መንስኤዎች ተዘርዝረዋል፡፡ እርስዎም ለ እያንዳነዱ ሃሳብ በምን ያህል ደረጃ እንደሚስማሙ በስተቀኝ ካሉት ከ 1- 7 ከተፃፈባቸው ሳጥኖች ውስጥ በ አንዱ ላይ ብቻ **የ (✓)** ምልክት በማድረግ ምላሽ ይስጡ፡፡

የስምምነት ደረጃዎች፡

(1)=በፍፁም አልስማማም (2)=አልስማማም (3)=በትንሹ አልስማማም

(4)=ለመወሰን እቸገራለሁ (5)=በትንሹ እስማማለሁ (6)=እስማማለሁ (7)=በጣም እስማማለሁ

መለያ	**የንድፈ ሃሳበ መለኪዎች**	በፍፁም አልስማማም	አልስማማም	በትንሹ አልስማማም	ለመወሰን እቸገራለሁ	በትንሹ እስማማለሁ	እስማማለሁ	በጣም እስማማለሁ
በውጤታምነት ረገድ (**Performance Expectancy**)								
PE1	የኢንተርኔት ባንክ በዕለት ተዕለት እንቅስቃሴ ጠቃሚ ሆኖ አግኝቼዋለው	1	2	3	4	5	6	7
PE2	የኢንተርኔት ባንክን መጠቀሜ ለኔ ጠቃሚ የሆኑ ነገሮችን እንዳሳካ እድል ፈጥሮልኛል	1	2	3	4	5	6	7
PE3	ኢንተርኔት ባንክን መጠቀሜ ነገሮችን በፍጥነት እንዳከናውን ረድቶኛል	1	2	3	4	5	6	7
PE4	ኢንተርኔት ባንክን መጠቀሜ ውጤታማነቴን ጨምሮታል	1	2	3	4	5	6	7
በጥረት ረገድ (**Effort Expectancy**)								
EE1	የኢንተርኔት ባንክ አጠቃቀምን መማር ለኔ ቀላል ነው	1	2	3	4	5	6	7
EE2	የኢንተርኔት ባንክ አጠቃቀም ግልፅ እና መረዳት የሚቻል ነው	1	2	3	4	5	6	7
EE3	የኢንተርኔት ባንክ አጠቃቀም ቀላል ሆኖ አግኝቼዋለው	1	2	3	4	5	6	7
EE4	የኢንተርኔት ባንክ አጠቃቀም የላቀ ክህሎት እንዲኖረኝ ማድረግ ለኔ ቀላል ነው	1	2	3	4	5	6	7
የማህበረሰብ ተፅዕኖ (**Social Influence**)								
SI1	ለኔ ጠቃሚ የምላቸው ግለሰቦች ኢንተርኔት ባንክን መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
SI2	ባህሪዬ ላይ ተፅዕኖ የሚያደርጉ ግለሰቦች ኢንተርኔት ባንክን መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
SI3	አስተሳሰባቸውን የማከብራቸው ግለሰቦች ኢንተርኔት ባንክን መጠቀም እንዳለብኝ ያስባሉ	1	2	3	4	5	6	7
ምቹ ሁኔታዎች (**Facilitating Conditions**)								
FC1	ኢንተርኔት ባንክን ለመጠቀም የሚያስፈልጉ ነገሮች አሉኝ	1	2	3	4	5	6	7
FC2	ኢንተርኔት ባንክን ለመጠቀም የሚያስፈልግ እውቀት አለኝ	1	2	3	4	5	6	7
FC3	ኢንተርኔት ባንክን ስጠቀም ለሚያጋጥሙኝ ችግሮች ከባንኩ በቂ ድጋፍ አገኛለው	1	2	3	4	5	6	7
FC4	ኢንተርኔት ባንክን መጠቀም በሚያስቸግረኝ ጊዜ ከሌሎች ሰዎች እርዳታን ማግኘት እችላለው	1	2	3	4	5	6	7
አስደሳች ማነሳሻዎች (**Hedonic Motivation**)								
HM1	ኢንተርኔት ባንክን መጠቀም አስደሳች ነው	1	2	3	4	5	6	7
HM2	ኢንተርኔት ባንክን መጠቀም ማራኪ ነው	1	2	3	4	5	6	7
HM3	ኢንተርኔት ባንክን መጠቀም የሚያዝናና ነው	1	2	3	4	5	6	7

የዋጋ እሴት (Price Value)								
PV1	የኢንተርኔት ባንክ አገልግሎት ክፍያ ተመጣጣኝ ነው	1	2	3	4	5	6	7
PV2	ለኢንተርኔት ባንክ የሚከፈለው ገንዘብ፣ ለሚሰጠው እሴት/ዋጋ ይመጥነዋል	1	2	3	4	5	6	7
PV3	አሁን ባለው ክፍያ፣ ኢንተርኔት ባንክ ተመጣጣኝ እሴት አለው	1	2	3	4	5	6	7
ልማድ (Habit)								
HT1	ኢንተርኔት ባንክን መጠቀም ልማድ ሆኖብኛል	1	2	3	4	5	6	7
HT2	ኢንተርኔት ባንክን መጠቀም ሱስ ሆኖብኛል	1	2	3	4	5	6	7
HT3	ኢንተርኔት ባንክን ለዕለት ተዕለት እንቅስቃሴዬ መጠቀም ግድ ሆኖብኛል	1	2	3	4	5	6	7
HT4	ኢንተርኔት ባንክን መጠቀም ከውስጤ ጋር ተዋህዷል	1	2	3	4	5	6	7
ባህሪያዊ ዝንባሌዎች (Behavioral Intention)								
BI1	ወደፊት ኢንተርኔት ባንክን መጠቀሜን እቀጥላለሁኝ	1	2	3	4	5	6	7
BI2	ወደፊት ለዘወትር እንቅስቃሴዬ ሁልጊዜ ኢንተርኔት ባንክን ለመጠቀም እሞክራለው	1	2	3	4	5	6	7
BI3	ኢንተርኔት ባንክን በተደጋጋሚ መጠቀሜን ለመቀጠል ዕቅድ አለኝ	1	2	3	4	5	6	7

የመጠቀም ስርፀት **(E-banking adoption/ USE)** ከዚህ በታች ያሉትን የኢንተርኔት ባንክ አገልግሎቶች በምን ያህል ድግግሞሽ እንደሚጠቀሙ በስተቀኝ ካሉት ከ 1- 7 ከተፃፈባቸው ሳጥኖች ውስጥ በ አንዱ ላይ ብቻ የ(✓) ምልክት በማድረግ ምርጫዎትን ያሳዩ	**ተጠቅሜ አላውቅም ≈ 0%**	**ከስንት አንዴ ≈ 10%**	**በጣም አልፎ አልፎ ≈ 30%**	**አንድ አንዴ ≈ 50%**	**በተደጋጋሚ ≈ 70%**	**ዘወትር ≈ 90%**	**ሁል ጊዜ ≈ 100%**
ሀ) ቀሪ ሂሳብዎን ማወቅ	1	2	3	4	5	6	7
ለ) የሂሳብ መግለጫ መጠየቅ	1	2	3	4	5	6	7
ሐ) የውጭ ምንዛሪ ለውጥ መረጃ መጠየቅ	1	2	3	4	5	6	7
መ) ወደ ሌላ የራስ ሂሳብ ቁጥር ገንዘብ ማስተላለፍ	1	2	3	4	5	6	7
ሰ) ወደ ሌላ ሰው የሂሳብ ቁጥር ገንዘብ ማስተላለፍ	1	2	3	4	5	6	7
ረ) የሂሳብ ቁጥር ወደሌለው ግለሰብ ገንዘብ ማስተላለፍ	1	2	3	4	5	6	7
ሸ) የተለያዩ ክፍያዎችን መፈፀም (የባስ ቲኬት፤የአየር ቲኬት፤ ፊልም… ወዘተ)	1	2	3	4	5	6	7
ቀ) የተለያዩ አገልግሎቶችንመጠየቅ (ቼክ፤ካርድ… ማስቆም፤ ማስጀመር... ወዘተ)	1	2	3	4	5	6	7

ለትብብርዎ በድጋሚ ከልብ አመሰግናለው!

Appendix v. Birds view for survey areas

Note: *Pictures are taken during travels to survey areas by the researcher from close distance during landing and some pictures might not show the downtowns.*

Participant Banks Logo

Dashen Bank

Wegagen Bank

Zemen BANK