ADDIS ABABA UNIVERSITY
SCHOOL OF BUSINESS AND ECONOMICS

DETERMINANTS OF USER-LEVEL FINTECH SERVICES ADOPTION: A CASE OF CUSTOMERS OF SUPERMARKETS IN ADDIS ABABA

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION

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JANUARY,2024

ADDIS ABABA, ETHIOPIA

DECLARATION

I, the undersigned, declare that this thesis project entitled "Determinants of User-Level FinTech Services Adoption: A Case of Customers of Supermarkets in Addis Ababa" is my original work and has been done under the guidance and advice of Mesfin Fikre (PhD), Assistant Professor of Information Systems (Institute of Development Policy and Research, College of Business & Economics). All the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

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Statement of Certification

This is to certify that the thesis work entitled "Determinants of User-Level FinTech Services Adoption: A Case of Customers of Supermarkets in Addis Ababa" under taken by Zerihun Guyassa for the partial fulfillment of degree of Masters of Business Administration at Addis Ababa University, to the best of my knowledge, is an original work and not submitted for any degree at this university or in any other university.

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This is to certify that this thesis prepared by Zerihun Guyassa, entitled "Determinants of User-Level FinTech Services Adoption: A Case of Customers of Supermarkets in Addis Ababa", is submitted in partial fulfillment for the requirement for the degree of Master of Business Administration, complies with the regulation of the university and meets the accepted standards with respect to originality and quality.

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ACKNOWLEDGEMENT

First, I would like to thank the Lord Almighty for the help He renders me in all my efforts including this thesis project. Next to that, I would like to thank my advisor, Mesfin Fikre (PhD), who first introduced me to the Structural Equation Modeling techniques and later helped me in all the journey of doing this thesis project. Thirdly, I would like to thank my family who has been by my side in all the efforts I make in life. Fourthly, I would like to thank my good friend, Wubshet Gebrewold, who helped me with challenges I faced while using the data analyzing software. Last but not least, I would like to thank Management of Shoa Supermarket, Bisrate Gabriel Branch, and each and every person who took out of their valuable time and responded to my questionnaires. Thank you All and God Bless you All!

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Acronyms

FinTech	Financial Technology
TAM	Technology Adoption Model
DoI	Diffusion of Innovation
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Utilization of Technology
AMOS	Analysis of Moment Structures
ATM	Automatic Teller Machine
POS	Point of Sale
ETAM	Extended Technology Acceptance Model (Also known as TAM2)
MM	Motivational Model
SEM	Structural Equation Modeling
CFA	Confirmatory Factory Analysis
AVE	Average Variance Extracted
CR	Composite Reliability
GOF	Goodness of Fit
RMSEA	Root Mean Square Error of Approximation
NFI	Normed Fit Index

Abstract

FinTech (a portmanteau of the words "financial" and "technology") is nowadays everywhere and has become an integral part of our daily lives. In other words, instead of being an exception and a luxury it has become an essential tool for our lives be it at individual level or organizational level. Though by understanding that fact both private companies (such as banks, telecom companies, and FinTech companies) and government have invested hugely in FinTech infrastructures, we witness a very low adoption of the use of the technology in our country even by Sub-Saharan countries standards. Therefore, this study tries to identify the parameters that affect FinTech adoption by using the customers of Shoa Supermarkets and Hypermarket located in different parts of Addis Ababa and suggests what should be done by each of the stakeholders of the FinTech eco-system to improve the existing low adoption rate. The study applied behavior-related theories such as Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB) and technology-related theories such as the Technology Adoption Model (TAM) and Unified Technology Adoption and Use II (UTAUT2) to identify those determining factors. After an extensive literature reviews the most relevant and major independent variables i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risks have been identified based on the UTAUT2 model along with their indicators and questions. As far as the modeling of variables is concerned, the Structural Equation Modeling (SEM) software SPSS AMOS 23 has been utilized to model the latent variables and carry out the analysis. The research findings indicated that while performance expectancy, effort expectancy, facilitating conditions, have a significant and positive effect on FinTech services and products adoption, perceived risk associated with the use of the technology has significant, but negative effect on its adoption. The research also revealed that the social influence has an insignificant, but positive effect on the adoption of FinTech services and products. Accordingly, the researcher recommends each stakeholder of the FinTech eco-system, be it private or governmental, should play its role in order to improve the adoption rate and hence exploit the benefits obtained from the technology and further studies be carried out in relation to the wider population and additional determinants.

Key words: FinTech, Technology adoption, TRA, TPB, TAM, UTAUT2, SEM

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Financial technology (FinTech) is nowadays a buzzword in the technology and finance sectors. According to the definition provided by Forbes Business Magazine, FinTech is a portmanteau word formed from the words "Financial" and "Technology". It is the use of Internet-based and mobile-based, and cloud-based digital technologies in the financial services industry, which results in new business models, applications, processes, or products in the industry (Kim et al., 2015; Liu et al., 2020; Milian et al., 2019). FinTech combines innovative business models and technology to enable, enhance and disrupt financial services thereby reducing the cost of financial transactions, meeting the financial needs of the unbanked and under-banked community, and increasing flexibility and security of financial services.

Technology adoption is generally the purchase and use of technology and services that are offered by providers (Davis, 1989; Rogers, 2003; Straub, 2009; Wu and Wang, 2015). With the backing of extensively developing technologies like artificial intelligence (AI), Blockchain, smart contracts, and machine learning, among others, the key technology services and products are here to stay. It is evident that there is a technological revolution taking place in the financial services sector, and this may be supported by looking for parallels from other previously disrupted industries, such as the music and mobile phone industries (Riemer & Johnston, 2019).

Despite having its roots in the world's largest financial centers, including New York, London, Hong Kong, and Singapore, FinTech services have experienced rapid global adoption in recent years (Buckley and Webster, 2016). In the nations where surveys were conducted in 2015, just about 15% of customers had embraced technology (Gulamhuseinwala et al., 2015; EY, 2019). Nonetheless, adoption in these nations increased to 64% in 2019 (EY, 2019), demonstrating the exceptional promise of these services.

The study by Ethiopian Policy Institute (PSI) revealed that Ethiopia has a low number of ATMs, with only 5.29 ATMs per 100,000 people in 2021, compared to the Sub-Saharan Africa average of 6.94. Furthermore, in Kenya, mobile money transactions reached US$109.9 billion in 2022, while in Ethiopia, it was only 470 million. Similarly, the amount of agent transactions in Kenya reached USD 14.8 billion in 2020, while in Ethiopia, it was about 445 million. The percentage of agent outlets in Ethiopia was about 25% compared to Kenya (Digital Finance in Ethiopia: Interbank Competition, Financial Inclusion, and Constraints", 2024).

With the introduction of NBE's new directives, "Licensing and Authorization of Payment Instrument Issuers Directive No. ONPS/01/2020" and "Licensing and Authorization of Payment system Operators Directive (ONPS/02/2020), National Bank of Ethiopia allows non-financial institutions such as technology companies to start offering payment processing and related services in the Ethiopia market by acquiring a payment system operator license. The directive is hoped to drastically reduce the cost of transactions by using fully-fledged technology services and products instead of using the high-cost first-generation technologies such as POSs or ATMs. The enormous potential of POS, aggregators, and ATMs to push digital payments has been impeded by the high cost of doing business and the banks' incapacity to create a revenue-generating business model for the digital channels.

In addition to other challenges such as regulatory and legal ones, the low adoption rate of FinTech services by users in Ethiopia has always been a challenge for FinTech service providers and hampered the population from reaping the benefits of the technology. By collaborating with mobile operators and paving the way for a new method of handling funds, FinTech in Ethiopia, if adopted and properly implemented, will be a turning point in altering the banking and financial sectors. FinTech technologies will make it possible for businesses in developing nations with constrained economic potential to transition to the digital age.

Different research has been done in identifying the factors affecting the adoption of FinTech services both at user-level and organizational-level, resulting in different findings. There is evidence of heterogeneity between and within countries (Ernst & Young 2019a). Even on the macro scale, diverging strands of evidence point to differing levels of impact of variables, e.g., financial literacy (Setiawan et al. 2021). On the individual level, FinTech use, and adoption are influenced by a host of factors (Islam et al. 2017). There are demographic factors (Clements 2020; Imam et al. 2022; Pedrosa and Do 2011), customers' evaluation of satisfaction (Alkhazaleh and Haddad 2021; Alwi et al. 2019; Barbu et al. 2021), security risk perception, perceived ease and usefulness (Al-Okaily et al. 2021; Poerjoto et al. 2021; Wang et al. 2019). Coffie et al. (2020) finds a host of human, business, and technology-centric factors creating the environment for optimal FinTech diffusion among SMEs. Gerlach and Lutz (2021) investigated the relationship concerning demographic variables (e.g., gender, age), economic variables (e.g., disposable income) and attitude variables (e.g., risk tolerance, knowledge regarding financial services). Accordingly, the purpose of this research is to find out systematically and scientifically which of the factors are important in determining the adoption and use of FinTech services in Addis Ababa focusing primarily on effort expectancy (perceived ease of use in TAM), performance expectance (perceived usefulness in TAM), Social Influence, Facilitating Conditions, Trust, and Price Value.

1.2 Statement of the Problem

FinTech is nowadays everywhere and has become an integral part of our daily lives. In other words, instead of being an exception and a luxury it has become an essential tool for our lives be it at individual level or organizational level. Though by understanding that fact both private companies (such as banks, telecom companies, and FinTech companies) and government have invested hugely in FinTech infrastructures, we witness a very low adoption and use of the technology in Ethiopia even by Sub-Saharan countries standards (Global FinTech Adoption Index 2019 – Ernest and Young).

According to the World Bank’s Findex (2021) and Global Findex Database (Demirgüç Kunt et al. 2018), only approximately 34% of adults in Ethiopia have a bank account. In other words, Ethiopian lags behind other Sub-Saharan countries in terms of financial inclusions and services compared to such countries as Kenya and Rwanda. On the other hand, one of the biggest benefits of FinTech is that it can help increase financial inclusion by becoming a financial accelerator in the country. There will be an automatic boost to the national economy as financial inclusion rises. It will contribute to raising the nation's standard of living for its citizens. That is why National Digital Payments Strategy (NDPS) for 2021–2024 The vision for the NDPS is to build a secure, competitive, efficient, innovative, and responsible payment ecosystem to support a cash-lite and financially inclusive economy.

FinTech also creates a more level playing field for retail investors to participate in the market by reducing information asymmetry in the marketplace, which enhances the capacity to connect investors, lenders, and borrowers. FinTech intermediaries contribute to the market's increased liquidity. This involves using technology to simplify processes, reduce operational costs and improve service equality (Saksonova, 2017).

Thirdly, the existence of FinTech will make a variety of financial services quicker and simpler. One advantage of FinTech for customers is the speed with which financial transactions, including payments, may be completed. The existence of Fintech has introduced various platforms and applications that enable individuals and companies to access, transact and manage their finances more quickly and effectively (Jarvi, 2021).

Fourthly, thanks to FinTech, the options for getting a loan will be more diverse, lower interest rates, more flexible, and effective and efficient. It provides lower fees compared to other types of conventional financial services thereby having a positive benefit for business companies as well as consumers. The flexibility in using financial services can be expressed as not necessarily going to the financial institutions in person and enabling consumers use the financial services and products 24/7. This therefore implies that people can engage in financial activity without limitations, at any time, and from any location. This gives every society the flexibility it needs to engage in particular financial activities.

FinTech, being one of those technologies, not only provides the above-mentioned benefits, but also become critical for societies such as ours who are highly under banked. In countries where the banking system is inefficient and almost without competition in some respects, FinTech enters and serves as a mediator between the banking system and societies. Financial inclusivity represents a commitment to providing access to financial services to all levels of society, regardless of income level, geographic location, or social status (Qi,2023). Traditional banks often do not pay attention to certain segments of the population, such as those living in remote areas, low income groups, or those without a strong credit history. Financial inclusivity aims to overcome this disparity (Jarvis,2021).

According to one of the technology ranking organizations, i.e., Findexable.com only six countries from Africa namely, South Africa, Kenya, Nigeria, Egypt, Ghana and Uganda have been included in the 2020 World technology rankings. In other words, the rest of African countries (including Ethiopia) are not even to be considered seriously when it comes to their achievements in technology so far. Hence this project tries to investigate the reasons behind this low ranking and tries to suggest ways to improve in the futures.

Fifthly, there are few theses (research) produced regarding technology adoption in general and FinTech adoption in particular in Ethiopia. Therefore, this research intends to fill that gap by investigating the technology adoption determinants at user level. It does so by reviewing theories for adoption models at the firm level used in information systems literature and discussing prominent models that are applicable to firm-level technology adoption.

Currently only limited businesses such as supermarkets, cafes and fuel stations are witnessed to adopt technology services in Addis Ababa. Hence, the low adoption rate of technology services by businesses in Ethiopia (Addis Ababa) means they are losing all the benefits of technology as well as their customers. It means paying more for a given financial service which make them less profitable and less competitive nationally or internationally. It means they are missing the opportunities that technology services would have brought to them such as raising capital by P2P to expand their business or a real-time accounting system. It can also mean loss of sales due to inconvenient or unavailable digital payment system to carry out an e-commerce.

Accordingly, this research tries to investigate the determinants or metrics that are prohibiting people in Addis Ababa from adopting FinTech services faster or keeping them from adopting all together. By doing so, not only the research intends to increase the adoption rate by the inhabitants, but it will also result in the efficient utilization of public resources invested in the technology-service-providing companies such as government and privates banks, Eth-Switch, Ethio-Telecom and other private technology companies. There are a lot of investments made by government and private sectors to help the public use this technology. But as we know that is not happening because of the low FinTech adoption rates and hence this research will try to find out what those determinants are for FinTech adoption and by working on that it will aim to tap into the result so that to make use of the public and private investments.

1.3 Research Questions

In view of the problem statement, the central research questions of this research project include:

What is the effect of performance expectancy on adoption of FinTech services by customers of selected supermarkets in Addis Ababa?

What is the effect of effort expectancy on adoption of FinTech services by customers of selected supermarkets in Addis Ababa?

What is the effect of social influence on adoption of FinTech services by customers of selected supermarkets in Addis Ababa?

What is the effect of facilitating conditions on adoption of FinTech services by customers of selected supermarkets in Addis Ababa?

How perceived risk affects FinTech adoption of customers of selected supermarkets in Addis Ababa?

1.4 Objectives of the Study

The following general and specific objectives have been identified for the study

1.4.1 General Objective

The general objective of this research shall be investigating which determinants or metrics are responsible for adopting and utilizing FinTech by customers of selected supermarkets in Addis Ababa.

1.4.2 Specific Objectives

To examine the effect of performance expectancy on adoption of FinTech by customers of selected supermarkets in Addis Ababa;

To determine effect of effort expectancy on adoption of FinTech services by customers of selected supermarkets in Addis Ababa;

To examine effect of facilitating conditions on FinTech adoption of customers of selected supermarkets in Addis Ababa;

To assess effect of social influence on FinTech adoption of customers of selected supermarkets in Addis Ababa; and

To evaluate the effect of perceived risk on adoption of FinTech by customers of selected supermarkets in Addis Ababa.

1.5 Significance of the Study

The result of the study can serve as an input for the stakeholders in the FinTech technology eco-system in general and FinTech service providers and users (customers) in particular. Firstly, it will help the customers to increase their adoption rate and by doing so exploit all the benefits that come along with that. Secondly, the result can help the policy makers and decision makers in government to formulate and implement regulations, policies and strategies that are suitable to boost FinTech services and products. That may not be limited to only the already-mature technology services such as payments and money transfers, but also include the future technology services such as Blockchain technology, remittance products, crowdfunding products and services, e-KYC (electronic know your customer) platforms, RegTech (regulatory technology), SupTech (supervisory technology) and digital banking. The recent Bank of Ghana technology sandbox to boost technology launch is a good example.

Thirdly, technology companies (both financial and non-financial) can be beneficiary of the study. By knowing those determinants that are crucial for customers to adopt the FinTech services and products, they can come up with the best solutions by using the factors as inputs.

The study will also be important for companies that are currently providing FinTech services and products and for companies that have plan to launch the service. Accordingly, this study will be important for Ethiotelecom and Commercial Banks in Ethiopia that provide the online banking services such as agent banks and mobile banking. Moreover, the study will be important for microfinances that provide the FinTech services. The study will provide information about customer focus to use the services. Furthermore, the study will be important for current empirical gap in adoption of FinTech and will be input for further studies in the area.

1.6 Scope of the Study

This study will have spatial (geographic) and technological delimitations. Geographically, this study will be scoped to Addis Ababa and will include customers of Shoa Supermarket, which is the largest supermarket in Addis Ababa, and it will include customers of different branches of the supermarket. There are different FinTech services provided in Ethiopia by banks, microfinances and Ethiotelecom. Hence, this study will include FinTech services by commercial banks, agent banking services and Telebirr. Although different studies have adopted different models to analyze determinants of FinTech adoption, because of its relevance, this study will adopt extended UTAUT model (UTAUT2). Hence, conceptually, this study mainly focuses on performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived risks.

In terms of the technology services scope is concerned, it only focuses on the most common type of technology services including payment, lending/borrowing, real-time accounting, and e-commerce. In other words, it does not deal with the emerging technology services related to such areas as insurtech, smart contract, Blockchaine, cryptocurrence, stock trading apps, big data, etc.

1.7 Limitations of the Study

As the FinTech service itself is very new it is difficult to find ample research papers on the fields that focus on societies in developing countries such as Ethiopia. Most technology research are often focused on societies in the developed world and there is opacity of research papers on societies of the developing countries. The other limitation is also related to the fact that the technology industry is relatively very new in developing countries such as Ethiopia and one cannot find ample research papers to refer to.

The other limitation arises from the type of data collected (financial) and the overall low tech-savviness of the population. Accordingly, the primary data sources were witnessed being reluctant and suspicious of providing the information required to be gathered. However, that challenge was overcome most of the time by explaining the purpose and importance of the research coupled with enormous assistance by the supermarket's management and staff in encouraging shoppers to cooperate in filling the questionnaire.

1.8 Operational Definitions

Performance expectancy (Perceived usefulness) can be defined as the degree to which a person believes that utilizing new technology would enable them to do a task more successfully (Venkatesh et al., 2003).

Effort expectancy (Perceived ease of use) can be described as the level to which an individual perceives the new technology will be easy to use (Venkatesh et al., 2003).

Social influence (SI), when it comes to new technology, social influence can be defined as an individual's perception of the technology's importance based on the beliefs of others (Venkatesh et al., 2003).

Facilitating conditions is defined as "the degree to which an individual believes that an organisation's and technical infrastructure exist to support the use of the system" (Venkatesh et al., 2003).

Perceived Risk The probability of negative effects, such as loss of passwords, wrong transactions, etc., to happen during the use of FinTech services. The use of a particular technology is closely correlated with people's perceptions of risk related to that technology (Laforet and Li, 2005).

User-level Technology Adoption refers to the rate at which users are accepting and using the new technology. Understanding user adoption is critical because it can help identify any issues or barriers that may be preventing users from fully embracing the technology.

Firm-level Technology Adoption

Firm-level technology adoption is a type of technology adoption concept that treats a firm or firms as its unit of analysis.

FinTech or Financial Technology

Any technology that uses software to provide financial services, such internet banking, mobile payment apps, or even cryptocurrency, is referred to as FinTech. Although there are numerous diverse technologies under the broad category of "technology," the main goals are to challenge existing financial services and alter how businesses and consumers access their finances (US Chamber of Commerce, 2021).

Types of Technology

There are many different types of FinTech technology, but some of the most popular areas are:

Digital Wallets (Mobile Wallets)

Applications and services known as digital wallets let users conduct transactions, store, and transfer money. To access a credit card that is digitally saved, one would open the digital wallet software, just like they would open a real wallet to pay for things. These are among the most prevalent kinds of technology businesses in Ethiopia, some notable examples are Telebirr, Amole, Awash Birr, and E-Birr.

Payment gateway API

Payment gateways are the intermediary between merchants and their clients or customers. The gateways encrypt the cardholder data and approve the customer's payment. Subsequently, it verifies the payment with the issuing bank and funds the merchant's account. They are usually called third-party payment processors as they only secure and facilitate the transactions between the business firm and its customers and do not deal with money as banks do.

Blockchain and cryptocurrency technologies are two of the most well-known and closely examined technological examples. Coinbase and Gemini are two cryptocurrency exchanges where consumers may purchase and sell bitcoins. In order to lower fraud, blockchain technology may potentially be applied to non-financial industries.

Robo-advisors consist of algorithm-based portfolio recommendations and management to lower costs and increase efficiency. Some popular robo-advising services include Betterment and Ellevest.

Stock trading apps, such as Robinhood and Acorns, have become a popular and innovative example of technology as investors can trade stocks from anywhere with their mobile device instead of visiting a stockbroker.

Insurtech companies have disrupted many different types of insurance, such as car and home insurance. Companies like Oscar Health and Credit Karma are examples of insurtech companies that have entered the healthcare and personal finance industry.

Intention to use a technology is a behavioral intention is the measure of the likelihood of a person employing the application.

1.9 Organization of the Paper

The arrangement of a research work establishes lines of discussion to demonstrate the coherence and central linkages of the chapters and is referred to as a conjunction to clarify the specifics of a thesis workflow, according to Evans, Gruba, and Zobel (2011). The aim of the study's organization is to provide a quick overview of how each chapter is designed to accomplish the research goals, as stated by Evereklioglu (2014) and Golding (2017). Stated differently, the research's arrangement typically serves as a roadmap or blueprint outlining the primary points of support the author employed for the study context, as well as a summary of what readers may expect to read throughout the thesis. Accordingly, this thesis is organized into five chapters and the details of each chapter are presented as follows.

Chapter One: This chapter serves as an overview for readers, outlining what to expect to read throughout the thesis work and providing a map of the study's background, problem statement, general and specific objectives, significance, scope, and limitations. It also includes operational definitions of terms.

Chapter Two: This chapter gives a thorough explanation of the analysis of relevant theoretical literature and real data from various contexts. This chapter provided a thorough presentation of the reviewed literature on technology adoption in this area. The article addresses many behavioral and technological adoption ideas.

Chapter Three: This chapter covers the research methodology that was used, including the kind of research method selected and the reasoning behind it, the sampling strategy used, the kind of data analysis tool, and any ethical issues related to the procedures.

Chapter Four: The outcomes of the quantitative and qualitative data analysis are shown here, together with discussions of the research findings, critical evaluations, and triangulations of the data. It also demonstrates the steps and methods taken during the research process to evaluate scientific data and come up with sensible answers to the original research questions based on the information that was acquired.

Chapter Five: This chapter summarizes the main conclusions from Chapter Four, offers recommendations for further research, and identifies areas that should be studied in the future in relation to FinTech adoption.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Theoretical Review

Generally, there are two groups of theories are applied to explain and predict the information technology adoption by individuals as well as firms or organizations. The first group of theories are those theories that analyze information technology adoption at individual level, i.e., factors that determine the reasons behind why an individual adopts a certain kind of information technology. They include such theories as TAM, UTAUT, TPB/TRA, etc. The second group of theories are those which are used to explain and predict the adoption of information technology at a firm level or organization level, and they include TOE, DOI and Technology Readiness Index (TRI). Each of them will be discussed in detail in the following sections of this paper.

2.1.1 Technology Acceptance Model (TAM)

Technology Acceptance Model, developed by Davis (1989), is one of the most influential research models used in studies of the determinants of information systems acceptance and adoption both by organizations and individuals. Technology Acceptance Model has received considerable attention of researchers in the information system field over the past decade to the point that it has been cited “too much”. According to Davis's (1989) technology acceptance model, a computer system's potential users will either accept it or not based on two factors: (1) perceived usefulness and (2) perceived ease of use. This model's primary characteristic is its focus on the opinions of possible users. In other words, even if a technological product's developer thinks it's helpful and easy to use, potential users won't embrace it until they also think that way.

Perceived utility or usefulness and ease of use are the two factors in the Technology Acceptance Model. The degree to which a person feels that utilizing a specific information system or information technology would improve his or her performance at work or in other areas of life is known as perceived usefulness. The degree to which an individual feels that utilizing a specific information system or information technology would be effortless is known as perceived ease of use. Perceived utility and simplicity of use have a good impact on people's attitudes about information systems, which in turn has a positive impact on people's intents to use and embrace the system. Furthermore, perceived usefulness is positively impacted by perceived ease of use, and perceived usefulness is influenced by perceived ease of use.

Technology Acceptance Model is more appropriate to be applied in online contexts for several reasons, even though Theory of Reasoned Action and Theory of Planned Behavior have the capacity to explore the system usage by incorporating subjective norms and perceived behavioral controls with attitudes toward using technology. Firstly, the Technology Acceptance Model focuses specifically on the application of the notions of usefulness and simplicity of use to information system utilization. Additionally, the Technology Acceptance Model is more frugal. Moreover, the Technology Acceptance Model exhibits greater resilience across a range of information system applications. As previously discussed, customized or particular models are useful because they offer precise instructions for modifying intention or its determinants. Applied researchers would be especially interested in some models (Taylor and Todd, 1995).

2.1.2 Technology Acceptance Model (TAM) Limitations and Criticism

Technology Acceptance Model (TAM) is derived from Theory of Reasoned Action (TRA) and predicts user acceptance based on the influence of two factors: perceived usefulness and perceived ease of use (Davies, 89). In other words, it assumes that the behavior of individuals is always rational or reasoned. But as we know in real life the behavior of individuals is sometimes irrational and that fact becomes one of the limitations upon which the TAM was founded. Due of its simplicity, the Technology Acceptance Model (TAM) has been cited by numerous scholars without considering real-world applications in their study. Various considerations need to be considered in order to apply a theoretical framework and researchers need to be acutely aware of the multiple limitations, which are inherent in endeavoring to do so.

The second shortcoming of the TAM relates to the user behavior variable, which is invariably assessed using subjective metrics like behavioral intention (BI) and interpersonal influence. However, interpersonal influence—which is defined as the subjective norm—means that an individual is impacted by the comments of a friend or coworker. While a superior can exert influence on a subordinate by instructing them to use technology to accomplish a certain task in accordance with their IT policy, a buddy cannot directly influence staff members who report to a line manager.

Another drawback is that the foundations of behavior are difficult to accurately measure in an empirical study due to a variety of subjective elements, including societal standards and values, individual characteristics, and personality traits. Therefore, the claim (Ang, Ramayah & Amin, 2015; Shan and King, 2015) that friends or relatives could exert intense social pressure to affect a person's usage of technology is highly falsifiable. While this may be true in theory or for individual tech use, it might not be realistic or believable in a professional setting. Therefore, rather than using behavioral intention to anticipate employees' intents regarding the usage of technology, Maruping, Bala, Ventakesh, and Brown (2006) suggested using behavioral expectations.

The well recognized Technology Acceptance Model (TAM) has shown to be useful in determining consumers' propensity to use information and communication technology (ICT). According to the idea, individual attitudes are determined by perceived ease of use (PEOU) and perceived usefulness (PU), and usage is influenced by behavioral intention (BI). Additionally, attitude is a deciding element of BI. Comprehending the application and adjustments made to the Technology Acceptance Model (TAM) is essential, since user confidence and acceptance are critical to the advancement and effective deployment of any new technology. A plethora of frameworks and models have been developed to characterize how users embrace contemporary advances. These models included elements that support user acceptability. This analysis addresses the application, adjustments, constraints, and objections to the Technology Acceptance Model (TAM). The approach has been applied in order to quantify the acceptance and usage of new technology. The body of research suggests that adding or removing variables, as well as occasionally including moderators or mediators, was the primary method of model modification. Literature-identified shortcomings of the concept include the challenge of accurately quantifying behavior in an observed study. Notably, there are also criticisms found in the literature, such as TAM's failure to recognize other factors, like cost and institutional imperatives that force users to adopt an innovation. This review study aims to provide an overview of the Technology Acceptance Model (TAM) and its applications, revisions, limits, and criticisms. The methodology has been applied to measure the uptake and usage of many new technologies. According to the research, adding or removing variables and, occasionally, moderators or mediators were the main ways that the model was modified. The model includes shortcomings that have been noted in the literature, such as the difficulty of accurately measuring behavior in an observational study. Furthermore, certain significant objections have been noted in the literature, such as TAM's failure to recognize additional issues, such as cost and institutional imperatives that force consumers to adopt an invention. TAM will continue to be accepted and modified according to the successful application of any new technology. This study can be used to enhance users' knowledge of usage, modifications, limitations, and criticisms of Technology Acceptance Model (TAM).

2.1.3 Extended Technology Acceptance Model (ETAM or TAM2)

TAM2, an extension of the TAM, was created by Venkatesh and Davis (2000) in response to the TAM's limitations with regard to explanatory power (R2). The TAM2 sought to maintain the original TAM constructs while incorporating additional significant variables that assessed the TAM's perceived utility and desire to be used. Furthermore, the study sought to understand how these variables' effects changed as users' familiarity with the target system grew (Venkatesh & Davis, 2000, p.187). Venkatesh and Bala (2008) incorporated the determinants of TAM's perceived ease of use and use intention constructs for robustness in TAM3, whereas TAM2 only focused on the drivers of TAM's perceived usefulness and usage intention components. Consequently, TAM3 provided a comprehensive nomological network of the factors influencing users' adoption of information technology systems (Venkatesh and Bala, 2008).

According to TAM2, people should depend on how well their work and the system's performance outputs match. This will establish their opinion of the system's value based on the work relevance. It was described as a person's assessment of how applicable the target system is to their line of work. The quality of the final product that the system produces for each individual is known as output quality. A person will take into account how well the system completes certain tasks. The system is assumed to assume that the user acceptance rate will decrease in the absence of any suitable output to improve individual performance.

2.1.4 TAM3

Rich explanations of the major factors influencing use intention had been given by TAM, TAM2, and data from other studies (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh & Davis, 1996). However, little study has been done on interventions that could be used to speed up the adoption of new technologies (Venkatesh & Speier, 1999). Venkatesh and Bala (Venkatesh & Bala, 2008) combined the antecedents of perceived usefulness and perceived ease of use in a single model and examined the relationship between antecedents and perception variables to exclude cross-over effects, in light of the criticism that TAM offered few practical guidelines to practitioners (Lee, Kozar & Larsen, 2003). One method was to offer a nomological network that gave a thorough explanation of how technology is adopted. In order to provide more clarity to the literature, which had been contradictory about the predictors of the two perception elements, different effects of variables on perceived usefulness and perceived ease of use were theorized (Agarwal & Karahanna, 2000; Venkatesh & Davis, 2000).

Subjective norm, image, job relevance, output quality, and outcome demonstrability are the factors that determine perceived usefulness; these factors did not alter from TAM2 (Venkatesh & Davis, 2000). In 2008, Venkatesh and Bala introduced new variables to the model: computer self-efficacy, perception of external control, anxiety, playfulness, perceived enjoyment, and objective usability. These variables are direct predictors of perceived ease of use. The justification for including these antecedents came from research on how people make decisions. Two sets of anchoring and adjustment elements are represented by the antecedents of perceived ease of use. Adjustment factors enter the picture once people have firsthand experience with information systems, whereas anchoring factors influence how easy something is considered to use initially (Venkatesh, 2000). Computer playfulness, computer anxiety, computer self-efficacy, and impression of outside control are the anchoring elements. Users' perceptions of technology and how to use it are reflected in the first three anchors (Venkatesh & Bala, 2008). Users are classified according to their level of fear or apprehension about using technology (Venkatesh, 2000), their confidence in their own ability to complete a task using the technology (Compeau & Higgins, 1995), and their perception of their access to the organizational and technical resources needed to support system use (Venkatesh et al., 2003). "The degree of cognitive spontaneity in microcomputer interaction" is the definition of computer playfulness (Webster & Martocchio, 1992). It stands for the innate drive that comes with using computers. Subjective satisfaction and objective usefulness are two adjustment elements. They gauge how much users enjoy using information systems and how much work they need to put in to finish certain activities (Venkatesh, 2000). The correlations between a) computer anxiety and perceived ease of use, b) perceived ease of use and perceived usefulness, and c) perceived ease of use and intention to use are additionally affected by three novel moderation effects of experience that TAM3 brings. Although people's impression of perceived ease of use is diminished when they gain firsthand experience and system knowledge, the influence of experience on perceived ease of use was not evaluated during the development of TAM2 (Venkatesh & Davis, 2000).

TAM3 has shown to be reliable. According to Venkatesh and Bala (2008), the model explained roughly 36% of the variation in use and 40% to 53% of the variance in behavioral intention. According to Venkatesh and Davis (2000), the explanatory strength was similar to TAM2, explaining between 37% and 52% of the variation in usage intention. Perceived usefulness and perceived ease of use are the two perception elements, and the formulation of a behavioral model of their antecedents is the main strength of the extension. This offers a comprehensive range of circumstances and situations in which technology adoption is most likely to take place. TAM3 provides a complete list of interventions that have direct implications for decision-making about IT implementation and management by outlining the links between antecedents, perceived ease of use, and perceived usefulness (Venkatesh & Bala, 2008).

2.1.5 Technology Adoption Curve

Sales of the iPhone were not as strong as many had anticipated when the company first began manufacturing them in 2007, accounting for 2.7% of all mobile device sales globally. Comparably, six years after its initial launch as a network exclusive to Harvard students in 2004, Facebook has amassed over one billion users worldwide. Similar to Facebook and the iPhone, most new technologies gain traction gradually rather than suddenly being well-known. Depending on how prepared they are to accept novel goods or services in comparison to the public, five adopter categories or segments are identified by the technology adoption life cycle for potential new technology users. Everett Rogers first presented this concept in 1962 as a component of his diffusion study. Returning to Rogers' research, we observe that even in the face of clear advantages, not everyone will embrace a disruptive notion right away. After years of study, Rogers discovered a few intriguing personality qualities that enable us to categorize the degree to which individuals will embrace an innovation. It appears that we take the following tacks when it comes to inventions.

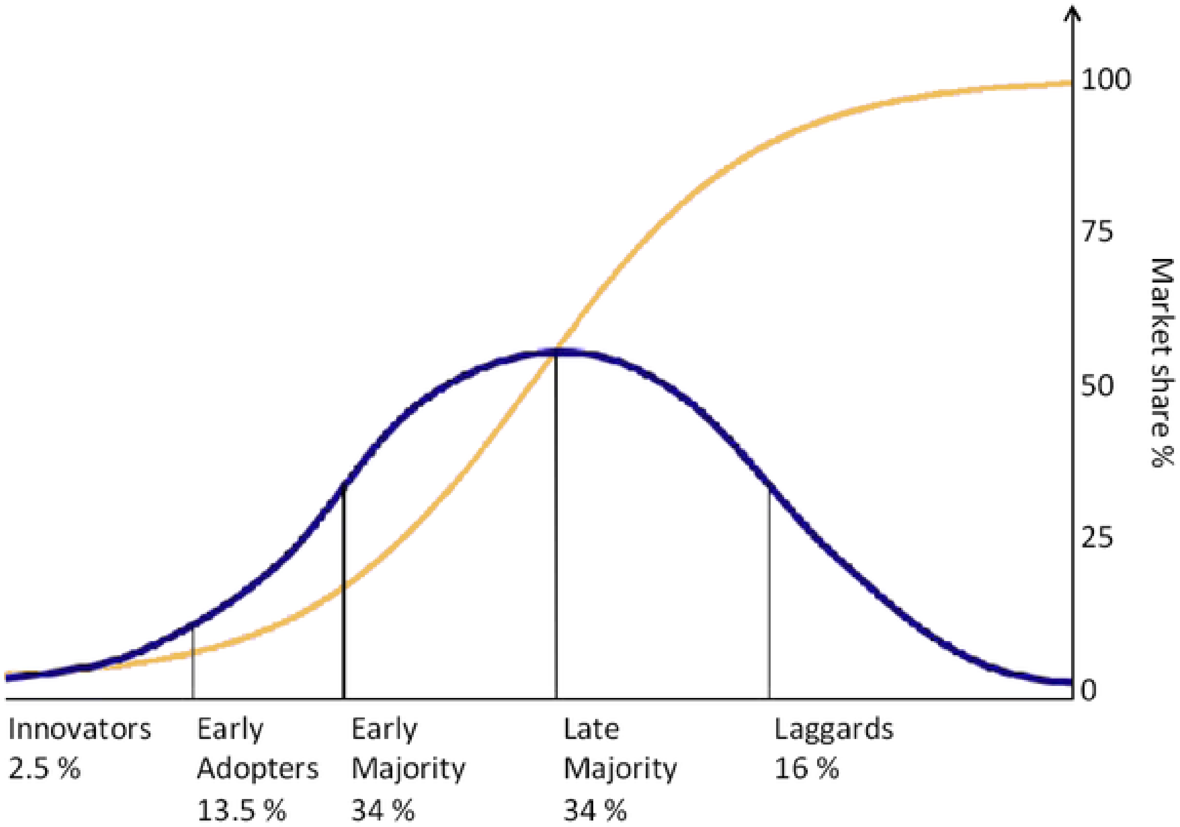
Those that accept innovations first are known as innovators (2.5%). Risk-takers who are also the youngest, most socially elite, highly financially literate, very gregarious, and with the closest access to scientific resources and other innovators are innovators. Their adoption of potentially failing technology is a result of their risk tolerance. These mistakes are lessened by financial resources. (Page 282, Rogers 1962, Fifth Ed.)

Early Adopters (13.5%): This group of people adopts innovations the second fastest. Compared to the other adopter types, these people exhibit the highest level of opinion leadership. Compared to late adopters, early adopters tend to be younger, more socially successful, more financially literate, more well educated, and more forward-thinking in their social interactions. more deliberate than innovators in their adoption decisions. Recognize that making a wise adoption decision will support them in keeping their position as the primary communicator (Rogers 1962, 5th ed., p. 283).

Early Majority (34%): People in this group accept innovations at different rates of time. Compared to innovators and early adopters, this adoption period is noticeably longer. Early Majority members typically communicate with early adopters, have above average social standing, take longer to adopt, and are less likely to occupy positions of opinion leadership within a system (Rogers 1962, 5th ed., p. 283)

Late Majority (34%): Individuals in this category will adopt innovations later than the average community member. These individuals are highly skeptical of advances, frequently only adopting them after the mass of society has done so. The Late Majority typically interacts with both the Early and Late Majorities, has below average social standing, is skeptical of advances, and demonstrates very little opinion leadership. They also have poor financial transparency.

Laggards (16%): Individuals in this category adopt new technology the slowest. Unlike some of the other categories, people in this category show little to no opinion leadership. These folks are typically elderly and hostile toward change agents in general. In general, laggards are more likely to be traditionalists, to be the oldest adopters, to have the lowest social and financial status, to communicate primarily with close friends and family.



Blue curve = Users adopting a new technology

Yellow curve = Market share, which reaches 100% upon complete adoption

Fig. 2.1 Rogers' Technology Adoption Curve

2.1.6 The Unified Theory of Acceptance and Use of technology (UTAUT)

Venkatesh et al. (2003) developed a technology acceptance paradigm called the Unified Theory of Acceptance and Use of Technology (UTAUT), which combines many perspectives on user and innovation adoption. The purpose of UTAUT is to elucidate users' intentions when using an information system and their actual usage patterns. According to the idea, there are four main concepts: enabling conditions, performance expectancy, effort expectancy, and social impact.

According to Venkatesh et al. (2003), the UTAUT posits that four fundamental constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—are the primary drivers of behavioral intention and, eventually, behavior. These constructs are further influenced by factors such as gender, age, experience, and voluntariness of use. The argument posits that through analyzing the existence of these constructs in an authentic setting, scholars and professionals can evaluate an individual's inclination to utilize a particular system, hence facilitating the discovery of the principal factors influencing acceptability within a particular context. These contributing ideas and models have been extensively and effectively utilized in several previous studies on the adoption and dissemination of technology or innovations across a range of disciplines, including information systems, marketing, social psychology, and management (Williams MD et al., 2015). Venkatesh et al. (2003) published the findings of a six-month study involving four firms. It was discovered that between 17 and 53 percent of the diversity in user intentions to use IT could be explained by the eight contributing models. UTAUT was found to outperform the eight individual models, with an adjusted R2 of 69% (Venkatesh et al., 2003).

The UTAUT application demonstrated that two perception criteria—perceived performance and perceived ease of use—were highly correlated with behavioral intention. For instance, the adoption of clinical decision support systems based on pharmacokinetics was examined using the technological acceptance framework. With the exception of facilitating conditions, which only affected the actual use of the technology, all constructs had a significant impact on intention (Chang et al., 2007). All of the UTAUT variables, moderated by gender, had a significant impact on the adoption of e-government by employees in a state organization in a developing country, with performance and effort expectancy showing the strongest effects (Gupta, Dasgupta & Gupta, 2008). The results of applying UTAUT2 demonstrated that behavioral determinants varied in importance and strength between cases. The role of performance expectancy, social influence, hedonic incentive, and habit was validated by using UTAUT2 to study the antecedents of mobile app adoption (Mütterlein, Kunz & Baier, 2019). Nonetheless, the significance of social effect on the adoption of mobile banking was not validated in two more research (Ajzen, 2011; Baptista & Oliveira, 2015). Baptista and Oliveira (2015) found that the most significant observable impacts were related to habit, hedonic motivation, and performance anticipation.

2.1.7 Moderating Variables' Effects in FinTech Services Adoption

Moderating Effect of Age

According to other studies (Chung et al., 2010; Venkatesh et al., 2003; Wang et al., 2003), age is a significant demographic factor that influences technological adoption, acceptance, and behavioral intention both directly and indirectly. The explanatory power of a TAM would be increased by include age as a moderator, according to Chung et al. (2010) and Phang et al. (2006). In contrast to older users, younger users are less impacted by acceptance issues, according to EUROSTAT (2011). According to Venkatesh et al. (2003), age played a significant moderating role in their UTAUT model. They discovered that younger employees had a larger association between performance expectancy (which is comparable to PU) and BI because they place more value on extrinsic rewards, such as perceived usefulness, which encourages them to utilize the new system. However, users who are older will be more impacted by other people's opinions (Sun and Zhang, 2006; Venkatesh et al., 2003). According to Morris et al. (2005), older users who might be less confidence in their abilities to use technology may find simplicity of use to be the most significant factor. H5b: The association between effort expectancy (perceived ease of use) and actual usage is mediated by age.

Moderating Effect of Experience

According to research by Saeed et al. (2008) and Karahanna et al. (1999), users with more experience have a better correlation between relative advantage—which is comparable to usefulness—and post-adoption IS usage. The impact of perceived ease of use on adoption will be mitigated by experience, making the effect smaller as experience increases. According to Venkatesh (2000), perceived ease of use refers to how simple or complex a system is to use. The influence of perceived ease of use on adoption, however, will fade as people become accustomed to the system and gain hands-on experience with it. As a result, when implementing the system, seasoned users will give perceived ease of use less weight. Perceived utility and perceived usability are regarded as low-level and high-level behaviors, respectively. According to their suggestions, users' perceptions of perceived usefulness—a high-level action—will be more strongly influenced by perceived ease of use, a low-level action, as they gain more experience. This is because users will be able to form opinions about their likelihood of achieving high-level goals—that is, perceived usefulness—based on information gleaned from their experiences with low-level actions. For instance, when using word processing software, creating a report of the highest caliber and utilizing a particular function are examples of low-level actions (Davis and Venkatesh, 2004).

The relationship between perceived utility and ease of use is moderated by experience. According to Fishbein and Ajzen (1975), a person's present behavior toward a particular object will be significantly influenced by their favorable prior experiences with it. More IT savvy users will discover that there is less risk involved in implementing the technology, which enhances their view of its value and eventually spurs real use (O'Cass and Fenech, 2003; Brynjolfson and Smith, 2001). Those who have previously made purchases online are more likely to do so because they anticipate greater benefits and have fewer issues with online media, according to a number of authors (Burton et al., 2000; Castaneda et al., 2007; Citrin et al., 2000; Hsu et al., 2007; Liao and Cheung, 2001; Miyazaki and Fernández, 2001). (Dholakia and Uusitalo, 2002). Research has demonstrated that people's prior online experience influences their acceptance of e-commerce (Kwak et al., 2002) and mobile services (Ristola, 2010). This enhances people's actual internet usage (Niemelä-Nyrhinen, 2009). As a result, experience has been viewed in this study as a moderator that reduces the influence of technological influence processes on the actual use of technology, including perceived ubiquity, perceived costs, perceived risks, and perceived benefits.

Moderation by Gender

Other models of technology adoption (such as TAM 2 and TPB) and the gender schema theory (Bem, 1981) introduced the idea of gender consideration in behavior models. According to earlier research, men and women make decisions differently and typically employ distinct socially built cognitive frameworks (Venkatesh & Morris, 2000). Previous research (He & Freeman, 2010; Venkatesh & Morris, 2000; Venkatesh et al., 2003; Wang et al., 2009) indicates that gender is a key predictor of usage behavior in the field of IS research. For example, Venkatesh et al. (2003) found that the explanatory power of TAM increased significantly to 52% when gender was included as a moderator. Specifically, it was found that PU, PEOU, SE, and SN's influence on BI and AU were moderated by gender (Venkatesh et al., 2003). Gender influences the association between BI and performance anticipation, which is similar to PU, according to Venkatesh et al. (2003). For men, the correlation is notably higher than for women. Their findings are consistent with the body of research in social psychology that emphasizes men's higher task orientation and pragmatic disposition in comparison to women (Minton, Schneider, & Wrightsman, 1980). Furthermore, it is claimed that males prioritize money more highly and are frequently motivated by a need for accomplishment (Hoffmann, 1972; Hofstede, 2005). This implies that males value the system's utility more than women do.

2.2 Empirical Review Related to FinTech Adoption Studies

An article's empirical review section details the procedures and conclusions of earlier, independent research investigations on the subject subjected to other writers. The names of the author(s), the title of the paper, the number of objectives and research questions addressed, the study's design, population and sampling techniques, the data collection tool, and the protocols and processes for data analysis are all important details to include in an ideal empirical review. The most significant findings of the investigation should be highlighted in addition to suggestions. Sometimes giving all of this information in a very cogent way is sufficient, but other institutions or supervisors might ask you to provide a more critical analysis of the reviewed empirical studies, particularly by emphasizing the advantages and disadvantages of the different tools, apparatus, and techniques used by the reviewed empirical study's author (or authors) (Punch, 2021). Considering this, the researcher has examined various peer-reviewed studies that concentrate on the adoption of FinTech.

UTAUT2 framework is utilized by several studies to explain various IT adoptions such as FinTech, e-commerce, e-business, Enterprise Resource Planning (ERP), Electronic Data Interchange (EDI), open systems, and Knowledge Management Systems. As part of empirical review for the research, 12 research papers related to FinTech technology adoption in different contexts within the past five years have been used and identified UTAUT2 framework to be mostly applied or adopted by the researchers to investigate adoption of technology at the user level.

2.2.1 Information Systems Research Approaches

In the field of information systems, research on technology adoption frequently looks at it from two angles: organizational and user. This paper examines the range of methodologies used to study the challenges associated with technology adoption at these two levels. The methods were selected following an examination of forty-eight peer-reviewed papers on technology adoption and usage that were published between 1985 and 2003. Among the journals that were reviewed were the MIS Quarterly, Information Systems Research, European Journal of Information Systems, Information Systems Journal, and other relevant IS periodicals. The findings suggest that the survey approach was largely used to investigate the topics of user adoption and technology usage. On the other hand, the case study approach is most usually used to analyze adoption issues at the organizational level. In the subject of information systems (IS), a great deal of reviews and classifications of research approaches have been attempted (Cheon, Grover, & Sabherwal, 1993; Galliers, 1992; Galliers & Land, 1987; Mingers, 2001, 2003; Nandhakumar & Jones, 1997; Orlikowski & Baroudi, 1991; Walsham, 1995a, 1995b).

Galliers' early work, which offered a taxonomy of popular IS research methodologies, proved influential. A variety of positivist and interpretive research methodologies, such as surveys, case studies, forecasting, simulation, reviews, action research, futures research, forecasting, forecasting, simulation, and role-playing were taken into account in this taxonomy. Orlikowski and Baroudi provided a philosophically contemplative work from a North American perspective in their other early study.

2.2.2 Technology Acceptance Model (TAM) Limitations and Criticism

A variety of considerations need to be made while applying a theoretical framework, and researchers need to be fully aware of the many limitations that come with doing so. Maruping, Bala, Ventakesh, and Brown (2016) state that in order to properly comprehend the elements that encourage increased IT usage, one must have a solid theoretical and practical understanding of the frameworks and models used to study IT use. The user behavior variable, which is always evaluated using arbitrary standards such as behavioral intention (BI) and interpersonal influence, is one of the TAM's weaknesses. However, interpersonal influence—, which is defined as the subjective norm—means that an individual is impacted by the comments of a friend or coworker. While an employer's IT policy may allow a superior to tell a subordinate to use technology to accomplish a particular goal, a buddy cannot impose directives on employees who report to a line manager. Another disadvantage is that a range of subjective factors, such as individual features, personality traits, and society standards and values, make it challenging to precisely quantify the foundations of behavior in an empirical investigation. As a result, it is extremely improbable that friends or family could apply strong social pressure to influence someone's use of technology (Ang, Ramayah & Amin, 2015; Shan and King, 2015). Although this might be true in principle or for personal technology use, it might not be plausible or feasible in a work environment. Therefore, Maruping, Bala, Ventakesh, and Brown (2006) recommended using behavioral expectations rather than behavioral intention to predict employees' intents about the use of technology.

2.2.3 Why UTAUT2?

The original UTAUT paradigm was developed by Venkatesh et al. (2003) and subsequently assessed in non-organizational contexts as well (Venkatesh, Thong & Xu, 2012; Venkatesh, Thong & Xu, 2016). The goal of the original paradigm was to predict and explain how technology would be adopted in an organizational setting. The theory's generalizability was enhanced by UTAUT's extensive application throughout time (Venkatesh, Thong & Xu, 2012; Neufeld, Dong & Higgins, 2007). The first research stream expanded the model to study it in new geographic and cultural contexts (e.g., India, China), apply it to new technologies (e.g., enterprise systems, e-health systems), and concentrate on new user segments (e.g., healthcare professionals) (Chang et al., 2007; Yi et al., 2006; Gupta, Dasgupta & Gupta, 2008). To investigate how effectively the model predicts the usage of web tools, for example, it was expanded to include a set of web-specific characteristics, such as trust and personal web innovativeness (Casey & Wilson-Evered, 2012). A distinct line of research that added more endogenous elements, like enjoyment and continuous intention to use (e.g., Sun, Bhattacherjee & Ma, 2009), expanded UTAUT (Maillet, Mathieu, & Sicotte, 2015). The third study stream addressed various characteristics that influence use and behavioral intention, including personality traits and task-technology fit (Zhou, Lu & Wang, 2010; Wang, 2005). Finally, other studies extended UTAUT by using additional contextual and moderating variables, such as employment, language, income, location, culture, ethnicity, religion, and employment (Im, Hong & Kang, 2011; Al-Gahtani, Hubona & Wang, 2007; Riffai, Grant & Edgar, 2012).

2.3 Research Gap

Being a recent technology to Ethiopian, one cannot find ample literatures on general technology adoption let alone on FinTech services technology adoption. Most of the literature found are those focusing on the FinTech adoptions in the developed countries or in some part of Asian countries such as India and China. In addition to that most literatures focus on such technologies as mobile banking adoption, and it is generally difficult to find or are almost non-existent those focusing on FinTech adoption. The other gap I noticed was that most of the literatures focus on technology adoption with respect to financial institutions such as banks, and do not focus on technology adoption within the context of businesses. Hence, I hope this thesis will serve as one input for filling that gap in some way in the future.

2.4 Research Hypotheses

The study was done based on the following hypotheses which were derived from the specific objectives.

Performance Expectancy

"The extent to which an individual believes that using the system will help him or her to attain gains in job performance" is the definition of performance expectancy (Venkatesh et al., 2003, p. 447). According to earlier studies, the best indicators of behavioral intention are performance expectancy and associated variables (Duyck et al., 2008; van Dijk, Peters, & Ebbers, 2008). According to Davis (1989), for example, people's decision to utilize a particular application depends on how much they think it will improve their ability to do their jobs. According to Venkatesh and Speier (1999), achieving desired results—like higher pay and better work performance—is a key driver behind the use of technology. In the context of FinTech, this could imply that individuals are more inclined to employ conventional methods of working if they think FinTech applications and technology won't improve their productivity or increase their income. Research by Kaasenbrood (2013) lends credence to this theory, arguing that businesses are reluctant to rely entirely on open government data for their business models due to a number of impediments, such as limited accessibility and a discontinuity in FinTech offerings.

For example, it's thought that the absence of user-friendly FinTech interfaces discourages FinTech consumers (Martin, 2014). Consequently, there could be significant variations in the types and contents of data used by various FinTech actors (Hunnius, Krieger, & Schuppan, 2014). We think that having access to FinTech technologies—such as platforms, software, tools, and interfaces—raises the bar for both individuals and organizations in terms of performance. We thus expect a direct and positive influence of performance expectancy on the intention to utilize and accept FinTech technologies, which is consistent with the theoretical considerations supporting UTAUT. In light of this, the following theory has been put out.

H1: *Performance expectancy has positive and significant effect on the adoption of FinTech services.*

Effort Expectancy

According to Davis (1989, p. 320), "even though potential users think a particular application is helpful, they might also think the system is too complicated to use and that the effort involved in using the application outweighs the performance benefits of usage." According to Venkatesh et al. (2003), effort expectancy is correlated with how easy a technology is to use and how much a person believes using a technology would not require any effort (Gwebu & Wang, 2011). The degree to which an individual or organization expects FinTech technology use to be effortless is known as effort expectancy. Regarding FinTech, we think that people assess how easy or difficult they think FinTech systems will be to use, and that this perceived ease of use affects people's propensity to utilize FinTech technology.

The amount of work required for FinTech technology might vary depending on several aspects. For example, finding publicly available data is difficult and expensive (Ding, Peristeras, & Hausenblas, 2012), as the data are available at numerous infrastructures and are occasionally difficult to locate (Braunschweig, Eberius, Thiele, & Lehner, 2012; Conradie & Choenni, 2014). There are many distinct forms in which datasets can be made available (Jeffery, Asserson, Houssos, Brasse, & Jörg, 2014; Verma & Gupta, 2012). Furthermore, distinct FinTech subtypes developed in disparate contexts can require divergent legal, cultural, or technological approaches. FinTech are gathered, shared, used, and perceived differently depending on the unique qualities and meanings of each situation. Additionally, FinTech sets can serve a variety of functions and have varying quality levels (Petychakis, Vasileiou, Georgis, Mouzakitis, & Psarras, 2014). According to research, OGD experience quality problems such inaccurate attribute values (Behkamal, Kahani, Bagheri, & Jeremic, 2014). Finding the precise FinTech sets that one is seeking for can be challenging due to the abundance, diversity, and fragmentation of existing datasets. Additionally, some datasets might not be accessible or available (Conradie & Choenni, 2014). Furthermore, different FinTech actors may have different rights on the usage of their data (Hunnius et al., 2014). Furthermore, people' internet-using abilities vary, according to Parycek and Sachs (2010), and Raman (2012) contends that citizens' comprehension of FinTech may differ as well. According to Martin (2014), prospective FinTech users are frequently under the impression that they lack the specialized knowledge needed to understand FinTech. The findings of T. G. Davies and Bawa (2012) support the idea that individuals possess varying capabilities for accessing and utilizing FinTech, and that these capacities influence the distribution, outcomes, and impacts of open government data advantages. The obstacles listed above may make it more difficult for an individual or organization to adopt and employ FinTech. According to Venkatesh et al. (2003), perceived ease of use—also known as effort expectancy—influences a person's propensity to utilize a FinTech technology. As a result, the subsequent hypothesis, H2, was produced.H2. *Effort expectancy has positive and significant effect on the adoption of FinTech services.*

Social Influence

According to Venkatesh et al. (2003), social influence is the extent to which a user values other people more than themselves, such as family, friends, leaders, etc., and supports the usage of new technology or systems. It is reasonable to suppose that social impact plays a significant role in UTAUT, supporting the prediction of user behavior that may indicate internalization, identification, and compliance (Zhou and Li, 2014). On the other hand, according to Yi et al. (2021) and Joa and Magsamen-Conrad (2022) compliance modifies a user's belief based on subjective norms, whereas identification and internalization cause a user's belief to depend on social status. Empirical research has, however, focused on the robust relationship between social influence and consumers' behavioral intention to utilize FinTech services in various circumstances. In a survey conducted in China, for instance, Xie et al. (2021) discovered that social impact strongly influences users' behavioral inclination to utilize FinTech services. Singh et al. (2020) conducted an additional empirical study in India. They concluded that there is a strong correlation between users' behavioral intention to use FinTech services and social influence. They discussed how social influence is an important indicator of UTAUT, which supports predicate the users' actual belief and intention towards FinTech services.

According to Venkatesh et al. (2003), p. 451, another definition of social influence is "the extent to which an individual perceives that important others believe he or she should use the new system". According to earlier research, social influence has an impact on people's behavioral intentions to use and adopt technology (Venkatesh et al., 2003). We hypothesize that social influence influences the intention to use FinTech since peers, superiors, and other people may have an effect on an individual's decision to utilize a FinTech system. The following hypothesis H3 was created.

H3. *Social Influence has positive and significant effect on adoption of FinTech services.*

Facilitating Conditions

In relation to the gender gap in the influence of facilitating conditions, males are more willing than women to put up the effort necessary to get past numerous roadblocks and challenges in order to achieve their objectives. On the other hand, women are more likely to concentrate on the quantity of work and the method required to accomplish their goals (Venkatesh et al., 2005). Therefore, it can be said that when males think about employing new technology, they usually don't rely on facilitating conditions. Women, on the other hand, are more likely to emphasize outside sources of assistance. Increased experience can help one become more accustomed to using technology and have better understanding of how to support learning, which can help one become less dependent on outside assistance (Kamaghe et al., 2020; Masadeh et al., 2016). Regarding the interaction between the industrial revolution and the environment, people's perceptions of technical advancements have shifted from negative to favorable. In addition, advanced technology produced data that may be utilized to optimize corporate networking, economic development, and the manufacture of goods (Choi et al., 2019). According to Paul et al. (2015), users with limited technology experience will rely more on facilitating conditions. In conclusion, the effect of facilitating conditions on adoption of FinTech is hypothesized as follows:

H4: Facilitating conditions has positive and significant effect on adoption of FinTech.

Perceived Risk

The probability that the seller would act opportunistically and cause the client to suffer a loss is known as perceived risk. Customers' view that they shouldn't make purchases online is influenced by privacy inhibitors (Venkatesh et al., 2021). It sends a bad message that using the internet for banking or shopping is fraught with danger and could lead to fraud. Furthermore, Yang and Lee (2019) talked on how users' perceptions of danger make them reluctant to divulge personal information while making online payments. Johnson and Reyes (2021) recently came to the conclusion that consumers' intentions to use FinTech services are lessened when they perceive risk. Accordingly, earlier research that looked into the relationship between users' behavioral intention to utilize FinTech services and perceived risk found that it was negatively correlated. For instance, Yuan et al.'s empirical study from 2022 revealed that consumers' perceptions of FinTech services are negatively impacted by their high perceived risks. Hence, it hypothesized as:

H5: *Perceived risk has negative and significant effect on adoption of FinTech.*

2.5 Conceptual Framework

The expected relationship between the variables in the investigation is shown via a conceptual framework. This diagrammatical form demonstrates how the independent and dependent variables are related to one another. As a result, it outlines the pertinent goals for the investigation and shows how these goals mesh to produce logical results. Conceptual frameworks can be written or graphic, and they are typically created by reviewing the body of research on the subject we plan to study.

Having said the above on conceptual framework, as far as the specific conceptual framework employed for this study is concerned, the below conceptual framework has been developed based on the UTAUT2 theory and the identified relevant and appropriate variables. The pictorial depiction of the conceptual framework is shown on the following page.

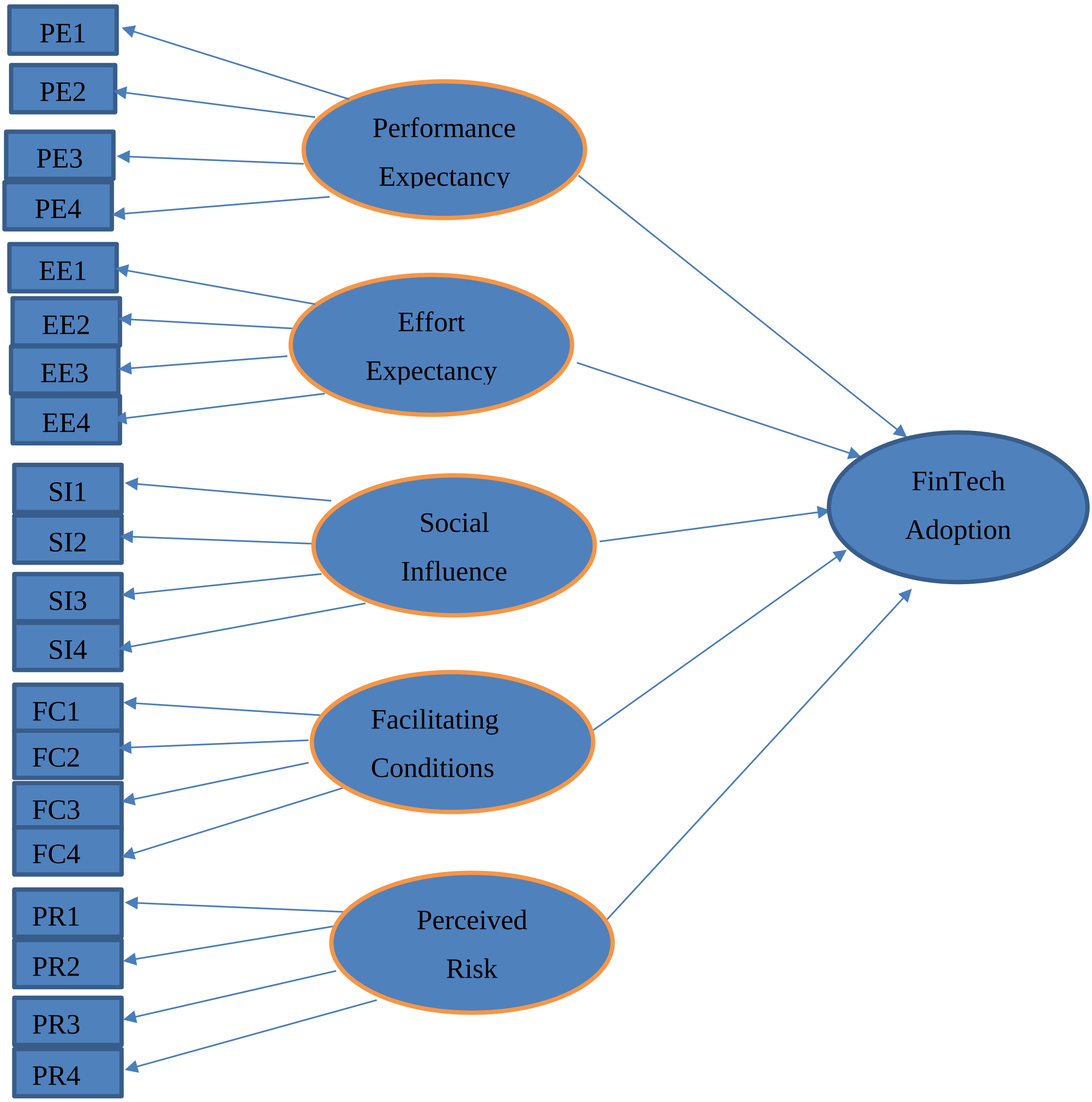


Fig. 2.3 Pictorial representation of the conceptual framework

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1 Introduction

Research methodology is the overall approach used to identify, select, process, and analyze information about a topic (Creswell, 2008). It is the blueprint plan for gathering the right data and apply the right techniques to arrive at a valid conclusion. It outlines the rationale for the research method used, whether the sample is representative of the population, whether the method is appropriate, sampling technique and sample size, the unit of analysis, the research design used, definition of target population inclusion and exclusion criteria, data collection methods, operationalization of variables, method of data analysis, and presentation and ethical considerations linked to the paradigm or theoretical framework (Mackenzie and Knipe, 2006).

In a research paper, the methodology section allows the reader not only to critically evaluate a study's overall validity and reliability, but also shares how the research was conducted, the methods used and why the method was chosen and show that the research can be replicated. It discusses and explains the data collection and analysis methods used in the research (Scot & usher, 1996). The methodology section of a research paper answers two main questions, how the data was collected and analyzed.

3.2 Research Design

Depending on the nature of the goal or research challenge, there are various sorts of research. Explanatory, descriptive, or exploratory designs can be used in research (Yin, 1994; Zikmund, 2000). Furthermore, Saunders et al. (2000) noted that a study may use multiple purposes. The distinctions between the categories are not always obvious, as Yin (1994) points out. This study used descriptive and explanatory research designs in response to the given challenge.

The purpose of descriptive research, according to Robinson (1993), is to "portray an accurate profile of a person, event, or situation." It may serve as an extension or a preface to exploratory inquiry. Zikmund (2000) states that descriptive research is carried out when the study problem is identified but the researcher is not fully aware of the circumstances. It makes sense that when a particular natural occurrence is being examined, study is needed to characterize, explain, and shed light on it (Huczynski and Buchanan, 1991). According to Zikmund (2000), descriptive research will answer the questions of who, what, where, and how, but it will not explain why the outcomes were as they were. This study employed descriptive design to describe factors related to adoption of FinTech and level of adoption of the FinTech.

In addition to the descriptive design, this study has applied explanatory research to examine the causal relationship between FinTech adoption and its factors. Explanatory research places a strong emphasis on examining an issue or phenomenon in order to determine the causal relationship between various factors (Saunders et al., 2000). Causal research is another name for explanatory research (Zikmund, 2000). Explanatory research typically aims to establish and explain patterns connected to phenomena of interest once exploratory and descriptive research has been completed (Saunders et al., 2000). Therefore, this study used an explanatory design to investigate the impact of the level of relevant factors on FinTech adoption and a descriptive design to report the state of factors connected to FinTech adoption.

The plan for gathering, calculating, and interpreting data and information is known as the research design. It is the investigation's plan and structure designed to yield answers to research inquiries. A research design is a comprehensive strategy that outlines the techniques and steps for gathering and examining the required data.

Generally, technology adoption research is done either at a user-level or an organization-level and employ two approaches, a quantitative survey approach and a qualitative case study approach respectively. Accordingly, this research, being a study at the user-level, employs the survey approach collecting quantitative primary data from customers. The quantitative research technique includes structures of inquiry like surveys and experiments and uses statistical tools to describe patterns of behavior and extrapolate findings from samples to the population of interest (Creswell, 2003).

Based on the UTAUT theory and the conceptual framework developed in the previous sections, there are latent variables or constructs or factors in the model, which cannot be measured directly, and that requires us to use one of the structural equations modeling’s (SEM) instead of a simple regression. The research is correlational/inferential in design which measures the degree of association (or relationship) between two or more variables or sets of scores (Creswell, 2012). In addition to the dependent variable and the independent variables, there will also be mediating, and moderating variables included in the final model. The Designs often employ cross-sectional data collected at a specific period from customers of Shoa Supermarkets and Hypermarket located at different locations of Addis Ababa.

Finally, the researcher will also use explanatory or descriptive designs to describe factors affecting the adoption of FinTech services by customers of the supermarket chains. Specific type of data analysis software shall also be applied to test the pre-stipulated hypotheses enabling the acceptance or rejection of null hypothesis and alternative hypothesis.

3.3 Target Population, Sampling Frame, and Sampling Unit

A clear and precise definition of the target population is necessary to ensure that the population of interest is adequately covered. Surveys of technology adoption at user-level use a certain group of individuals or user of a technology as the primary sampling unit (PSU). In this research case the sample frame will be the list of all customers of Shoa Supermarkets and hypermarket. Currently Shoa Supermarket has seven branches' supermarkets and one hypermarket located at different parts of Addis Ababa. Accordingly, the customers of those branches shall be the target population and their list the population frame.

3.4 Research Design and Approach

A defined strategy for selecting a sample from a specific population is known as a sample design. It alludes to the method or process the investigator would use to choose objects for the sample (Kothari, 2004). A cross-sectional research design will be used in this study, and primary data will be gathered for analysis in accordance with the sample computation that is detailed in the sections that follow. The quantitative data to be gathered will be via 5-point Likert scale surveys. The specific method of sample size calculation, the type of software to be used to analyze the data, the type of methods used to confirm that the results obtained are not by chance, methods to confirm the internal consistency of the data (such as the Cronbach's alpha), validity, reliability, etc. will also be explained in the following sections.

3.5 Study Population and Unit of Analysis

The study uses supermarkets customers as a unit of analysis because the researcher believes that supermarket customers are usually well-to-do citizens with better technology knowhow and the resources to use one of those technologies. Secondly, such retail business is also one of the businesses where the FinTech services are widespread next to financial institutions and that make them a good candidate to carry out the study.

We employed purposive sampling techniques to select Shoa supermarkets and hyper market customers as the supermarket has a long history of good reputations in the retail business and has a lot of tech-savvy customers. It is also where other relatively well-educated residents prefer for casual and recreational business services. As far as the unit of analysis is concerned, obviously, the customers of the supermarket shall be the unit of analysis for this thesis and data were collected while customers are conducting shopping as well as those customers who are customers of the retail business but filled the questionnaire at their conveniences.

3.6 Target Population and Sampling

This study targeted users of FinTech in Addis Ababa. For this purpose, the study has selected customers of Shoa Supermarket that purchase at different shopping centers in Addis Ababa. Since the number of users of the FinTech that shop at the supermarket is unknown, this study has no fixed number of target population.

Hence, the sample size is determined based on following formula:

$$n = \frac{Z^2 x p(1-p)}{d^2}$$

Where; Z2 = 95% of confidence level and equals 1.96; P = expected prevalence which equals 50%; d^2 = is the level of precision or sampling error and equals 5% (0.05)

Hence, sample size for this study is computed as

$$n = \frac{1.96^2 x 0.5(1-0.5)}{0.05^2}$$

$$n = 385$$

Therefore, this study was conducted by using samples of 385 individual users of FinTech. The study has selected only users of the technology that are convenient for the study. The users were randomly checked. The study has randomly selected 10 shopping centers of the supermarket; where from 5 shopping centers 38 respondents were selected, in each center; and from the other 5 shopping centers 39 customers, from each center, of supermarket were randomly selected.

3.7 Procedure of Data Collection

This study has used primary data that was collected from primary sources. The study has used users of FinTech, and their perception was collected by using structured questionnaires. The data collection was conducted at randomly selected Shoa Supermarket shopping centers in Addis Ababa and Shoa Supermarket customers who were not necessarily shopping at the time of filling the questionnaires. For those who filled the questionnaire while shopping, the data collection was initiated by selecting shopping centers of the supermarket. In the selected shopping centers, managers of the shopping center were informed about the study and their cooperation was requested. Following permission of the managers, customers of the supermarket were approached with support of dedicated staffs from shopping center of the supermarkets. The customers were asked before starting their shopping. First, the customers were asked whether they use FinTech or not. Then, questionnaire was provided if the customers use FinTech's of banks (mobile banking and agent banking) and ethiotelecom (Telebirr). The questionnaire was collected on spot. Among the selected shopping centers, for 5 shopping centers 38 questionnaires for each center and for the other 5 shopping centers 39 questionnaires were distributed for each center.

3.8 Measurement scales

Based on its objectives, this study has developed five hypotheses, drawing on previous research on the measurement of UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating condition, and behavioral adoption to use) (Venkatesh et al., 2003); additionally, it has added privacy risk (Venkatesh et al., 2021). Prior studies have consistently demonstrated the significance, validity, and reliability of the aforementioned constructs when evaluating users' behavioral intention toward FinTech services (Ali et al., 2018; Hassan et al., 2022; Chan et al., 2022). The measurement items for the constructs were all drawn from previous studies conducted by Venkatesh et al. (2021), Kaur and Arora (2020), Azman and Zabri (2022), and Chan et al. (2022). Nonetheless, taking into account its context, this study has changed a few aspects. A "five-point Likert scale (1 = Strongly Disagree; 2 = Disagree, 3 = Neutral, 4 = Agree and 5 = Strongly Agree)" was used to measure each of the measurement items (Alkhwaldi et al., 2022).

3.9 Method of Data Analysis

As far as the quantitative data are concerned quantitative data analysis method was employed to analyze the gathered data. Accordingly, the structural equation modeling (SEM) application software AMOS 23, is employed to develop the model and carry out the analysis. Based on the conceptual framework of the research independent variables (indicators), constructs, and dependent variables will be simulated first using the aforementioned software and appropriate analysis will be carried out on the model to arrive at the statistics useful to make inferential statements. On the other hand, the statistical analysis took a form of descriptive and inferential statistics.

The frequency, percentage, tables, mean, and standard deviation of the descriptive statistics are used to characterize the socioeconomic traits and the degree of demand for financial technology. To comprehend the factors influencing the demand for financial technology, inferential statistics will be employed. To evaluate the socioeconomic and demographic determinants of the dependent variable, multiple logistic regressions will be employed. In addition to the descriptive analysis, the statistically significant variables influencing the demand for financial technology were found using the econometrics model, also known as the binary logistic model. Two commands were executed in the process: the first displays the ordered log-odds coefficient, and the second displays the coefficients in terms of marginal values.

For the study at hand, this study has applied descriptive and inferential analyses based on the research design. The descriptive analysis is conducted to assess general characteristics of users of FinTech, services of FinTech in Ethiopia, level of adoption of FinTech and factors related the FinTech adoption. For these purposes, this study has used descriptive statistics such as frequency, percentage, mean, standard deviation. In addition, the inferential analysis was applied following the explanatory design, and it is intended to indicated causal relationship among the study variables. This method of data analysis was applied by using Conformity Factor Analysis (CFA) and Structural Equation Model (SEM).

There have been several phases to the data analysis. First, in order to meet the multivariate assumption, this study used a data screening procedure and testing. The goal of this is to determine if the data is appropriate for use in statistical analysis. As a result, the study has used normality testing, outlier identification, and handling of missing data. Second, factor analysis has been used in the study to determine the fundamental structure of the variables (Hair, Tatham, Anderson, & Black, 2006). CFA is used in the measuring model to apply this. This analysis was specifically done to perform reliability and validity tests. Third, SEM was used to do the data analysis in accordance with the CFA result. SEM is a popular technique for analyzing survey data. It is a statistical methodology that applies a complete statistical approach to testing hypotheses concerning relationships between observable and latent variables (Hoyle, 1996) and a confirmatory approach to the examination of a structural theory bearing on some phenomenon (Byrne, 2001). This method, which examines the structural link between measurable variables and latent constructs, combines multiple regression analysis and component analysis. This method's benefit is that it can estimate the structural model and measurement model at the same time. Validity factor analysis is used in the measurement model to validate the construct's measurement scale (Hair et al., 2006). After passing this analysis test, the variables are used in the structural model analysis to look at how the study's exogenous and endogenous variables relate to one another.

3.10 Data Source and Instruments

Accordingly, questionnaires that contain questions (indicators) that are intended to gather information over the constructs are drawn up and sent out to the customers. Appropriate and relevant questions (indicators) that are meant to describe our five constructs are included in the questionnaires to gather the data. For the qualitative analysis part, detailed and semi-structured interviews will be prepared to gather relevant data on the topic. The interviews were done with selected customers of the supermarket to obtain an in-depth information concerning their FinTech adoption factors.

3.11 Designing the Questionnaires

The questionnaire is divided into two main parts which consist of general information of respondents (Profile and experience and the other part related to main cause of time and cost overrun. The severity will be categorized on five-point Likert scale as follows: strongly disagree, disagree, neutral, agree and strongly agree. The questionnaire comprises a 5 –point Likert scale of 1 -5 where 1 shows a high level of disagreement and 5 shows a high level of agreement. During administration of question, the instruction was given to the respondents by the researcher and other helpers.

3.12 Ethical Considerations

Prior to the data collection, the organization's consent was sought. Respondents were fully informed about the aim and benefits of the study, as well as their complete right to decline or accept participation, at the time of questionnaire delivery. The responders were informed that their identify would not be revealed and that their response would be kept private. There was no personal harm done to research subjects, and everyone participated in the study had the right to privacy and dignity of treatment. The researcher maintains absolute confidentiality over the information gathered. All help, other people's cooperation, and the informational sources were acknowledged.

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1 Introduction

This study was conducted to identify determinants of FinTech at user level by using customers of selected supermarkets in Addis Ababa. Based on this aim, the study has sampled 385 customers of the selected supermarkets and collected data primary data from the customers by using structured questionnaire. The data was analyzed by using inferential statistics, CFA and SEM. This chapter presents result of the data analysis, interpretation of result of data analysis and discussion on findings of the study. The first section of the chapter presents descriptive analysis about the respondents, factors related to FinTech adoption and level of adoption of the FinTech. The second and the third sections present result CFA and SEM.

4.2 Response Rate

This study has distributed questionnaires to 385 respondents who are customers of selected supermarkets. Among the questionnaires distributed, 369 questionnaires were returned adequately filled. Hence, the response rate of the questionnaires was 95.84%, where 95.84 % of the questionnaires were returned and the study has proceeded data analysis. The data analysis was started by following data handling procedures, such as, missing data handling and outlier identification.

4.3 Data Handling

4.3.1 Missing Data Handling

In the data collected, there were 18 observations with missing data. Hence, first, the study has followed missing data handling procedure before conducting statistical analysis. Hair et.al. (2010) stated that missing data is information required from the target respondent but not available in the questionnaire. According to Hair et.al. (2010) analyzing a missing dataset could be catastrophic, especially when the pattern of the missing data is non-random. Hence, it is important to effectively neutralize the adverse effects of missing data by detecting and ruling solutions for missing data problems.

The missing data can be either ignorable or non-ignorable (Hair et.al. 2010); the ignorable missing data are occurred because of the research design; the non-ignorable missing data occurred for unknown reasons such as accidental skipping, non-volunteer to answer a specific question, and do not know the answer of specific cases at all (Cooper and Schindler, 2014).

There are two main methods suggested to handle missing data namely: list wise /pair wise/ deletion and model-based approach and imputation/substitution/ methods. However, different authors did not support deletion because if one respondent missed one case/question/ then the whole survey would be dropped from the analysis (Cooper and Schindler, 2014; Collier, 2020). Nevertheless, Hair, Black, Babin and Anderson (2009) also asserts that if random missing data of less than 10% of the number of cases, then any approaches of missing data remedies are appropriate. Accordingly, it suggested that cases with missing data can be eliminated from the dataset and further analysis can be conducted. Therefore, this study has dropped 18 cases from the dataset and proceeded to next step of data handling, i.e., outlier identification and removal of the outlier cases.

4.3.2 Outlier Identification

It is advised that before performing any statistical study, outliers should be located. The statistical outcome could be distorted if an analysis is conducted using a dataset that has irregular and inconsistent measurements. Unusually high or low values in relation to the data values are called outliers. Extreme scores that deviate significantly from the norm and are outside the data's general trend are known as outliers. Observations that have a substantial residual (ei) relative to the other observations are considered outliers. Outliers can be inaccurate and misleading because they are extreme measurements that differ from the remainder of the sample (Bowerman, O'Connel, and Hand, 2001). As a result, the assumption of outliers proposes that the sample should be reduced to include only normal observations and that there shouldn't be any outliers. Bordens and Abbott (2018), in contrast, advise keeping outliers in place if there is a good reason to keep them there.

However, this study has no unique justification to maintain the outliers instead of removing them. Accordingly, this study has followed procedure of removing the outliers and it was examined by using result of CFA models. The Mahalnobis Distance (MD) critical values were used to find outliers; cases with critical values more than 71.5 MD were deemed to be outliers and were not included in the analysis. As a consequence, 7 observations were removed from the dataset based on the outlier treatment approach; consequently, 344 observations were used for additional data analysis.

4.3.3 Normality Test

It is imperative to verify the normality of data before employing inferential statistical techniques for data analysis (Butt, 2009; Mukerji, 2008). It is discovered that analyzing non-normally distributed data sets with higher kurtosis and skewness can produce inaccurate findings (Butt, 2009). According to Field (2009), regardless of the population distribution, a sample size of 30 or more would generally result in a normal sampling distribution. Additionally, Meyer et al. (2005) asserted that the larger the sample size used in the investigation, the more reliable and precise the population parameter estimates for statistical inferences would be. This study's sample size (n=344) was sufficient to meet the normalcy criteria. Thus, before the analysis, this study evaluated each variable's distribution.

According to Mukerji (2008) normality of data can be checked by looking at some descriptive values such as skewness and kurtosis. For normally distributed data, it is suggested that the skewness values fall within the range of -2 to +2 and the kurtosis values fall within the range of -7 to +7 (Mukerji, 2008). Based on these standards, this study has checked normality assumption and the details were presented in Table 4.1 below.

Table 4. 1: Normality Test

Variable	skew	c.r.	kurtosis	c.r.
EE1	-.883	-6.689	-.265	-1.005
EE2	-.823	-6.230	-.116	-.439
EE3	-.703	-5.325	-.286	-1.084
EE4	-.583	-4.416	-.518	-1.963
FA1	-.704	-5.334	-.620	-2.349
FA2	-.616	-4.663	-.688	-2.606
FA3	-.641	-4.852	-.569	-2.153
FA4	-.746	-5.648	-.521	-1.971
FA5	-.593	-4.491	-.650	-2.460
FC1	-.766	-5.800	-.436	-1.650
FC2	-.728	-5.516	-.570	-2.159
FC3	-.929	-7.036	-.087	-.331

FC4	-1.096	-8.300	.239	.904
FC5	-.628	-4.754	-.744	-2.817
PE1	-.501	-3.791	-.716	-2.709
PE2	-.631	-4.774	-.398	-1.509
PE3	-.399	-3.024	-.714	-2.705
PE4	-.754	-5.713	-.476	-1.801
PR1	-1.068	-8.087	.077	.292
PR2	-.893	-6.759	-.307	-1.162
PR3	-.721	-5.461	-.495	-1.874
PR4	-.800	-6.059	-.520	-1.970
PR5	-.744	-5.633	-.471	-1.781
SI1	-1.275	-9.656	.979	3.707
SI2	-1.240	-9.392	.720	2.726
SI3	-1.134	-8.586	.391	1.481
SI4	-.695	-5.260	-.622	-2.355
Multivariate			**178.119**	**41.741**

Source: Survey Data, 2023

Based on the standards adopted (Butt, 2009; Mukerji, 2008), this study computed that there is no evidence of excessive skewness and kurtosis; where the largest skewness and kurtosis values were 1.275 and 0.979 respectively. This suggests that the normality assumption is not violated for the data used in the study.

4.4 Characteristics of Users

Characteristics of the respondents include demographic and social factors of users of FinTech. These factors include gender, age, education, and average monthly income. The survey result is summarized by using frequency and percentage and the result is presented in Table 4.2 below.

Table 4. 2: Characteristics of Respondents

Factor	Categories	Count	Percent
Gender	Male	249	72.4
	Female	95	27.6
Age	Below 31	71	20.6

	31 - 40	189	54.9
	41 - 50	70	20.3
	Above 50	14	4.1
Education	Primary/Secondary Schools	17	4.9
	Diploma/TVET	132	38.4
	Degree and above	195	56.7
Income	Below 10,001	84	24.4
	10,001 – 20,000	97	28.2
	20,001 - 30,000	86	25.0
	Above 30,000	77	22.4

Source: Survey Data, 2023

As shown in Table 4.2 above, 72.4% of the respondents were male and 27.6% were females. This is suggestive that FinTech is more practiced by males than females. This shows that although the FinTech services are similar to males and females, male customers of the selected supermarkets have higher intention to use the technology than the female customers.

In addition, age of the respondents is presented by four categories; namely, below 31 years, 31 to 40 years; 41 to 50 years; and above 50 years. It is computed that majority of the respondents were at age category of 31-40 year that include 54.9% of the cases. This shows that, if purchasing from the selected supermarkets is equally practiced in all levels, FinTech has highest adoption rate by customers at age between 31 years to 40 years.

Further, it is computed that users of FinTech are at three education levels: ranging from primary/secondary schools to degree achievers. The survey result shows that majority (56.7%) of the selected users have educational qualification of Bachelor's degree and above. However, using FinTech does not need advanced educational level and theoretical background. Instead, it can be used by customers that can read and understand services they want from the FinTech services. However, high educational level might support decision to use the services by providing different justifications.

Furthermore, this study has assessed income level of users of the technology if users with higher income might have larger number of transactions than users with lower income level. However, it is computed that very similar number of users were in different categories of income. Relatively, largest number of users (28.2%) earn monthly income ranging from 10,001 to 20,000 Birr. This suggests that using FinTech is indifferent to income level of the society and the FinTech providers are providing inclusive services for all group of society.

4.5 FinTech Adoption Practices

FinTech adoption is indicated by different parameters. Based on objectives of the FinTech and services included by the FinTech owners, this study has assessed adoption of FinTech by using different indicators. Hence, in this study adoption of practices of FinTech are indicated by types of FinTech adopted by users, purposes, experience and frequency of using FinTech, and channels/platforms to use the FinTech.

This study has used multiple responses approach to assess types of FinTech adopted by users and purposes of using the FinTech. This is because different type of FinTech by single user and the FinTech adopted by a user can be used for different purposes. This study has included three different types of FinTech that include Telebirr, Mobile Banking, and Agent Banking. In addition, this study has included three major categories of purpose of the FinTech; first, using for shopping and making payments; second, pay utilities (e.g., water, electricity, tele bills and airtime, DSTV, etc.)); and third, making informal payments (transfer money to family, friends, co-workers, own account). The survey result is summarized in Table 4.3 below.

Table 4. 3 Types of FinTech and Purposes of Using the FinTech

		Responses		Percent of Cases
		N	Percent	
Type	Telebirr	262	48.3	76.2
	Mobile Banking	194	35.7	56.4
	Agent Banking	87	16.0	25.3
Purpose	Shopping and make payments	113	20.5	32.8
	Pay utilities	145	26.4	42.2
	Informal transfers	292	53.1	84.9

Source: Survey Data, 2023

As depicted in Table 4.3 above, the customers use different types of FinTech services and single user adopted more than 1 service. Comparatively, Telebirr is most used FinTech by the customers and it includes 76.2% of users of FinTech. It is followed by mobile banking, and this include 56.4% of selected customers. However, smallest number of customers use agent banking that include only 25.3% of FinTech users in this study. This result indicated that Telebirr is most convenient FinTech for the users and users prefer Telebirr to mobile banking and agent banking. This might be due to Telebirr include majority of services of mobile banking and agent banking.

Further, in Table 4.3 above, it is presented that FinTech is mainly used for informal services that include transfers to families, friends, coworkers, and own accounts. This is practiced by 84.9% of users of the technologies. However, using FinTech for this purpose is not out of objectives of providing the service. The FinTech firms provide largest concern of using FinTech for formal payments to facilitate shopping and formal payments for transactions.

On the other hand, the FinTech were used to make payments for shopping and transactions and to pay utilities. It is identified that 42.2% adopted the technologies to make payments for shopping and formal transactions. In addition, 32.8% of users adopted the technologies to pay utilities.

In this study, other indicators of FinTech adoption are experience of using the service, monthly usage frequency of the services, and channels preferred by the users. These indicators show familiarity of users with the FinTech; where, it is assumed that users with higher experience and frequency have higher familiarity than users with lower experience and frequency of usage. In addition, users that use applications of the FinTech have higher familiarity that the application presents different products simultaneously; however, the USSD channel needs user order to show available services. The survey result about these indicators is summarized in Table 4.4 below.

Table 4. 4: Familiarity of Users with FinTech

		Count	Percent
Experience	Below a year	87	25.3
	1-3 years	210	61.0
	Above 3 years	47	13.7
Frequency (monthly)	Rarely	88	25.6
	Sometimes	232	67.4
	Often	24	7.0
Channels	USSD (*No#)	99	28.8
	Application	94	27.3
	Both	151	43.9

Source: Author's Computations, 2023

As shown in Table 4.4 above, majority of the users (61%) have experience for the FinTech for 1 to 3 years. The smallest number of users have the experience for more than 3 years and this includes 13.7% of the users. On the other hand, 25.3% of the users have the experience for less than a year. This study argue that services provided by the FinTech providers do not need high experience; instead, they are easily practicable. Hence, the adoption of FinTech maters convenience of the services provided to users.

Frequency of usage is an important indicator of adoption of FinTech. In this survey it was observed that majority (67.4%) of users use the service somedays in a month for different purposes. In addition, 25.6% of the users of FinTech use the service rarely in a month. however, only 7% of the users often use the service in a month. This shows that users of the service have low frequency of using the service; however, they are focusing optional methods, e.g., cash payments or bank transfers, for their payments.

FinTech services included in this study are presented with two channels/platforms: USSD and application. The service providers prefer their users to use applications to USSD. This helps them the customers easily to view different products without order. In contrast, USSD platform has security concern because there is third party involvement, telecom company. This study has observed that majority of users of the FinTech use both channels. However, very few numbers of customers use either USSD or an application.

Finally, this study has assessed level of adoption of FinTech by using perception of the users. This presents perception of users about regular use of the service, recommendations to other, future usage, usage for balance checking and making transfers. Furthermore, it is used as dependent variable in SEM. The perceived adoption of FinTech is summarized in Table 4.5 below.

Table 4. 5: Perceived Adoption of FinTech

FinTech Adoption	Mean	Std. Dev
I use FinTech on regular basis	3.95	1.103
I recommend others to use FinTech	4.00	0.999
My use of FinTech continues in the future	4.04	0.960
I check balance of my account on the platform of FinTech	4.08	0.991
I make a transfer on the platform of FinTech	4.01	0.991

Source: Author's Computations, 2023

As shown in Table 4.5 above, the mean scores are closer to 4 suggesting that the users have adequately adopted FinTech services. It is indicated that they use the services regularly, recommend others to use the service, they expect that they similarly use in future, and they use the service to check balances and to make transfers.

4.6 Perceived Features of FinTech

This study was conducted to examine determinants of the FinTech adoption by mainly focusing on perceived quality of the services. Based on the theoretical framework adopted and empirical literatures reviewed, this study has assessed five features of FinTech: namely, performance expectance, effort expectancy, social influence, perceived risk and facilitating conditions. Based on these features, perception of users of the technology was assessed by using different indicators for each feature. Perception of the users was summarized by using descriptive statistics and result of the summary statistics is presented in Table 4.6 below.

Table 4. 6: Summary Statistics on Features of FinTech

	Mean	Std. Dev
Performance Expectancy		
I find FinTech useful in my financial management	3.87	0.992
FinTech enables me to accomplish financial tasks quickly	3.95	0.946
FinTech increase my efficiency in financial management	3.99	0.869
FinTech services improve my payment convenience	4.06	1.014
Effort Expectancy		
My FinTech is clear and understandable	3.98	1.132
It is easy for me to become skillful at using FinTech	3.97	1.086
I would find FinTech easy to use	3.86	1.087
I expect that learning to use FinTech would be easy for me	3.84	1.043
Social Influence		
My friends and family would value the use of FinTech	4.33	0.897
I believe that the people that influence me would use FinTech	4.31	0.910
I beleive that FinTech would be trendy	4.28	0.925
Using FinTech makes me look professional in managing my finances	4.06	0.996
Perceived Risk		
Buying from FinTech would involve financial risk	4.23	0.996
Buying from FinTech would involve product risk	4.13	1.004
I believe personal privacy will be disclosed by using FinTech	4.06	1.001
Risk related to buying online through FinTech is high	4.15	0.964
I feel FinTech services may not work when needed	4.10	0.988
Facilitating Conditions		
I have the resources to use FinTech	4.08	0.999
FinTech is compatible with other technologies that I use	4.11	0.978
FinTech can work 24/7 without problems	4.15	1.001
My payments require payment/transfers through FinTech	4.23	1.006
FinTech has lower cost than optional methods	4.05	0.975

Source: Author's Computations, 2023

As shown in Table 4.6, mean statistics is like all indicators of features of FinTech. Value of the statistics is closer to 4.00 with small variation. This result indicates that FinTech meets performance expectancy and effort expectancy, the users were socially influenced about

FinTech, and the users have different facilitating conditions for intention to use the technology. However, the study has identified that the users feel that there are different risks in using the technology.

In particular, the users perceive that FinTech is convenient for payments, useful for personal finance management, and improve speed and efficiency of financial tasks. In addition, it is indicated that the technology is clear, understandable, easily adoptable and easy to use. Further, it was observed that users of the technology were influenced by family, role models, modernity and advancements. The users were influenced by compatibility of the services with available resources for users and other technologies used by them, time the service is provided, comparative cost advantage, and payment requirement by other parties. However, despite interest of the users based on other characteristics of the services, the users perceive that there are risks from using the technology. These risks include financial risk, product risk, privacy risk, risks from online purchases, and service failure. Therefore, this study revealed that although the users feel that it is risky, the FinTech meets performance and effort expectancy, and suggested by social groups and favored by different opportunities.

4.7 Measurement Model

According to Byrne (2010) and Hair et al. (2010), creating a structural model and testing the study hypotheses should come first in order to ensure construct validity. Convergent and discriminant validity are used to assess construct validity. Conformity factor analysis (CFA), which connects observed indicator variables with latent variables, is used to test it. Furthermore, according to Brown (2006), CFA generates correlations between the indicators derived from the measurement model. Moreover, it allows free inter-correlation among the latent variables (Wang and Wang, 2020; Brown 2006). Hence, as a procedure of SEM, first, this study has examined construct validity by using CFA.

In this study, the measurement model includes set of items about adoption of FinTech and its determinants. It is constructed from 27 observed variables: 5 items about adoption of FinTech and 22 items about determinants of adoption of the FinTech. The number of items in measurement model were adjusted based on results of construct validity. First, this study has constructed full measurement model by using 27 observed variables and 6 latent variables by allowing free inter-correlation among the latent variables. Second, based on this model, convergent validity was tested. Third, after the convergent validity was established, the study has tested discriminant validity. Fourth, the study has conducted reliability analysis after fitting discriminant validity. Finally, the study has used result of measurement model to test content validity in SEM.

This study has initiating CFA based on full measurement model and the full measurement model is constructed as shown in Figure 4.7 below.

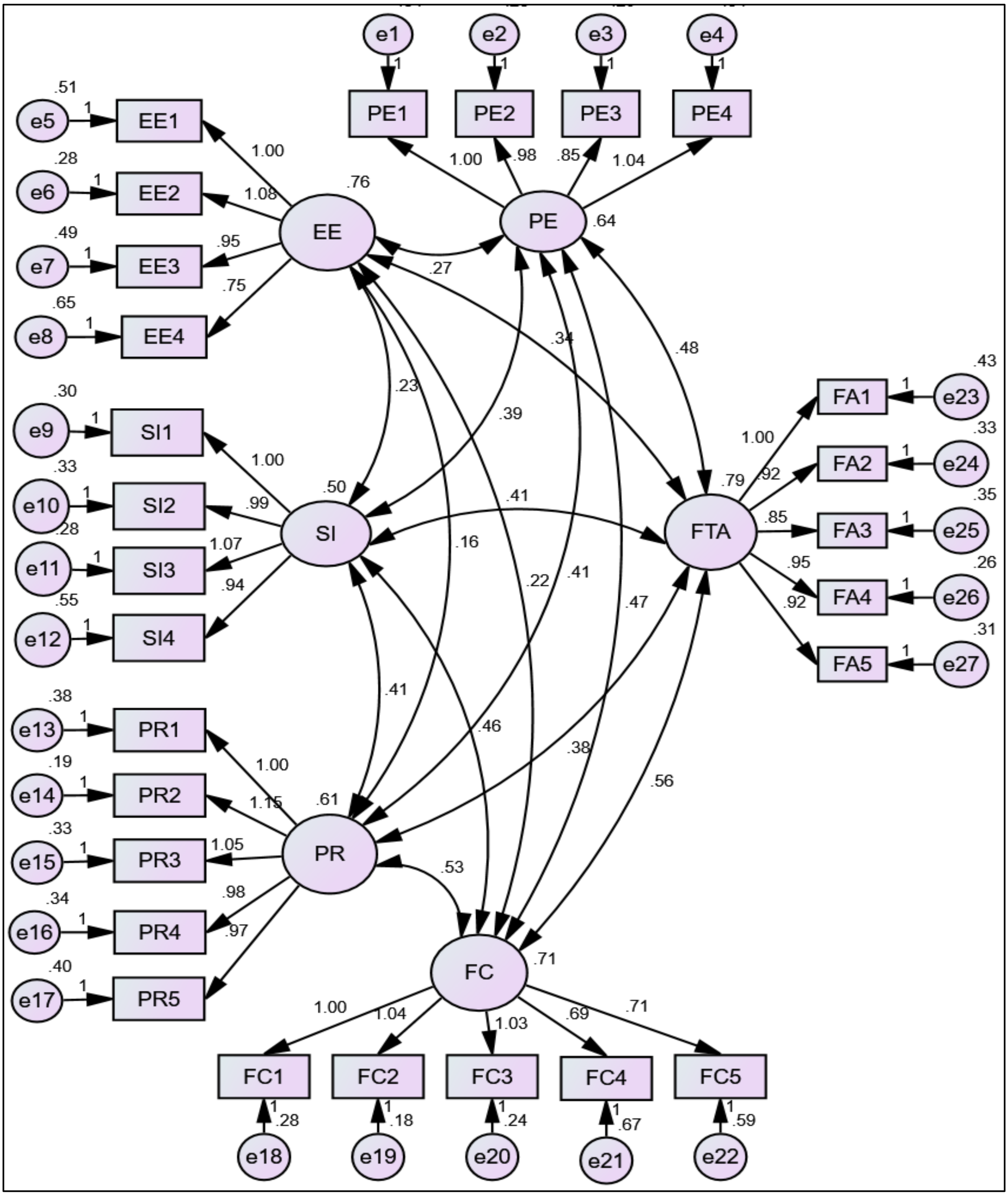


Figure 4.7: Full Measurement Model

Source: Author’s Computations, 2023

The maximum-likelihood approach was used in this study to assess the theoretical model's parameters, and variance-covariance matrices were the basis for all tests (Hair, et.al., 2014). Suggested fit indices were used to assess the model's fitness following CFA using the entire measurement model. Hair et al. (2014) and Kline (2015) evaluated a few fit indices to gauge how well the measurement model suited their data. The chi-square value ($\chi2$) was utilized to ascertain the measurement model fit. The ratio of the ($\chi2$) static to its degree of freedom/or adjusted chi-square ($\chi2$/df) was used instead of the $\chi2$, since it was found to be too sensitive to the size of the study sample and is not always the best indicator of model fit (Kline, 2015). A value < 3.0 indicates an acceptable value. The goodness-of-fit index (GFI), normed fit index (NFI), root mean square residuals (RMSR), comparative fit index (CFI), adjusted goodness-of-fit index (AGFI), and the root mean square error of approximation (RMSEA) are some of the additional fit indices that were applied in this study in addition to the one recommended by Hair et al. (2014) and Kenny (2020). The suggested and actual values of model fit indices are presented in Table 4.7 below.

Table 4.8: Fit Indices of Full Measurement Model

Fit Indices	Model Value	Recommended Value	Decision
$\chi2$	1087.82	$\chi2$ > df	Fit
df	309	df $\geq$ 0	Fit
$\chi2$/df	3.520	≤ 3.0	Not fit
GFI	0.805	≥ 0.9	Not fit
AGFI	0.761	≥ 0.8	Not fit
CFI	0.885	≥ 0.9	Not fit
RMSR	0.069	≤ 0.1	Fit
RMSEA	0.086	≤ 0.08	Not fit
NFI	0.847	≥ 0.8	Fit

Source: Author's Computations, 2023

As shown in Table 4.7 above, the measurement model fails to fit majority of the suggested standards of fit model. This indicates there is no fit between observed data and the conceptualized model. Hence, the model fails to meet construct validity. As a result, construct validity is checked by conducting convergent validity and discriminant validity tests. First, convergent validity test was conducted based on results of full-measurement model. Second, after establishing the convergent validity, discriminant validity was examined.

4.9 Convergent Validity

Convergent validity, according to Engellant, Holland, and Tiper (2016), is the degree to which a measure concurrently relates to another measure to which it is intended to link. Its goal is to determine whether or not the elements of a construct measure the same thing. Convergent validity, according to Hair et al. (2006), shows how closely an observable variable and a latent construct are related. Collier (2020) said that poor convergent validity shows indicators are weakly measuring the construct or indicators are a better measure for a separate and/ or similar construct. Convergent validity was drawn from the full measurement model and the estimates of SRW and SMC are summarized in Table 4.9 below.

Table 4. 9: Convergent Validity - Full Measurement Model

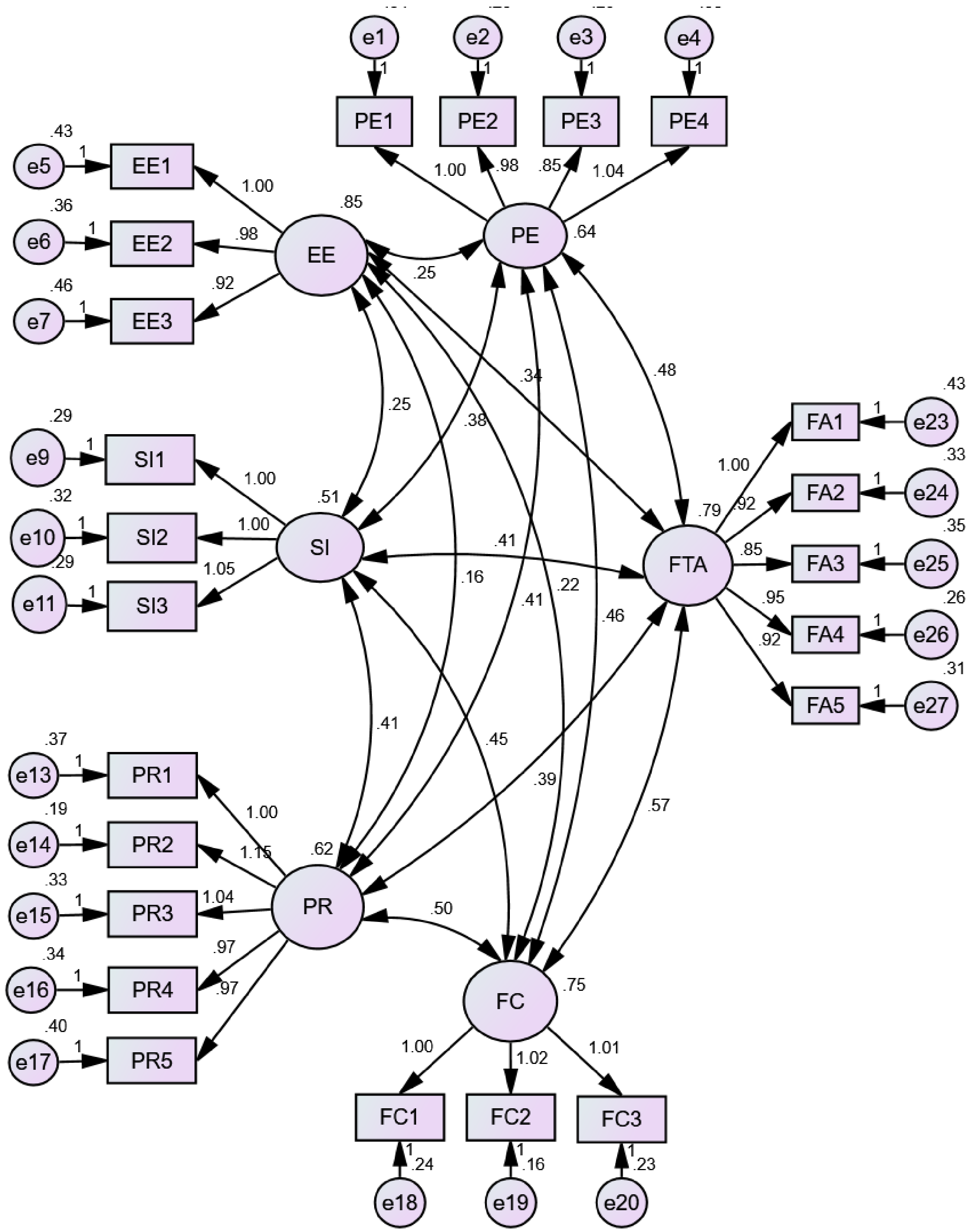
Items	Model1	Model2	AVE
PE1	.651	.650	0.655
PE2	.682	.681	
PE3	.615	.615	
PE4	.673	.674	
EE1	.598	.667	0.658
EE2	.761	.695	
EE3	.586	.613	
EE4	.400		
SI1	.624	.638	0.640
SI2	.596	.616	
SI3	.672	.665	
SI4	.446		
FC1	.716	.757	0.665
FC2	.806	.830	
FC3	.757	.772	
FC4	.333		
FC5	.379		
PR1	.618	.623	0.786
PR2	.810	.809	
PR3	.672	.670	
PR4	.631	.629	

PR5	.592	.592	
FA1	.647	.648	0.670
FA2	.670	.670	
FA3	.622	.621	
FA4	.729	.730	
FA5	.681	.680	

Source: Author's Computations, 2023

In model on the previous page, some of the items fail to meet convergent validity that the SRW and SMC values were below the cutoff point of 0.7 and 0.5, respectively. These items include EE4, SI4, FC4 and FC5. This indicates that these items fail to meet convergent validity. Hence, including expectation of users easily to learn to use FinTech is not valid measure for effort expectancy. In addition, it is not valid to include professional looking from using FinTech for finance management as social influence indicator. Further, payment requirement through FinTech and lower cost of FinTech than conventional methods are not valid items to measure facilitating condition feature of FinTech.

Hence, 4 items; EE4, SI4, FC4 and FC5 were removed from measurement model and the full measurement model is respecified by using 23 items. The respecified measurement model is presented in Figure 4.2 below.



Accordingly, new CFA was conducted on respecified model. Estimates of the respecified model is summarized in Table 4.9 below.

Table 4. 10: Convergent Validity - Respecified Model

Items	Model1	Model2	AVE
PE1	.651	.650	0.655
PE2	.682	.681	
PE3	.615	.615	
PE4	.673	.674	
EE1	.598	.667	0.658
EE2	.761	.695	
EE3	.586	.613	
EE4	.400		
SI1	.624	.638	0.640
SI2	.596	.616	
SI3	.672	.665	
SI4	.446		
FC1	.716	.757	0.665
FC2	.806	.830	
FC3	.757	.772	
FC4	.333		
FC5	.379		
PR1	.618	.623	0.786
PR2	.810	.809	
PR3	.672	.670	
PR4	.631	.629	
PR5	.592	.592	
FA1	.647	.648	0.670
FA2	.670	.670	
FA3	.622	.621	
FA4	.729	.730	
FA5	.681	.680	

Source: Author’s Computations, 2023

The loadings of the items in Table 4.9 are higher than the suggested threshold of 0.7. According to Hair et al. (2019), loadings above 0.70 for reflective measurements are advised since they show that the concept accounts for more than 50% of the variance in the indicator. When it comes to reflection measurements, the AVE level that is often suggested for satisfactory validity in convergent validity assessments is 0.5 (Kock, 2020). This suggests that the item's dependability is also acceptable. This suggests that more research should be done on the 23 items that were left. Consequently, this study continued to measure discriminant validity as well as reliability in order to assess and validate if the “psychometric properties” of the measurement model were satisfactory.

4.10 Discriminant Validity

According to Engellant et al. (2016), discriminant validity quantifies the degree to which latent variables differ from one another and shows that the measures of various constructs diverge or minimally correlate with one another (Collier, 2020). Correlations between various constructs can be used to evaluate discriminant validity; significant correlations (above 0.8 or 0.9) between constructs are indicative of a lack of discriminant validity (Holmes-Smith 2007). By comparing the factor correlation and squared root of AVE scores for every pair-wise construct, discriminant validity is found. When the squared roots of AVEs exceed the values of the correlation between latent variables, the condition is satisfied.

This study has examined discriminant validity based on results from the respecified model and correlation among the constructs was compared to square root of AVE values for the constructs. The summary statistics for discriminant validity measurement is presented in Table 4.10 below; where, the diagonal values are square roots of AVE.

Table 4. 10: Discriminant Validity Test

	PE	EE	SI	PR	FC	FTA
PE	**0.809**					
EE	0.341	**0.811**				
SI	0.668	0.375	**0.800**			
PR	0.660	0.221	0.723	**0.815**		
FC	0.665	0.272	0.719	0.740	**0.887**	
FTA	0.675	0.413	0.648	0.555	0.744	**0.819**

Source: Author’s Computations, 2023

When a construct's row and column values are less than the diagonal values, or square roots of AVE, the discriminant validity of the construct is met. Every concept, as indicated in Table 4.10, satisfies the discriminant validity requirement that the square root of AVE be greater than the correlation coefficient of the constructs. Thus, the respecified measurement model's discriminant validity is proven. This demonstrates how specific FinTech aspects can be explained by performance expectancy, effort expectancy, social influence, perceived risk, and enabling conditions. Furthermore, FinTech adoption is not the same as FinTech features.

Construct validity of measurement items is established that both convergent validity and discriminant validity of the measurement model were established. In addition, it is important to check the respecified model fit measures subject to the recommended values. Fit statistics of the modified measurement model is presented in Table 4.11 below.

Table 4.11: Fit Measures of Respecified Model

Fit Indices	Model Value	Recommended Value	Model Fit Status
χ^2	562.479	$\chi^2 > df$	Fit
df	215	$df \geq 0$	Fit
χ^2/df	2.616	≤ 3.0	Fit
GFI	0.881	≥ 0.9	Not Fit
AGFI	0.847	≥ 0.8	Fit
CFI	0.940	≥ 0.9	Fit
RMSR	0.044	≤ 0.1	Fit
RMSEA	0.069	≤ 0.08	Fit
NFI	0.907	≥ 0.8	Fit

Source: Author’s Computations, 2023

As presented in Table 4.11, the model fit summary shows that the model fits all measures of fit model except GFI. Since the model meets majority of the standards of fit model, it is revealed that model meets construct validity. In addition, as shown above, the respecified measurement model meets convergent validity and discriminant validity. This indicates there is fit between observed data and the conceptualized model. As a result, after meeting the convergent and discriminant validities, this study proceeds to checking reliability of the items.

4.11 Reliability Analysis

Once all of the measurement parameters supporting the research construct have been empirically derived and validated, the instrument's dependability is evaluated before proceeding with the structural model (Lewis et al, 2005). Reliability, which assesses the consistency of the items used to test a construct, guarantees the credibility of measurement instruments. Two statistics that are frequently used to evaluate dependability are composite reliability (CR) and the coefficient of internal consistency, also known as Cronbach's Alpha. This statistic needs to be computed for each element that passed each validity test. According to Hair et al. (2010), the criterion that is commonly accepted and advised in the literature is 0.7. The reliability data are shown in the following Table 4.12.

Table 4.13: Reliability Statistics

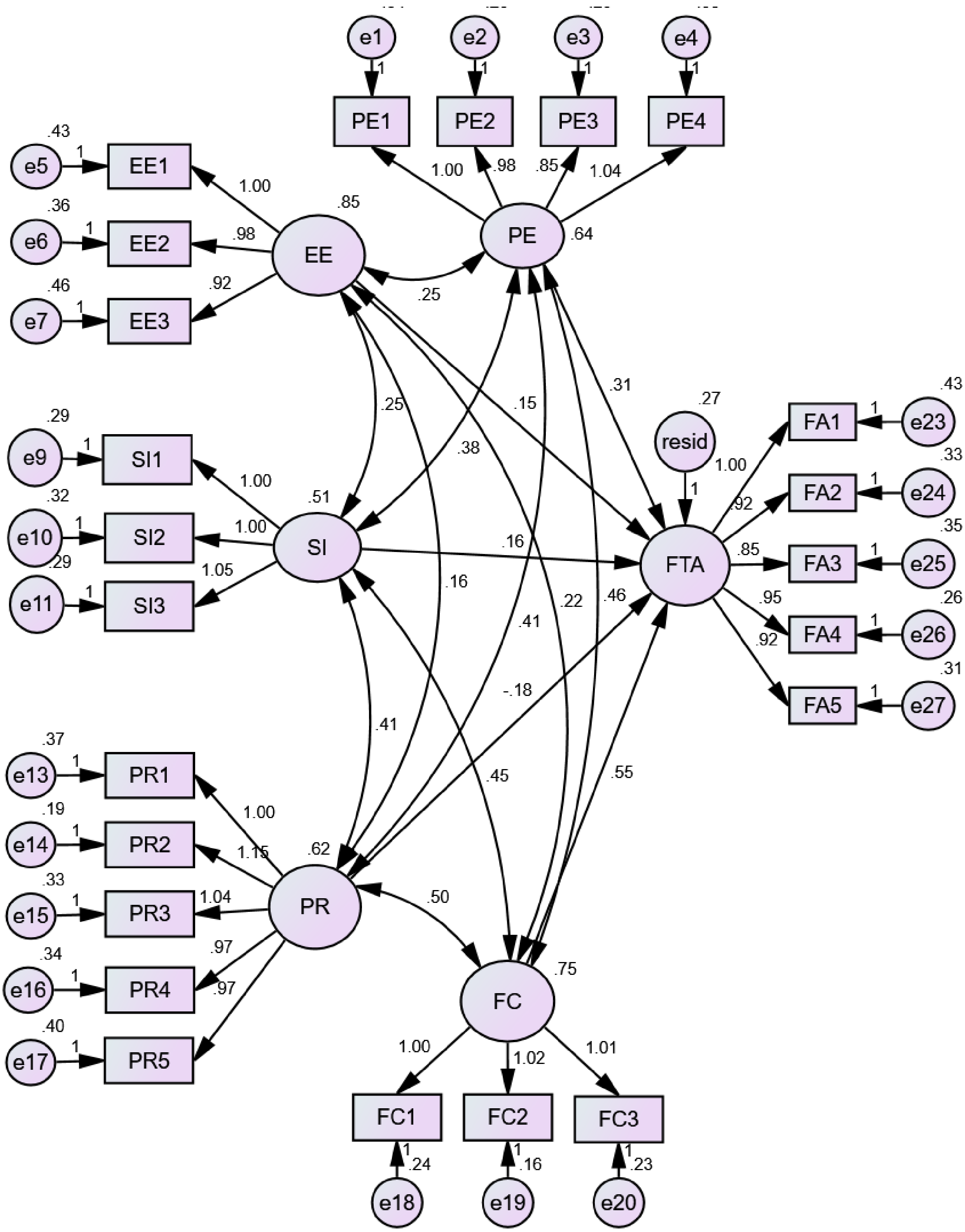
	Cronbach's Alpha	Composite Reliability	N of Items
PE	0.882	0.883	4
EE	0.852	0.853	3
SI	0.842	0.842	3
PR	0.908	0.908	5
FC	0.917	0.917	3
FTA	0.910	0.910	5

Source: Author's Computations, 2023

As presented in Table 4.12 above, reliability scores of variables in the study are all above 0.7, which satisfies the recommended threshold in the literature. Thus, the measurement items are reliable.

4.12 Structural Equation Model

According to Byrene (2010), the purpose of the structural model is to define how specific latent variables affect shifts in the values of other latent variables within the model. Only once sufficient measurement and construct validity are proven can the structural model be tested (Hair et al., 2006). The results of the measuring model were provided in earlier sections of this work. Determining how effectively the observed variables of a postulated construct relate to one another is the aim of testing the measurement model. It was presented that the measurement models are fitted for data of the study. Following results of measurement model, this study has developed structural model for the hypothesized research model by incorporating the individual latent variables. This section of the chapter presents result of the structural model. The structural model is constructed based on the respecified measurement model and it is constructed as follows in Figure 4.3 below.



4.13 Construct Validity

The first step in structural model is evaluating fit statistics of proposed model. The structural model's fit statistics are evaluated and depicted in Table 4.13 below.

Table 4. 14 GOF statistics of Structural Model

Fit Indices	Model Value	Recommended Value
$\chi2$	562.479	$\chi2$ > df
df	215	df ≥ 0
$\chi2$/df	2.616	≤ 3.0
GFI	0.881	≥ 0.9
AGFI	0.847	≥ 0.8
CFI	0.940	≥ 0.9
NFI	0.907	≥ 0.8
RMSR	0.044	≤ 0.1
RMSEA	0.069	≤ 0.08

Source: Author's Computations, 2023

The normed chi-square, $\chi2$/df, (2.616) of the model is within the acceptable range, ≤ 3.0. With respect to both CFI and NFI, the model is deemed acceptable as all incremental fit indices surpass the lower threshold value of 0.90. The model's absolute fit index values for RMSEA (0.044) and RMR (0.069) are also within the advised range, and the findings fall between the threshold values of < 0.1 and ≤ 0.08, respectively. In light of the chosen fit indices in the SEM literature, the structural model is therefore validated and supported.

Sufficient construct validity is the second prerequisite for a structural model, according to Hair et al. (2010). The construct validity of the structural model is tested by examining GOF indices and contrasting the factor loadings of the structural model with those of the underlying measurement model. According to Hair et al. (2010), the difference between the two shouldn't be bigger than 0.05. Table 4.14 below summarizes the construct validity for the structural model.

Table 4. 75: Construct Validity-SEM

Item	Construct	CFA	SEM	Difference
PE1	PE	.806	.806	.000
PE2	PE	.825	.825	.000
PE3	PE	.784	.784	.000
PE4	PE	.821	.821	.000
EE1	EE	.817	.817	.000
EE2	EE	.834	.834	.000
EE3	EE	.783	.783	.000
SI1	SI	.799	.799	.000
SI2	SI	.785	.785	.000
SI3	SI	.816	.816	.000
PR1	PR	.789	.789	.000
PR2	PR	.900	.900	.000
PR3	PR	.819	.819	.000
PR4	PR	.793	.793	.000
PR5	PR	.770	.770	.000
FC1	FC	.870	.870	.000
FC2	FC	.911	.911	.000
FC3	FC	.879	.879	.000
FA1	FTA	.805	.805	.000
FA2	FTA	.818	.818	.000
FA3	FTA	.788	.788	.000
FA4	FTA	.854	.854	.000
FA5	FTA	.825	.825	.000

Source: Author’s Computations, 2023

The discrepancy between the entire measurement model and the structural model's standard estimate loading is less than the threshold. In this sense, the structural model's loading estimates and the measurement model's loading estimations are nearly identical. This shows that there is parameter stability between the measured items in the two models, which lends more credence to the structural model's validity.

4.14 Hypothesis Testing and Discussion

Finally, the size, direction and significance of the structural parameter estimates were investigated. The result of regression weights is summarized in Table 4.15 below.

Table 4. 86: SEM Estimates

			Estimate	S.E.	C.R.	P
FTA	<---	PE	.312	.075	4.166	***
FTA	<---	EE	.150	.045	3.325	***
FTA	<---	SI	.157	.100	1.559	.119
FTA	<---	PR	-.175	.085	-2.057	.040
FTA	<---	FC	.550	.080	6.912	***

Source: Author's Computation, 2023

The first hypothesis of this study states that performance expectancy has positive and significant effect on adoption of FinTech by consumers of selected supermarkets in Addis Ababa. This study has computed that coefficient of performance expectancy (β = 0.312, t-value= 4.166, p-value=0.000) is positive and statistically significant at 0.01 significance level. As a result, H1 is accepted. This result indicates that perceived performance expectancy positively affect adoption of FinTech. This research also demonstrates that Addis Ababa FinTech consumers are self-assured and think FinTech services greatly increase their overall work efficiency when doing financial transactions. Alkhwaldi et al. (2022) have proven that performance expectancy is a significant factor in predicting users' propensity to employ FinTech services. According to Chan et al. (2022), another empirical study, performance expectancy is a crucial UTAUT model dimension that gives users the confidence to use FinTech services.

Second hypothesis of this study states that effort expectancy has positive and significant effect on adoption of FinTech in Addis Ababa. The result of SEM model shows that coefficient of effort expectancy (β = 0.150) is positive and statistically significant (t = 3.325; p-value is significant at 0.01). This suggests that adoption of FinTech by customers of supermarkets is positively and significantly affected by effort expectancy. This suggests even further that FinTech application users are labor-efficient and have little trouble understanding and utilizing financial activities. The results of this study are therefore consistent with the UTAUAT model, which suggests that effort expectancy is one of the primary indicators of FinTech adoption.

Furthermore, this result is consistent with other empirical studies. Ramos (2017), for instance, empirically verified a positive relationship between effort expectancy and FinTech service uptake. The results of Darmansyah and colleagues (2020) corroborate the presence of the same association. Furthermore, Rabaa'i (2021) talked about how users connect with FinTech applications without exerting more focus or effort if they have a higher degree of effort anticipation toward FinTech. According to Fanto et al. (2020), effort expectancy is a measure of how simple FinTech services are to use.

Third, this study with conducted to examine effect of social influence on adoption of FinTech services by users of the service. Hence, this study hypothesizes that social influence has positive and significant effect on adoption of FinTech by customers of supermarkets in Addis Ababa. Based on the survey result, it is computed that coefficient of social influence ($\beta = 0.157$) is not statistically significant (t-value = 1.559; p-value = 0.119). This shows that social influence positively but insignificantly affect adoption of FinTech. Hence, H3 is rejected, and it is stated that adoption of FinTech by customers of supermarkets in Addis Ababa is not affected by social influence. In theory, social influence is a component of UTAUT that helps forecast consumers' adoption of a technology or system that their peers suggest. Similar to this idea, this study found that peer referral had a small but favorable impact on the uptake of FinTech services.

Fourth, this study was conducted to analyze effect of perceived risk on adoption of FinTech services by customers of selected supermarkets in Addis Ababa. Based on this objective, this study has hypothesized that perceived risk negatively and significantly affects adoption of FinTech services by customers of the supermarkets. The result of SEM shows that path coefficient of perceived risk ($\beta = -0.175$) is negative and statistically significant ($t = -2.057$ & $p = 0.040$) at 0.05 significance level. Based on this result, this study revealed that perceived risk of FinTech negatively and significantly affects its adoption by customers of supermarkets in Addis Ababa. Hence, H4 is accepted. According to Kheira (2021), most customers believe that FinTech organizations might steal their data and misuse it, making FinTech services still a fresh notion. In a similar vein, Alswaigh and Aloud (2021) brought to light the perception held by FinTech customers that these businesses might not offer safe and effective financial transaction services. Empirically, Tang et al. (2020) found that perceived risk negatively impacts the adoption of FinTech services. Additionally, it is stated that the service's adoption rate is unreliable for carrying out any financial operations. Users of the technologies consider that if they provide personal and financial data access to FinTech companies, there will be no privacy, and someone can easily access the privacy (Suzianti et al., 2021).

Finally, this study has examined effect of facilitating conditions on adoption of FinTech by customers of supermarkets in Addis Ababa. For this purpose, based on theoretical foundations and different empirical studies it is hypothesized that facilitating conditions positively and significantly affect adoption of FinTech. Based on the empirical approach it is computed that coefficient of facilitating condition ($\beta = 0.550$) is positive and significant ($t = 6.912$; p-value = 0.000) at 0.01 significance level. This indicates facilitating conditions significantly and positively affects adoption of FinTech by customers of supermarkets in Addis Ababa; hence, H5 is accepted.

CHAPTER FIVE

5. Summary, Conclusions and Recommendations

The goal of the research was studying what factors really determine the adoption of FinTech among customers of supermarkets using the customers of Shoa Supermarket as a population. Accordingly, five major variables in technology adoption were identified after extensive investigation of theories on human behavior and technology adoption and relevance of those variables to the practical situation of our country. The data were collected using the questionnaire instrument and analyzed by one of the latest data analyzing software, i.e. AMOS 23. As aforementioned the five identified major determining factors were performance expectancy (perceive benefits in earlier theories), effort expectancy (perceived ease of use in earlier theories), social influence, perceived risk, and facilitating conditions. The conclusions of the findings are also presented as follows.

5.1 Summary of Major Findings

This study was conducted to identify determinants of FinTech adoption. Based on this purpose, the study has applied case study and selected customers of selected supermarkets in Addis Ababa. based on previous studies in the area and application of concepts, this study has drawn five specific objectives. The study has followed quantitative research approach and collected quantitative data by using structured questionnaire. Further, the study has applied descriptive and explanatory research designs; and the study data was analyzed by using descriptive and inferential statistics. based on the research objectives, this study has mainly used the inferential statistics and employed SEM. Based on the research methodology followed, this study has reached on following major findings.

- The result of SEM has shown that coefficient of performance expectancy (β =0.312) is significant ($t = 4.166$, $p = 0.000$) at significance level of 1%. This indicated that FinTech adoption is positively and significantly affected by performance expectancy users of the FinTech
- Like performance expectancy, coefficient of effort expectancy (β =0.150) is positive and statistically significant ($t = 3.325$, $p = 0.000$) at 1% significance level. Hence, the study has indicated that effort expectancy positively and significantly affects adoption of FinTech.

- Third, this study has effect of social influence on adoption of FinTech. Based on this purpose, the study has computed that coefficient of social influence (β =0.157) is not statistically significant (t = 1.559, p = 0.119). This indicates adoption level of FinTech is not affected by social influence.
- Fourth, this study has examined effect of perceived risk on adoption of FinTech. It is empirically computed that coefficient of perceived risk (β = -0.175) is negative and statistically significant (t = 2.057, p = 0.040) at 5% significance level. As a result, this study revealed that perceived risk has negative and significant effect on adoption of FinTech.
- Finally, this study has analyzed the effect of facilitating conditions on adoption of FinTech. The estimation result has shown that coefficient of facilitating condition (β = 0.550) is positive and statistically significant (t = 6.912, p = 0.000) at 1% significance level. Moreover, the empirical result has shown that this factor is most significant factor with largest coefficient and significance values. This indicates that facilitating conditions has positive and significant effect on adoption of the technology and this factor is most influential factor for adoption of FinTech in Ethiopia, particularly, by customers of supermarkets in Addis Ababa.

Accordingly, the major findings are summarized in simple terms as follows: While the performance expectancy, effort expectancy, and facilitating conditions have significant and positive effect on the adoption of FinTech services among customers of supermarket, perceived risk has significant, but negative effect on the adoption of the technology. The remaining factor, social influence, on the other hand has insignificant, but negative effect on the overall adoption of the technology among the customers.

5.2 Conclusions

Based on the findings of this study, the following conclusions are drawn.

- There is favorable perception about FinTech by different users of the technology. Customers of the supermarkets have good practices of using FinTech provided by ethiotelecom and different commercial banks in Ethiopia. Moreover, the customers are attracted by the technology. In particular, the technology meets performance expectancy and effort expectance of its users for the services. In addition, there is high social influence and different facilitating conditions about services of the technology. In contrast, the users feel that there are different risks associated to the FinTech services. Hence, on overall, this study revealed that current level of adoption of FinTech is influenced by characteristics of the service and facilitative environment for the technology.

- The customers used the technology for financial management, and it has provided them quick, efficient and convenient service to accomplish the finance tasks. This caused higher level adoption of the technology.
- The FinTech providers have established clear service, operable with low skill, and easily usable. This resulted good level of adoption of FinTech services.
- Despite existence of high social influence in other social areas, social influence has not affected the level of adoption of the technology. Hence, adoption of the technology is not influenced by social attachment. The adoption of FinTech is linked to product features and other favorable environment.
- Although adoption of the technology is favored by performance and effort expectancy, it is discouraged by existence of perceived risk. The customers that consider risk of FinTech has low intention to use the technology and perform transaction via FinTech. They discouraged by product risk, financial risk and privacy risk that limited the usage.
- Finally, usage of FinTech is favored by different environmental factors such as easy availability resources, compatibility with other technologies and time of availability of the services. Hence, adoption of the technology is increased due to easily available resources, like mobile phones and compatibility with the telecom service.

5.3 Recommendations

Based on the above findings, to improve the adoption of FinTech services in Addis Ababa, I would say different measures should be taken. To start with and as the effort expectance affects the adoption significantly and positively, all the stakeholders in the technology ecosystem need to make the technology easy to use and increase the awareness of the users all the time. They should make their applications easy to download, install, and use. They should come up with ideas and encouragements that result in people trying their products and services.

The second variable affecting the adoption significantly and positively is performance expectancy. That is nothing but what people believe the technology will bring them. The FinTech service providers should increase the awareness of the people as to why they should use their technologies be it in making transaction easier for them, reducing the effort and time they waste in paying bills or the risk of carrying a large amount of cash around.

Thirdly, it is the perceived risk that significantly and negatively affects the FinTech adoption among customers of supermarkets in Addis Ababa. Obviously, risk is one of the factors that negatively influence the adoption of almost every technology be it in Ethiopia or elsewhere. In this regard, the companies that provide the services need to make their system as secure as possible. They should be proactive and invest well in their cybersecurity infrastructures. Even at times they need to give guarantee to their users over their finances and confirm to them take corrective measures swiftly when breaches of security happen.

Fourthly, it is the facilitating conditions that significantly and positively affects the adoption of FinTech services and products. In this regard, since most of the facilitating conditions are taken by government bodies, they need to make the overall technology ecosystem suitable for both the service providers and users alike.

Finally, as the social influence has positive effect, though insignificant, we still use the influence of social classes to encourage one another to try and use the available technology services and products including FinTech. Though the concept of social classes is nascent in Ethiopia, Ethiopians give greater value to family and family members. Accordingly, those family members who are innovator and early technology adopters can encourage their other family members to adopt the FinTech services and products.

5.4 Future Study

Application of FinTech is not limited to supermarket customers and almost any business can benefit from the reduced transaction cost and convenience of the technology. The fact that both public and private sector is investing in and obliging the use of the technology, the case of the recent regulation by Government to use mobile payments in fuel stations and the expansion of FinTech services by banks respectively makes the use of FinTech services not only essential but also a must. As other countries are also embracing the use of FinTech services and products aggressively, lagging in the adoption rate will leave Ethiopian business less competitive globally and less profitable financially. Hence, I would recommend other researchers do additional research in other fields of business and find out which factors decide the adoption of FinTech services and products in Ethiopia so that all stakeholders and can exploit the findings and increase the adoption rate of Ethiopia.

Further to the above recommendations, I would also recommend the effect of moderating variables be studied to fully understand the FinTech adoption in our country. As I tried to briefly discuss in the sections, generally there are three major variables that have high moderating effects on technology adoption including FinTech adoption. The three major variables are age, gender, and experience and I would recommend other researchers including the moderating effect of those variables to obtain bigger and fuller picture of FinTech adoption in our country.

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APPENDIX I: QUESTIONNAIRE

SCHOOL OF GRADUATE STUDIES

MASTER OF BUSINESS ADMINISTRATION PROGRAM

Dear Respondent,

My name is Zerihun Guyassa and I am currently a Master of Business Administration (MBA) student at College of Business and Economics, Addis Ababa University (AAU). The aim of this questionnaire is to solicit information that would help in determining the determinants (factors) for the adoption of FinTech services and products by customers of supermarkets Addis Ababa. I would like to assure you that the information you provide will be used only for the research purpose and kept confidential. Your genuine responses are regarded as a great input to the quality of the research outcomes. Hence: I do believe that you will assist me by participating in the study your honest and thoughtful responses invaluable.

Thank you in advance for your participation

I kindly request you to participate in this research study by completing this questionnaire. To ensure that all information will remain confidential please do not include your name anywhere in the questionnaire. I also sincerely request you to respond to the questions as honestly as possible and return the completed questionnaire. Knowing that your time is valuable, please take a few minutes of your time to complete the questionnaire.

With best regards,

Thank you very much for your cooperation!

General Information

There is no need of writing your name.

Please select the right answer to the best of your knowledge and put the "√" mark in the boxes.

For questions that require your further opinion, please respond clearly and faithfully.

For any queries – Mob. 0966926508 or E-mail: zerihun.guy@gmail.com

Part one: General Personal Data

1.1 Demographic and Socio-economic Characteristics

1) Gender

☐ Female ☐ Male

2) Age Group

☐ 18-28 ☐ 29-39 ☐ 40-50 ☐ Above 50

3) The highest level of education:

☐ High School ☐ Diploma ☐ First Degree ☐ Master's Degree ☐ PhD

4) Monthly income (average in Birr)

☐ Less 10,000 ☐ 10,001-20,000 ☐ 20,001-30,000 ☐ Above 30,000

1.2 FinTech Experience

5) Have you heard of the word FinTech before?

☐ Yes ☐ No

6) Which FinTech service(s) do you use for your shopping purposes? (Multiple responses are possible)/Do you use any FinTech service? If yes, which one(s) don you use?

☐ TeleBirr ☐ CBE Birr ☐ Amole ☐ AwashBirr ☐ E-Birr ☐ POS

☐ Other, please specify ______________________________

7) Experience of respondent with FinTech:

☐ <1 year ☐ >1 year and <2 years ☐ > 2 years ☐ Other

Part Two:

Section II. Questionnaires related with factors affecting FinTech adoption.

Instruction: Below are list of statements pertaining to adoption of FinTech Shopping. Please indicate whether you agree or disagree with each statement by ticking ( ) in the spaces that specifies your choice from the options ranging from "strongly disagree" to "strongly agree". Each choice is identified by numbers ranging from 1 to 5.

Note:

SD=Strongly Disagree=1, D=Disagree=2, N=Neutral=3, A=Agree=4, SA=Strongly Agree=5

	1. Performance Expectancy (PE):	**SD**	**D**	**N**	**A**	**SA**
		1	**2**	**3**	**4**	**5**
PE1	I find FinTech services to be useful in enablement to accomplish my shopping more quickly.					
PE2	FinTech shopping services improve my payment convenience.					
PE3	Using FinTech services enhance my shopping transaction quality.					
PE4	Using FinTech shopping services increase my efficiency in conducting my shopping tasks.					
PE5	Using FinTech services increase my productivity in handling my shopping tasks.					
PE6	Using FinTech Shopping would enable me to accomplish my tasks quicker.					
PE7	Overall using FinTech for shopping is advantageous.					

		SD	D	N	A	SA
	2. Effort Expectancy (EE):	**1**	**2**	**3**	4	5
EE1	Learning how to use FinTech apps would be easy.					
EE2	Interaction with FinTech apps does not require a lot of mental effort.					
EE3	It is easy to make payments using FinTech in shopping					
EE4	Using FinTech shopping does not require training.					
EE5	I have the knowledge and capacity necessary to use the system					
EE6	It is easy to use FinTech to accomplish my shopping tasks.					
EE7	I believe only those people who are highly educated can use FinTech services					

	3. Social Influence (SI):	SD	D	N	A	SA
		1	**2**	**3**	4	5
SS1	People who influence my behavior think that I should use FinTech for shopping.					
SS2	People who are important to me, believe that I should use the system					
SS3	I believe the use of FinTech is one of the behaviors for social acceptance					

SS4	My family and friend value or highly regard the person who uses FinTech services					
SS5	I believe use of FinTech services is one of the indicators of higher social class					
SS6	I believe using FinTech makes one fashionable/trendy					
SS7	Overall using FinTech services for shopping make me feel to belong to higher social class.					

	4.FACILITATING CONDITIONS:	**SD**	**D**	**N**	A	**SA**
		1	**2**	**3**	4	5
FC1	I think the existing devices can be used for FinTech services					
FC2	I think the telecom network is good enough to use FinTech services and prodcuts					
FC3	I think the existing network is capable enough for FinTech services and products					
FC4	I think FinTech companies have capable staff for FinTech services and products					
FC5	I think the cost equipment of equipment to use FinTech services and products are low					

FC6	I believe cost of using FinTech services are fair					
FC7	I think using FinTech services is not costly in terms of time:					

	5. PERCEIVED RISK (PR):	**SD**	**D**	**N**	A	**SA**
		1	**2**	**3**	4	5
PR1	FinTech shopping may not perform well because of network problem.					
PR2	Overall using FinTech in shopping is risky					
PR3	I am not comfortable of using FinTech shopping as carrying my pone and my code together will expose me to frauds.					
PR4	In using FinTech shopping, I believe that my transactions are secured.					
PR5	In using FinTech shopping, I believe that my privacy is secured.					
PR6	In using FinTech shopping, I believe that all my information is kept confidential					
PR7	When transferring money through FinTech shopping I am worried of making mistakes in inputting such info as account number, amount of money, etc.					

2.2. Level of Adoption of Fintech

The following statements presents level of using FinTech. Please rate your level of using fintech, very low to very high, based on following statements; where (**1=Very Low, 2=Low, 3=Moderate, 4=High, 5=Very High)**

Code	Fintech Adoption (FA)	1	2	3	4	5
FA1	I use FinTech on a regular basis					
FA2	I recommend others to use FinTech					
FA3	My use of FinTech continues in the future					
FA4	I check balance of my account on the platform of FinTech					
FA5	I make a transfer on the platform of FinTech					

Thank you for your cooperation!