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Consumers Perspectives on Using Biometric Technology With Mobile Banking

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Rodney Alston Clark

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Abstract

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MIM, University of Maryland University College, 2012

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Management

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Abstract

The need for applying biometric technology in mobile banking is increasing due to emerging security issues, and many banks' chief executive officers have integrated biometric solutions into their mobile application protocols to address these evolving security risks. This quantitative study was performed to evaluate how the opinions and beliefs of banking customers in the Mid-Atlantic region of the United States might influence their adoption of mobile banking applications that included biometric technology. The research question was designed to explore how performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), perceived credibility (PC), and task-technology fit (TTF) affected customer adoption of biometric technology with mobile banking. The conceptual framework extended the unified theory of acceptance and use of technology by including PC and TTF. The responses to a web-based questionnaire that was distributed to 228 mobile banking customers were analyzed using SPSS AMOS (Version 23) to create structural equation models, a multiple linear regression model, and an analysis of variance (ANOVA) model. The results showed that PE, EE, TTF, and FC were the significant factors affecting customer acceptance of biometric technology with mobile banking. SI and PC were nonsignificant factors and had low positive correlations. The results of this study suggest that biometric technology can mitigate the risks associated with security attacks by identifying the customer during the bank transaction. The results also support positive social change by demonstrating how biometric technology can secure banks from fraud, prevent crime, and improve liveness detection.

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Dedication

I devote this research to my mother, who has guided me through life with inspirational words of wisdom and spirituality. Also, I would like to devote this paper to my wife and daughter for their steadfast support. Last, I dedicated this work to the African people living in the diaspora of the world, and may this study contribute to emerging the world into a unified place.

Acknowledgments

My first intent is to recognize the supreme being of the universe, let the spirit continue to flow in me. Second, I express thanks to my chairperson, Dr. Mohammad Sharifzadeh, whose leadership guided me through the dissertation and assisted me in accomplishing my dream of obtaining a doctoral degree. I extend gratitude to my committee member Dr. Bharat Thakkar, for contributing divine insight and competence that significantly impacted the quality of my study.

I also extend appreciated to my friends and immediate family, who encourage and supported me throughout the doctoral process. To the Management Program Director, Dr. Sandy Kolberg, I expressed appreciation for the great words of encouragement and support; I am indebted! To the Institutional Review Board (IRB) for their dedication and hard work. Also, I thank the University Research Reviewer (URR) staff for all their support and special gratitude for Dr. Anton Camarota for his critique and thorough evaluation. Finally, I thank Walden University College of Management and Technology students, faculty, staff with a special appreciation for Walden University Library staff for their insights, and professional work etiquette.

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Chapter 1: Introduction to the Study

Mobile banking is a part of social interaction, and customers use mobile devices for electronic bank transactions with many different mobile apps. Because customers are using banks' apps more often, biometric technology has become a new mobile banking method. Because of the increase of bank security issues and identity fraud, customers welcome the use of their physiological traits with mobile apps. Banks use different security features and solutions for their security protocols to help customers against phishing attacks, identity theft, and bank fraud, and biometric technology is considered the most secure (Svilar & Zupančič, 2016). Biometric technology will provide multiple layers of security for customers during mobile bank transactions. Also, biometric technology is intended to ensure the correct person is trying to access their account, so no ambiguous tries during the bank transactions (Rui & Yan, 2019).

More than 87% of customers use online or mobile banking, and customers feel their bank accounts are vulnerable to cybercriminals (Sharma, 2017). Therefore, customers are demanding solutions to feel safer during their mobile bank transactions. Biometric technology gives customers strengthened security during bank transactions with mobile devices because of the multilayer security versus the traditional authentication method. Mobile device safety is essential because data on mobile devices get compromised, so more protection is necessary because of the rise in customers' usage (Chung-Hua et al., 2017). In 2014, over 40% of U.S. customers used mobile banking, and a recent report by Juniper Research showed that mobile banking customers reached one billion in 2016 (Aggarwal & Varghese, 2014; Smith, 2016). Customers use their mobile

devices to store information like text messages, contacts, passwords, pictures, bank information, and other personal data types they do not want to be compromised by cybercriminals or other unauthorized people. The sensitivity and amount of data that get stored on mobile devices create concerns for efficient and flexible management of mobile devices (Crawford & Renaud, 2014).

To help with potential threats on smartphones, graphic passwords, personal identification numbers, and passwords are used for security measures. Because of customers' unsafe practices or how easily the traditional security methods can crack, the need to examine other solutions is necessary. Using biometric technology will help recognize the unique individual during the bank transaction, and the data remain the same over the entire lifetime of the person's use. The current problem is the customers' lack of biometric technology use while using a mobile device. Using secure bank transactions is critical for the bank's online mobile authentication to verify customers' identity while using mobile devices. Community bank decision-makers highlight strengthening mobile banking applications with biometric technology because of customers security-related concerns with using their biological characteristics (MengHui et al., 2015).

Background of the Study

Mobile banking has changed the way customers check their bank accounts and has moved from a face-to-face platform to a mobile market. Mobile banking apps offer the bank customers more convenience and services without face-to-face with the physical bank. During the 1980s, internet banking joined the World Wide Web to set up online banking for customers to access their accounts on personal computers. Internet banking

leads to bank customers making bank transactions anytime and anywhere (Milić et al., 2017). However, since the advent of internet banking, customers have changed, and mobile banking now dominates internet banking (Milić et al., 2017). The bank apps used on mobile devices allow customers to access their bank accounts and make transactions remotely (Baabdullah et al., 2019). The online presence for mobile banking has risen throughout the years because of customers' demands to have access anytime. Also, the internet has change how customers look at banking services and mobile banking technology has become the primary choice for customers (Kiheung et al., 2016).

Internet technology has changed the way customers access their personal information because of their bank's convenience services (Al-Sharhan et al., 2019). However, today's community banks are lagging because of the lack of information technology and the effort they are putting into the simplicity of customers' day-to-day business of new technology (Milić et al., 2017). Because of customers' increasing use of online services, security-related issues have risen, and customers' personal and private data being accessible by intruders are community banks' main issues (Kiheung et al., 2016). For mobile banking apps to work, customers must trust in the product before they start using it; therefore, security features need to be in place to help secure customer's data (Kiheung et al., 2016).

The banking industry reported over 35 million online banking frauds during 2010–2011, and hackers continue to find loopholes in modern banking application (Tassabehji & Kamala, 2012). In Addition, security issues were reported by customers during 2005–2014 because they were using new technology (Tarhini et al., 2016).

Therefore, avoiding cyberattacks is a primary concern for community banks (Kiheung et al., 2016). The System Usability Scale (SUS) is used to test biometric technology for e-banking and collect information on customers' views of the new service (Tassabehji & Kamala, 2012). Customers navigate e-banking services through internet-driven devices, such as laptops, desktops, automated teller machines (ATM), or smart devices (Milić et al., 2017). The services offered through a mobile application give customers convenient access to financial information about the banks' services, and customers have the choice to perform financial transactions (Milić et al., 2017). To expand e-commerce and e-banking is essential for the services through a bank's mobile application, and banks have inferred that online banking provides many benefits which make customers banks transaction safer and more convenient.

A study conducted at a Nevada Credit Union with over 80,000 members showed that 70% of customers use remote channels (mobile and online), and about 30,000 switched to mobile devices only (Gamble, 2018). The evolution of e-commerce in the United States has risen since the mid-1990s and has cause internet banking to facilitate customers' daily banking needs (Susanto et al., 2013). Prior research has supported the importance of trust, security and privacy, customer satisfaction, and loyalty for Internet banking implementation, including more security layers (Susanto et al., 2013). Since customers use mobile devices to access their information, data needs to be secure so potential intruders may not gain the customer's data. In the online mobile application, the primary way to prevent information from being lost is to have an individual confirm their identity. The banking industry uses modern technology to push biometric technology to

improve login authentication for customers when using mobile banking apps (Gamble, 2018).

Problem Statement

Mobile users in the United States reached 95 million, and with the adoption of mobile banking, mobile users rose to 40% in 2013 and reached over 1 billion globally in 2017 (Aggarwal & Varghese, 2014; Smith, 2016). In the United States, despite customers' lack of acceptance of mobile banking security, over 63% of smartphone users prefer mobile banking over any other business channel (Aggarwal & Varghese, 2014). The Federal Trade Commission (2019) reported more security and privacy issues have arisen because of mobile technology increase. Researchers found that using biometric technology will enhance the banks' security protocols while addressing the common issues by customers (Malaquias & Hwang, 2019). In this study, the general problem is that community banks have no general idea about customers' behavioral intentions (BI) with their acceptance and use of biometric technology with mobile banking (Shareef et al., 2018). Specifically, biometric technology is new to research, and bank customers are not aware of the benefit's biometric offers.

Due to reports of persistent login attempts and security violations, customers have found biometric technology with mobile banking more secure than traditional login tries (Cook, 2017; Hess & Van Der Stad, 2016; Vanian, 2015; Zalud, 2016). The specific problem is customers' lack of adoption of biometric technology, and bank managers do not understand the reasons that influence mobile banking adoption in the Mid-Atlantic region of the United States. By the year 2020, mobile banking users will continue to grow

to 1.4 trillion because of the millennial demographic buying power (Evon & Leby Lau, 2016).

Purpose of the Study

The purpose of this quantitative study was to develop a conceptual model with a conceivably more eminent explanatory power about mobile banking technology adoption. A conceptual framework was developed by extending the unified theory of acceptance and use of technology (UTAUT). The extension of the UTAUT2 incorporating two more factors: perceived credibility (PC) and task-technology fit (TTF). A quantitative approach based on a web-based questionnaire survey was used to collect data from 228 mobile banking customers in the Mid-Atlantic region. The data were analyzed using structural equation modeling (SEM) based on the analysis of a moment structures (AMOS, Version 23). Understanding customers' adoption of biometric technology can guide decision-makers of banks to be innovative with security protocols. The participants included college students and bank users from three independent banks. Participants in the study were voluntary. The respondents who chose to participate completed a web-based survey questionnaire providing their opinions and beliefs with the use and acceptance of biometric technology with mobile banking.

In this quantitative study, the independent variables included (a) performance expectancy (PE), (b) effort expectancy (EE), (c) social influence (SI), (d) perceived credibility (PC), (e) task-technology fit (TTF), and (f) facilitating conditions (FC). I used LimeSurvey (https://www.limesurvey.org/) to host the web-based survey, and Cint (https://www.cint.com/) was used as a host platform to recruit participants. The web-

based survey was used to collect data from 228 bank customers in the Mid-Atlantic region of the United States.

Research Question and Hypotheses

The question guiding this research was this: To what extent do performance expectancy, effort expectancy, social influence, perceived credibility, task-technology fit, and facilitating conditions affect the behavioral intentions of customers to adopt biometric technology with mobile banking?

Table 1 defined the study's independent and dependent constructs, and Table 2 shows the constructs and their roles by describing the independent, dependent, and moderate relationships of each construct.

Table 1

Independent and Dependent Constructs

Constructs	Items	Measures
Behavioral Intention	BI	BI is the behavioral intention to use or reject a system.
Performance Expectancy	PE	PE the belief of customers using a system will determine more security.
Effort Expectancy	EE	EE is how the effort of ease of a system.
Social Influence	SI	SI is the opinion of customers and how others feel the system works
Perceived Credibility	PC	PC is how easy the system works.
Task-Technology Fit	TTF	TTF is the degree of whereby the technology will fit the customer’s needs.
Facilitating Conditions	FC	FC is how customers feel the organization will support the system
Actual Usage	AU	AU is the actual use of the product or services by the customer’s

Table 2

Constructs and Their Roles

Constructs name	Independent variables	Moderator variables	Dependent variables
Behavioral Intention			X
Performance Expectancy	X		
Effort Expectancy	X		
Social Influence	X		
Perceived Credibility	X		
Task-Technology Fit	X		
Facilitating Conditions	X		
Actual Usage		X	

Hypothesis 1: *Performance expectancy* (PE) is defined as extracting utilities for timesaving, convenience, money, less effort, and faster service during banking activities (Venkatesh et al., 2003). PE is where an individual thinks the system will help them perform the work of their jobs better (Oye et al., 2014). Thus, the following hypothesis is postulate:

$H1_0$: Performance expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H1_1$: Performance expectancy will affect customers' behavioral intention to use biometric technology with mobile banking.

The independent variable is PE, and the dependent variable is the BI. Factor analysis and multiple regression analysis was used to test the hypothesis.

Hypothesis 2: *Effort expectancy* (EE) is related to how comfortably an individual believes in the systems and how easily they can use the system (Oye et al., 2014). Thus, the following hypothesis is postulate:

$H2_0$: Effort expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H2_1$: Effort expectancy will affect customers' behavioral intention to use biometric technology with mobile banking.

The independent variable is EE, and the dependent variable is the BI. Factor analysis and multiple regression analysis was used to test the hypothesis.

Hypothesis 3: *Social influence* (SI) is the person's opinion of whether they should perform the behavior in question (Tarhini et al., 2016). Thus, the following hypothesis is postulate:

$H3_0$: Social influence will not influence customers' behavioral intention to use biometric technology with mobile banking.

$H3_1$: Social influence will influence customers' behavioral intention to use biometric technology with mobile banking.

The independent variable is SI, and the dependent variable is the BI. Factor analysis and multiple regression analysis was used to test the hypothesis.

Hypothesis 4: Research by Tarhini et al. (2016) argued that integrating *perceived credibility* (PC)C into UTAUT will better predict customers' BI toward using mobile banking. Thus, the following hypothesis is postulate:

$H4_0$: Perceived credibility will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H4_1$: Perceived credibility will affect customers' behavioral intention to use biometric technology with mobile banking.

The independent variable is PC, and the dependent variable is the BI. Factor analysis and multiple regression analysis was used to test the hypothesis.

Hypothesis 5: The theory is by applying a proper *task-technology fit* (TTF); this will increase customers' behaviors to use the technology (Tarhini et al., 2016). Thus, the following hypothesis is postulate:

$H5_0$: Task-technology fit will not influence customers' behavioral intention to use biometric technology with mobile banking.

$H5_1$: Task-technology fit will influence customers' behavioral intention to use biometric technology with mobile banking.

The independent variable is TTF, and the dependent variable is the BI. Factor analysis and multiple regression analysis was used to test the hypothesis.

Hypothesis 6: The *facilitating conditions* (FC) are defined as where customers feel the organization and security will support the system (Venkatesh et al. (2003). Thus, the following hypothesis is postulate:

$H6_0$: Facilitating conditions will not influence the actual usage of biometric technology with mobile banking.

$H6_1$: Facilitating conditions will influence the actual usage of biometric technology with mobile banking.

The independent variable is FC and BI, and the dependent variable is the actual usage. Factor analysis and multiple regression analysis was used to test the hypothesis.

Table 3 describes the hypothesis constructs, directionality and the constructs they represent in the study.

Table 3

Hypotheses, their Directionality, and the Construct they Represent

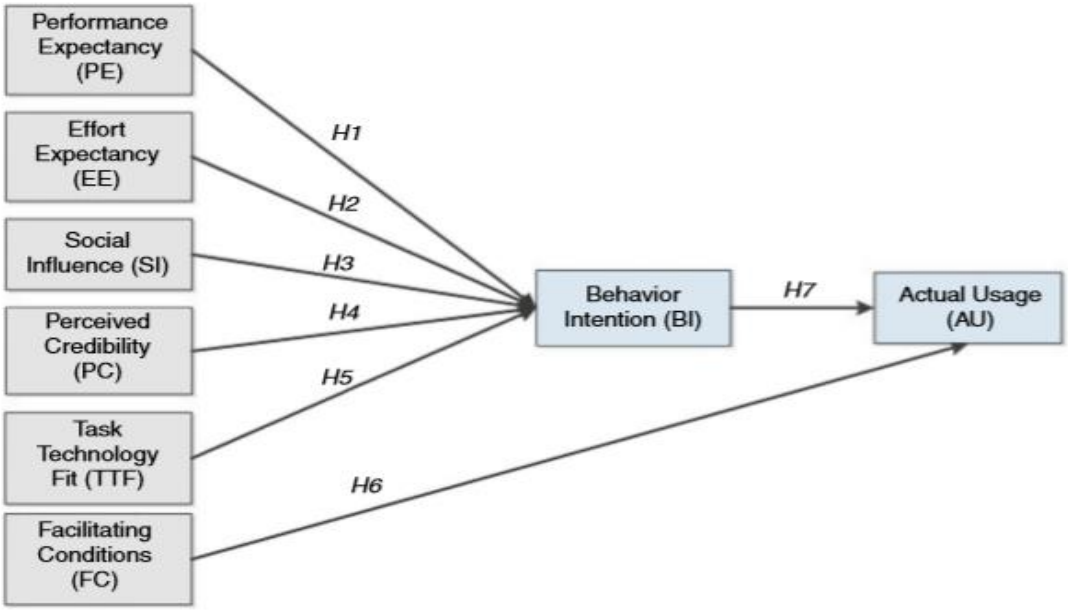
Hypothesis	Construct #1	Construct #2	Directional
$H1_1$	Performance Expectancy	Behavioral Intention	(+)
$H2_1$	Effort Expectancy	Behavioral Intention	(+)
$H3_1$	Social Influence	Behavioral Intention	(+)
$H4_1$	Perceived Credibility	Behavioral Intention	(+)
$H5_1$	Task-Technology Fit	Behavioral Intention	(+)
$H6_1$	Facilitating Conditions	Actual Usage	(+)

In this study's connection, it is expected that if customers find mobile banking with biometric technology easy to use, they will more likely use and adopt it. In contrast, if the customers consider mobile banking with biometric technology challenging to use, they are less likely to embrace it. PE has been used to understand customers' BI of adopting mobile banking (Lee et al., 2019; Tarhini et al., 2016). EE positively affects PE when customers feel mobile banking is easy to use, and not much effort is required (Rahi et al., 2018). SI affects customers' intention to adopt mobile banking services. The individual who believes a new product or service is vital to others will be more inclined to use new technology (Rahi et al., 2018).

Hypotheses 1 through 6 were tested by running the following multiple regression model: $BI = \beta_0 + \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 PC + \beta_5 TTF + \beta_6 FC + €$. See Table 1 for independent and dependent constructs and see Table 2 for the constructs' roles. No single case has proclaimed the relationship between BI and online mobile banking adoption in the Mid-Atlantic region of the United States. According to Tarhini et al. (2016), there was no critical relationships between PE, SI, FC, TTF and PC that was shown in previous investigations (Tarhini et al., 2016). Previous literature identified a significant difference in the moderating effect of experience in using mobile apps between FC and intentions to use (Palau-Saumell et al., 2019). Other researchers also examined the moderating effects of gender and age using the UTAUT model, and they did not find any significant results among mobile banking customers (Palau-Saumell et al., 2019). The study filled the gap by extending the UTAUT by using PC and TTF. Also, the specific variables like age, gender, and experience, which are part of the original UTAUT, had two theoretical constructs (PC and TTF) to moderate various UTAUT relationships. Figure 1 shows a research model for the described constructs.

Figure 1

Proposed Theoretical Model



Note. From "Extending the UTAUT model to understand the customers' acceptance and use of Internet banking in Lebanon: A structural equation modeling approach," by A. Tarhini, M. El-Masri, M. Ali, and A. Serrano, 2016, 29(4), 834. Copyright 2016 by Tarhini, El-Masri, Ali, Serrano. Reprinted with permission (see Appendix E).

Theoretical Foundation

The theoretical base for this study was Venkatesh et al.'s (2003) UTAUT. This theory is used to determine user acceptance and use behavior (Onywoki & Opiyo, 2016). Tarhini et al. (2016) used the UTAUT model and found it to be a valuable and valid research tool for predicting the adoption behavior and BI with an emphasis on PE, EE, SI, and FC. A theoretical framework was used by extending the UTAUT by incorporating two more factors; the PC and TTF (UTAUT2) model (Tarhini et al., 2016). The adoption

of biometric technology by customers' when using mobile banking will help with security and risk associated with their mobile application transactions. By extending the UTAUT to incorporate PC and TTF, a more comprehensive theoretical perspective of user technology acceptance was provided (Tarhini et al., 2016).

Theoretical Framework

A theoretical framework was used by extending the UTAUT with PC and TTF model the UTAUT2 (Tarhini et al., 2016). The adoption of biometric technology when using banking through mobile devices by customers will strengthen security and risk associated with their online transaction and how technology will fit the customer's TTF. By extending the UTAUT to incorporate PC and TTF, a more comprehensive theoretical perspective of user technology acceptance was provided (Tarhini et al., 2016). Extending the UTAUT improves mobile devices' safety by exploring the time to authenticate mobile devices by narrowing down the application's sensitivity level (Alotaibi et al., 2015). Security is considered a priority for many mobile banking customers. Previous research showed 31% of customers would buy added protections for security features, 63% would switch accounts for greater security, and 71% would change accounts to banks that provide more protection to their accounts (He et al., 2015).

Nature of the Study

The nature of this study was a quantitative method using a survey research design. In quantitative research, survey results are quantifiable to a known degree of accuracy because of the representation (Rea & Parker, 2014). In this study, the survey was used to collect quantitative information from mobile users in the Mid-Atlantic region of the

United States, where the data were analyzed using SEM, which is a tool for specific confirmatory factor analysis models, regression models, and sophisticated path models (Ramkissoon et al., 2013). SEM has been used by many scholars to describe the between-person structure of human actions (Hunter, 2018). The specific population was from three colleges and three community banks in the Mid-Atlantic region. Community banks are creating new strategies for current and future customers, and because of hackers' abilities to compromise traditional systems and improve their approach to breakthrough new security models.

In this study, I looked at customers who use smart devices and examined whether the FC and BI affect biometric technology's actual use (AU) with mobile banking apps. This study examined PE, EE, and SI behavior intentions with biometric technology on mobile devices during mobile banking transactions. I also examined PC and TTF customer's BI with biometric technology on mobile devices during mobile banking transactions. A quantitative approach was used based on the web-based questionnaire survey polls. The data were analyzed using SEM based on Statistical Package for the Social Sciences (SPSS) AMOS from local colleges and independent community banks in the Mid-Atlantic region. By using surveys and sample surveys, this method will lead to a known level of accuracy (Rea and Parker, 2014). The general population was three independent banks and three colleges in the Mid-Atlantic region. The bank customers used mobile banking apps with biometric technology as an authentication method.

Definitions

The terms below are descriptive to the study, and their operational definitions are as follows:

Biometric authentication: A security system method that authenticates the traits of the human body for confirming the actual person (Vanian, 2015).

Biometrics technology: Method to confirm the identity of a person by verifying the individual's physical attributes. Biometric features of the individual provide bank systems a positive declaration of the identity of the unique person (Zalud, 2016).

Continuous authentication: Designed to have customers authenticate themselves after the initial login and throughout the login for added security (Kroeze & Malan, 2016).

Commercial banks: Banks that offer full-service with a wide range of services for customers and businesses (McFarland, 2013).

Community banks: Banks that are local in the community and focus on local business and families and have less than $10 billion in assets according to the Federal Reserve Board (Gehrke, 2019).

Cybersecurity: The goal is to protect electronic information systems and networks from being attacked by threats and vulnerabilities (Sosin, 2018).

Direct attacks: Method that gets tried at the sensor level, and it deals with synthetic biometric samples typical to mobile phones like the iris, face images or voice to fraudulently access a system (Das et al., 2016).

E-banking: Where individuals use a transaction with their bank account, and the technology does not use internet access (Milić et al., 2017). E-banking is an emerging subject in banking because of the rapid advancement of technology. E-banking is timesaving, customer-friendly, and it reduces the cost for banks (Malarvizhi & Geetha, 2017).

E-commerce: Enabled services powered through websites that used interactive product displays to process online sales transactions and information exchange (Lim & Ayyagari, 2018).

False acceptance rate (FAR): This ascertains how often an intruder can successfully bypass biometric authentication. The lower the FAR, the more secure the system is (i.e., a FAR of 1% declares the chance of fooling the system is 1:100; Gautam & Dawadi, 2017).

Equal error rate (EER): FAR and FRR, also known as the crossover error rate (CER) have a converse relationship, but they sometimes do not show linear on a graph. EER is where the FAR and FRR would be equals, and the best technologies have the lowest EER rate (Gautam & Dawadi, 2017).

False rejection rate (FRR): This refers to how often a user will not get verified successfully. A high rate renders into more user retries, affecting the usability of the system (Gautam & Dawadi, 2017).

Hackers: The terms “hacker” or “hacking” is used to describe someone or activity with either good or bad intentions, and the universal term is almost with a negative connotation (Grimes, 2017).

Identity theft: Deliberate use of someone else identity to gain some financial gain or other benefits. The White House reported that identity theft is the fastest growing crime in America, which has caused losses of $12.7 million to $16 billion of U.S. dollars (Loker, 2018).

Indirect attacks: Method that gets carried out at the digital level where data flows get intercepted, which attacks the feature extractor or the weak points in the communication access (Das et al., 2016).

Information assurance: Measures that protect and defend data and information systems by ensuring their availability, integrity, authentication, confidentiality, and nonrepudiation (Sosin, 2018).

Information protection: The Consumer Privacy Bill of Rights adopted by the Obama Administration in 2012, protects information privacy as the individual control principle, where customers control what personal information is collected (Baek et al., 2014).

Information security: Subdomain of information assurance and focuses on the CIA triad: confidentiality, integrity, and availability (Sosin, 2018).

Information systems: Describes the organization of people and procedures for collecting, processing, generating, storing, transferring, displaying, information distribution (Milić et al., 2017), used for collection, management, data analysis, and distribution of the information needed for effective decision-making within the organization (Uri, 2014).

Information technology: A discipline that focuses on systems management, computer applications, and end-user services (Bagadia & Bansal, 2016).

Internet banking: Banking service where customers can access their account(s) and performs financial transactions from anywhere with an internet-connected computer and from any other device which gets connected to the internet (Milić et al., 2017).

Liveness detection: Used by artificial intelligence (AI) computer systems to detect the human physical presence and not an inanimate spook artifact (IEEE, 2020).

Mobile applications. Called apps for short, they are software programs developed for mobile devices, specifically smartphones, but used on other devices like tablets, smartwatch, and laptops (Flair, 2019).

Mobile banking: The International Data Corporation reported that more smartphones got sold in 2012 than desktop and laptop computers combined (Crawford & Renaud, 2014). Mobile banking is an electronic transaction that enables customers to perform financial transactions and other services through mobile platforms (Sreejesh et al., 2016).

Mobile users: Smartphone or tablet users. These include users of internet services like web browsing, games, and other various communication services such as instant message and telephone (Hong, 2019).

New technology: Technology that gets described as any productive techniques that will offer significant improvement over the previously proved technology for a given measured by either increased output or savings in costs (Scott & Marshall, 2015).

Personal information: Information related to customer's physical identities, such as social security numbers, physical address, health records, and other real-world identities (Baek et al., 2014).

Phishing attacks: Cybercriminals known as phishers who use social engineering techniques to follow electronic communications from a trustworthy source and steal credentials or install malicious software (Jensen et al., 2017).

Relative Operating Characteristic Curve: A characteristic graph of a system where the x-axis represents the threshold of the system and y-axis represents FAR and FRR values (Gautam & Dawadi, 2017).

Risks: Risks can be anything that has a measure of worth, be it monetary, time, or opportunity cost (Jordan, 2016). In connection to biometrics, risks get based on trust and risk probabilities of each transaction and measured by a probability during each transaction (Waggett, 2016).

Threats: Used to describe a person, people, event, weakness, or the possibility of attack, and it can describe viruses and malware and behaviors (Shostack, 2014).

Transparent authentication: Method used to remove barriers caused by security tasks, and this authenticates over security measures in the background so the customers can achieve their intended work (Crawford & Renaud, 2014).

Web-based applications (web app): Any program that is accessed over a network connection using a website as the interface or front end (Fortunato & Bernardino, 2018).

Assumptions

Assumptions are defined as unexamined beliefs, judgments, and expectations, which can impact the self-knowledge to help active learning (Briscoe, 2017). Researchers use assumptions to join scientific data, and the rule is to understand that assuming can have some benefits. Still, quality, explication, and non-existence are the issue (Armstrong & Kepler, 2018). The assumptions govern the overall research process. Therefore, I conducted this research under the following assumptions:

- Participants answered the questions honestly. If customers are unwilling to reveal specific information, the surveys may fail to characterize population preferences (Funk, 2016) accurately. However, in previous research, survey respondents included internalized norms, and the survey behavior reported prominence and salience into consonance (Brenner & DeLamater, 2016).
- The participants are mobile bank customers and are representative of the general population of the Mid-Atlantic region of the United States
- The participants have mobile devices and have biometric technology implemented with their bank apps. Multilayered protocols are tools uses by banks to help relived customer's assumptions, and the multilayered approach reduces attacks (Ivaturi & Janczewski, 2013).
- Community banks will have advanced security protocols, such as biometric technology, that work with a mobile bank application. Previous studies showed that enterprise systems had witnessed breaches and malicious

intrusions into network systems, so improving information access has created new challenges against emergent security risks (Yazdanmehr & Wang, 2016).

- Customers who use mobile bank apps will have fewer security risks associated with biometric technology. D'Arcy et al. (2014) explained how assumptions are the evidence that backs up the information system. No support for a theory-driven investigation to help with the effects of organization security requirements.
- Customers and bank managers understand risks (e.g., identity theft, data loss, and other security risks) with mobile banking. Shrivastava (2016) explored how managers and leaders need to understand the hazard during information systems that enabled the organizations' processes and business functions. Shrivastava explained how assumptions are where managers and leaders need to understand their duties and know they are held responsible for handling information security risks.
- All mobile bank customers have some biometric recognition and or some unique bodily characteristics. Assuming all customers have biometric identification assumes that all the mobile banking customers are similar, and every individual will have a clear audible voice, fingerprints, iris, and a recognizable face.
- All participation responses from the web-based survey were considered.
- The web-based survey was not biased, and the participants answered in a manner that was purposely intended.

- The web-based survey was explicitly limited to mobile bank customers that used biometric technology.

Scope and Delimitations

The scope of this research involves community banks and bank customers from the U.S. Mid-Atlantic region whom I recruited using a purposeful random sampling approach. The participants were bank customers that use biometric technology with mobile banking apps in the Mid-Atlantic region. The collected data are relative and helpful to bank managers and customers about implementing biometric technology with mobile devices. A web-based survey was presented to volunteer bank customers from three independent banks and three colleges in the Mid-Atlantic region for data collection. The data results were analyzed by using a SEM based on the quantitative data tools. The purpose statement lists the intent of the study and explains the overall intentions and accomplishments.

Delimitations for this study were determined by me and include (a) research question and hypotheses, (b) variables, (c) population, and (d) framework for the study. For the study, the population was delimited to only college bank customers and local independent bank customers who use mobile banking technology.

I only included participants from the community banking industry. Also, delimitations included using the UTAUT to shape the independent and dependent variables (see Table 2) and the survey questionnaire. The method of a web-based questionnaire survey approach was another delimitation; however, I included an extension of the UTAUT with PC and TTF, but no other research method was selected.

The results of the study were generalizable to the millennium generation who (a) use mobile banking (b) use new technology (c) live in the Mid-Atlantic region of the United States and (d) have mobile devices.

Limitations

There has been limited research and analysis of behavioral characteristics and mobile device use for open approve systems in the banking industry (Alotaibi et al., 2015). Below are limitations of previous literature that addressed the usability of the millennial demographic, e-banking, continuous authentication, transparent, biometric technology and community banks.

- *Millennial Demographic Limitations.* The banking industry has explored the oncoming wave of the millennial generation and the importance of capturing that demographic market to ensure the movement viability (Bosch et al., 2019). Over 81 million millennials in America were born between 1982 and 2000, outnumbering the baby boomer generation, and millennials are expected to turn the financial services world upside down (Bosch et al., 2019). Previous research showed that combining TTF and the UTAUT would determine a customer's attitude (Saputra et al., 2018). Saputra et al. (2018) administered an online questionnaire for TTF and UTAUT, which asks questions about customers task, technology, task-technology, expectation, effort, social influence, and use purposes, and the review could explain 54.9% of the variance of the customers' behavior toward technology (Saputra et al., 2018). Therefore, it is critical to research on the millennials generation who are the

future bank account holders, and this generation will help guide the next generation into new technology. In this study, the millennial generation was included in the research model as a control variable.

- *E-Banking Limitations.* Security professionals are recommended to do risk and cost-benefit analyses of their e-banking ecosystem, so the best decision is made for mobile device implementation (Vila et al., 2014). E-banking transactions used in mobile devices require an interface to communicate with bank customers (Goyal et al., 2016). Ivaturi and Janczewski (2013) noted the bank's limitations only provided social engineering attacks (e.g., phishing) attacks, and they did not include other forms of aggression. Only focusing on one attack is less helpful because of all the additional information about new and emerging attacks on online bank systems.
- *Continuous Authentication Limitations.* Mobile devices have become susceptible to many privacy issues, and if the data on the devices are compromised, legal actions can get used against the bank (Handa et al., 2018). The use of one-step authentication (i.e., username and password) on mobile devices does not take into consideration fraudulent activities after the initial login has taken place (Handa et al., 2018). Therefore, to deal with the one-step login, continuous authentication technology is becoming more popular because it can monitor the customers after the initial login process is complete (Handa et al., 2018). Zhou et al. (2010) examined how post-log-in continuous authentication has brought new attention from researchers. However, none of

the previous studies examined mobile user authentication at entry authentication and post-log authentication stages simultaneously. Also, existing authentication systems get described as the usual trade-off between security and usability. Therefore, Zhou et al. proposed Harmonized Authentication based on Thumb Stroke dynamics (HATS) that assists both entry-point and post-log-in user authentication with mobile devices to address the limitations. HATS integrate password, gesture, keystroke, and touch dynamics-based authentication methods to address the vulnerabilities of individual processes to specific security attacks (Zho et al., 2016).

- *Transparent Authentication Limitations.* The device-centric process uses independent functions, and continuous authentication is not recognized when data get used with different applications. This process does not identify critical components of the software applications getting used, which causes frequent authentication overhead (Alotaibi et al., 2015). Also, the customers could have more than one device, which can confuse the system when customers are accessing the applications from different devices.
- *Biometric Technology Limitations.* Previous literature found using biometric technology systems is only reliable if the performance rates are acceptable; for example, two conventional metrics used to evaluate biometrics' performance are (a) false acceptance rates and (b) false rejection rate (Vila et al., 2014). Also, the security professionals introduced the mobile application to deliver it with the e-banking systems (Vila et al., 2014).

- *Community Banks Limitations.* In this study, the sample used was evenly distributed and adequate for the data analysis but was small (N = 228), compared to the population of the Mid-Atlantic region of the United States. The study did not include large commercial banks with assets over the U.S. $10 billion. As stated, community banks have less than the U.S. $10 billion in assets (Gehrke, 2019). The larger banks have fewer total banks but hold significantly more assets, product offerings, geographic areas, and size advantage than smaller community banks. These limitations restrict the range of mobile banking accounts compared with services provided by large commercial banks. Consequently, larger banks' modus operandi involves different business models than those used by community banks. Even though the results confirmed the study's value, it is an exploratory factor in biometric technology implementation during mobile banking transactions. This study was conducted on community banks and needed to be related to a broader range of banks.

Significance of the Study

The findings of my study may explain the gaps to determine customers' intention to use biometric technology with mobile banking. The result could help bank chief executive officers (CEOs) recognize the challenges and barriers to implementing mobile bank apps that use biometric technology during the adoption and planning phases. Understanding the challenges and barriers could guide bank CEOs with a more efficient and effective implementation of mobile banking apps using biometric technology. This

study may provide further knowledge for managers and other decision-makers in the banking industry on implications that may encourage the adoption of mobile banking.

Risk Assessment

Software development companies have developed and popularized mobile devices, and the banking industry has included mobile apps for customers' mobile banking needs. Community banks have responded to mobile devices' constant threats and how this affects customer's privacy concerns (Chen & Liu, 2015). Therefore, community banks implementing mobile banking risk management and mitigation strategies will help with cybercrimes. This paper used the SEM to investigate and review the top 10 risks that could arise from mobile apps. The Open Web Application Security Project (OWASP, 2019), a worldwide nonprofit organization focused on improving web application software security, did a survey to determine the top 10 mobile application risks (see Appendix B). According to the Community Bank Connection, four main risks are relevant for community banks (Combs, 2014). Listed below are the four main risks for mobile apps.

- Insecure data storage. The loss of customers' mobile devices and the possibility of malware where intruders can gain access to the device.
- Weak server-side controls (WSSC). WSSC pertains to weak back-end mobile devices that the mobile banking process will need to use.
- Insufficient transport layer protection (ITLP). ITLP pertains to the insecure data that get transported over public networks.

- Poor authorization and authentication. Weak data encryption on mobile devices and potential identification data left on devices even after data wipes or resets.

When the banking industry introduced mobile banking, it presented new security risks, threats, and challenges (Combs, 2014). Mobile banking became ubiquitous for community banks after the portable internet, electronic bank (e-banking), and smart-chip-embedded handsets appeared. Mobile banking (MB) enables customers to access their bank account to conduct financial transactions or use other banks' services. Still, the possibility of loss, theft, malware, and exposure of stored personal financial information presents obvious risk on the other side (Bagadia & Bansal, 2016). Even though no mitigation scheme can eliminate risk, community banks should develop practices to adequately secure the mobile banking process. Mobile technology for mobile services offers low costs and provide ease of use to customers, and mobile banking apps are still in their early development stages (Bagadia & Bansal, 2016). By understanding the security risks and developing effective ways mobile banking can service customers, a community bank can minimize and manage their legal and reputational risks (Combs, 2014). Also, community banks must study suitable and adaptable conditions for banking customers (Bagadia & Bansal, 2016). Understanding customer's wants will help decision-makers with designing mobile banking services.

Risk Mitigation

The banking industry witnessed a new era of technological advancement in information technology, specifically smartphones. For community banks, mobile banking has created a breakthrough in remote banking services; however, many customers have doubts about the new technology's security (Muñoz-Leiva et al., 2017). In this study, I used the UTAUT model and integrated the extension of the UTAUT with PC and TTF. The two theories help with what factors determine user acceptance of mobile banking apps. As a mitigation strategy, bank managers will advise community banks to adopt a new approach to build customer satisfaction. As a mitigation strategy, offering better products while reducing bank operation costs to overcome significant changes in delivering financial services will help all stakeholders (Bagadia & Bansal, 2016). Because of rising numbers of online customers, the traditional bank's importance has declined, which has decreased the cost for community banks and customers (Bagadia & Bansal, 2016).

Community banks join the global network to offer better conditions to customers who decide to use mobile banking apps (Muñoz-Leiva et al., 2017). The most effective channel for offering bank services was the internet and mobile apps, but banks had to respond to customers' demands and provide safer solutions (Muñoz-Leiva et al., 2017). Since electronic banking first appeared, it gave customers limited remote access to their bank account. Then, web applications gained rapid popularity and created more advantages like comfort and ease (Muñoz-Leiva et al., 2017). Online banking provides more features and services at a lower cost than traditional banking activities (Muñoz-

Leiva et al., 2017). Previous studies have shown that mobile banking is the top-rated electronic delivery channels provided by community banks for a branchless distribution of services to customers (Bagadia & Bansal, 2016).

Mobile banking services provide many benefits, but there is a lack of use because of customers' belief for potential financial harm and sensitivity to the features' security (Bagadia & Bansal, 2016). The power to access your bank account anytime and anywhere is a natural draw for customers. Also, mobile banking apps provide customers with many advantages, but mobile banking apps have not increased because of the system's lack of trust (Muñoz-Leiva et al., 2017). A previous survey by Price Waterhouse reported 157 managers in America, Europe, Asia-Pacific explained how mobile banking would increase by 64% in the future because of information systems for financial institutions (Muñoz-Leiva et al., 2017). If customers do not find any safe or beneficial reason to use mobile banking, they will not use it. If a customer feels mobile banking is useful, easy to use, and secure, they will adopt it. However, if mobile banking gets perceived as risky, customers will not choose it (Bagadia & Bansal, 2016).

A survey conducted by community banks is embracing mobile banking to capitalize on the benefits it provides to customers' services (Chavali & Kumar, 2018). Online banking offers more features and services at a lower cost than traditional banking activities (Muñoz-Leiva et al., 2017). The banks that use better technology will have a competitive edge over the other banks that do not provide the new customer market services. Biometric technology integrated with a mobile banking security system can

make a positive social change by aiding in securing banks from fraud and crime prevention and proving liveness detection.

Significance to Theory

In this study, I explored the variables that influence bank customers' intentions to adopt biometric technology with mobile banking in the Mid-Atlantic region of the United States. The study promoted community banks development of biometric technology with mobile banking to mitigate the risk associated with bank fraud and financial loss prevention. This study filled the gap in the present literature about customers' adoption of biometric technology with mobile banking. Given that this topic has limited research on it, I used theories such as PC, TTF, and the UTAUT to understand customers' opinions and beliefs about biometric technology with mobile banking.

In this study, I added proven theories (UTAUT model with PC and TTF) to get more clarification and detailed answers on the topic. The goal of the study was to raise awareness among bank CEOs in the banking industry, particularly about the challenges and obstacles that may arise when implementing a secure banking application that uses biometric technology to mitigate bank fraud risk. Also, I want to give bank customers more information on the benefits of using biometric technology with mobile banking.

Significance to Practice

Community banks CEOs may use this study's findings to improve the security features of mobile banking. The results could lead to a positive social change and help bank CEOs' make appropriate decisions on how to measure and implement a successful mobile banking application using biometric technology.

- *Mobile application layer*. Mobile banking apps allow customers to access their accounts from any location and at any time, and this creates an advantage over traditional banking (Muñoz-Leiva et al., 2017). Any new technology will offer benefits and risks to customers, and mobile banking will not be an exception to this rule. Participants revealed that lack of privacy, time, financial risk, and performance risk were the most predominant risk factors in adopting a mobile banking application (Chavali & Kumar, 2018). Ease of transacting is the main focal point for the banking industry (Chavali & Kumar, 2018).
- *Security layer.* Security architecture recommends securing mobile banking platforms during a mobile transaction. Biometric technology is used to strengthen the traditional methods of information security by providing more protection for customer information. Using biometric technology, customers can benefit and have more secure identification, which can reduce credit card fraud and identity theft. Biometrics can improve the security authentication performance of banking in mobile devices by minimizing error rates and reducing the risk of successful intrusion (Wójtowicz & Joachimiak, 2016). Biometric technology is a critical tool for confirming customer's identification at will offer several advantages over traditional authentication methods to access the bank's mobile application.
- *Customer trust*. Introducing mobile banking made customers feel hesitant about adopting this new technology (Malaquias & Hwang, 2016). Therefore,

trust is a critical element that reduces customers' concerns, and it is one aspect that increases their intention to use mobile banking (Malaquias & Hwang, 2016). Previous researchers discussed the importance of risk in operating new technology and services (Bagadia & Bansal, 2016). Once the customers feel risks to the system, they may opt-out of the technology (Bagadia & Bansal, 2016). Customers want to access their accounts through the safest method. In turn, bank fraud is at an all-time high, and intruders are getting more sophisticated and implacable at compromising bank accounts (Heun, 2015). Therefore, spending money on a good data security system is vital for banks to sustain in the industry. Also, having a proper security system can help prevent data breaches that could inflict the bank's brand and the careers of top executives (Heun, 2015).

Significance to Social Change

In this study, I discussed the positive changes biometric technology will bring to mobile banks' apps by reducing security violations by unauthorized users. Biometric technology can help prevent unauthorized users' unauthorized attempts while providing solutions to confirm trust and convenience in people's lives. This study affirms the Walden University mission of making a positive change. As a scholar-practitioner, my goal is to help bridge the gap between academia and a real-life situation. The banking industry has developed new strategies to prevent intruders from comprising their online or mobile apps because of evolving security attacks. Security systems are something

community banks will invest in to sustain their place in the banking industry, which can help banks spend less money in case of a security breach (Heun, 2015).

Mobile banking by customers has grown more than any other delivery channel, and community banks are expanding their services in the mobile channel because of both parties' security issues (Bagadia & Bansal, 2016). Biometric technology has also affected community banks' services, particularly in authentication (Hess & Van Der Stad, 2016). Replacing passwords with biometric technology can offer more security for customers during the login process and continuous use with their mobile banking apps (Hess & Van Der Stad, 2016). Due to increased fraud threats and data breaches, biometric technology can enhance security and reduce risks associated with the traditional username, password, and other conventional security systems (Hess & Van Der Stad, 2016). Security measures allow a customer to exclude many types of banking fraud; for example, biometric used with mobile banking services provide customers with acquisition and managing liquidity (Abdullaev et al., 2019). Most online banking services use the traditional login system of single-factor authentication, which solely consists of the customer's username and password, personal identification number, and text-based login process (Putra et al., 2017). Risk mitigation techniques for mobile banking apps include customers using biometric technology, which offers a chance to secure transactions for customers to help prevent fraudulent activities.

Using biometric technology allows community banks to enforce internal security measures and create an audit trail to work with other technology to detect fraud (Hess & Van Der Stad, 2016). Community banks understand the need to use a mobile application

to reach their customers (Akoramurthy & Arthi, 2016). Biometric technology plays a significant role in supplementing mobile banking apps during the authentication process by positively identifying the person (s) participating in the operation. Social and ethical concerns related to biometric technology deployment are significant for any bank to protect their copyrighted information (Tiits et al., 2014). However, due to the widespread of the Internet and the expansion of smart devices, information technology (IT) security attacks have risen. The primary concerns for community banks are identity theft, customer privacy, and lack of secure authentication. The study promoted the development of biometric technology with mobile banking to mitigate the risk associated with bank fraud and financial loss prevention. The goal of the study was to increase both public and stakeholders understanding of security with mobile banking application and enable bank CEOs' to better prepare for cybercrimes.

Summary and Transition

Chapter 1 introduced how biometrics technology is considered a reliable process for the community bank's authentication process with mobile devices. I discussed how biometric technology is research by many companies, and banks are starting to implement the technology architecture in their security system. To apply new security protocols, banks will have to develop a process and follow the guidelines to enhance the bank security system. Every year, security issues are reported, which has caused customers to lose trust in mobile banking apps. Business-to-business (B2B), business-to-consumer (B2C), and consumers-to-consumers (C2C) transactions can develop a trusting relationship by using biometrics technology with their mobile devices. Using biometric

technology with mobile banking apps can offer customers more reliable and secure bank transactions. Biometrics provides a safe environment for banking transactions and customer's banking experience. I discussed mobile device users' problems in the United States and how securing the bank application within mobile devices is a top priority for customers, especially with the rise of new cybercrimes committed daily.

The study's purpose was to explore the relationship between customer acceptance and the use of biometric technology with mobile banking apps in the Mid-Atlantic region. The research question asked about PE, EE, SI, PC, TTF, and how it affects customers' BI of customers to adopt biometric technology with mobile banking. The study sought to evaluate whether FC and BI affect customers' AU to use biometric technology with mobile banking. The theoretical foundation for this study was the UTAUT model and was used to predict user acceptance and user behavior. A theoretical framework was used from the UTAUT and extending it with two additional factors: the PC and TTF model. The study's nature was a survey design utilizing quantitative research methods, and I used the SEM to analyze the data. Chapter 1 included essential definitions, assumptions, scope, limitations, the main points of the study, theory, and social change. In Chapter 2, I provide the position of the UTAUT framework and an analysis of current and relevant literature.

Chapter 2: Literature Review

In this chapter, I reviewed current and relevant research on biometric technology with mobile banking using the framework of the UTAUT and by extending the UTAUT with PC and TTF. In this quantitative study, I identified how customers adopt biometric technology with mobile banking security. The behavior plans affect the acceptance and use of biometric technology with mobile banking transactions. The study detected factor analysis and multiple regression using a quantitative research method (Rea & Parker, 2014) by studying BI at three local colleges and three local banks in the United States' Mid-Atlantic region. The research design includes bank customers who use a mobile banking application with biometric technology.

Literature Search Strategy

For this literature review, I sought current, peer-reviewed research studies about the UTAUT theory. The literature review also includes peer-reviewed studies that address limitations, weaknesses, and potential for future research in each category. Other sources include statistical reports and scholarly books. The Walden Library databases were the primary resource to obtain the sources. Search routines included full-text, scholarly, and peer-reviewed articles. Keywords in the search criteria included *biometric technology, mobile banking security, frauds prevent, crime prevention, liveness detection, UTAUT,* and *extending the UTAUT,* with two more factors: the *perceived credibility* and *task-technology fit model*. The literature review focuses on peer-reviewed studies that were less than 5 years old. The materials I used are related to biometric technology and how

this can positively impact the environment by providing solutions to security concerns by bank customers.

The goal of the framework is to create a practical method for liveness detection. In biometric systems, liveness detection tests for the presence of liveness or vitality signs, including human pulse, temperature, oximetry, and others (Okereafor et al., 2017). In biometric authentication, two types of attacks are adopted by intruders: direct and indirect. The search strategy object was to identify all published articles related to biometric features with mobile devices. Most of the literature was on mobile banking systems with liveness detection features. For the literature review, I used standard search strategies from the Thoreau search feature that went through all databases in Walden's library using keywords limit to full text, peer-reviewed scholarly journals, and books with publication dates from 2013 to 2018. The databases used were from IEEE Explore, ProQuest, Science Direct, Business Source, Research Library, Emerald Management, Psychology Database, Arts & Humanities, Library Science, and ABI/INFORM. The publication type was a search by academic journals, conference materials, magazines, news, trade publications, reviews, reports, books, eBooks, electronic, audio, videos, standards, primary source documents, and biographies. Once the search results populated, I evaluated the publications by relevant articles and publication types. Also, the Google Scholar search engine was used for querying all websites and articles related to biometric technology and mobile banking security.

Review of Theoretical Approaches

Security is considered a priority for many mobile banking customers. In a previous study, 31% of clients stated they would pay for increased security features, 63% were ready to switch accounts for better security features, and 71% were eager to change accounts to a bank that guaranteed losses and reimbursed (He et al., 2015). In the United States, 65% of adults who use the Internet have had cybercrime, computer scams, fraud, virus, and malware attacks against them (He et al., 2015). A previous study by Crawford and Renaud (2014) explained that 30% of participants had no security process for accessing their mobile devices. Even though over 73% of participants felt that biometric technology was more secure than traditional methods (Crawford & Renaud, 2014). There are 4 billion mobile cellular subscriptions throughout the world, and mobile networks can offer mobile banking to over 61% of the world population (Yadav, 2016).

As technology develops, mobile devices are being used for more than just placing calls and texting people. Because of the mobile device's capability, customers use their smartphones as a tool for many banking needs. Customers' ability to use a mobile device has gained popularity with the adoption of smartphones, and community banks focus on connecting mobile users to their mobile technology (Bagadia & Bansal, 2016). Mobile banking apps allow customers to access their accounts from any location and at any time, and this creates an advantage over traditional banking (Muñoz-Leiva et al., 2017). The banking industry offers many services with mobile banking like account balance, money transfers, and other services where the customers can easily access their mobile phones. A report by Tassabehji and Kamala (2012) showed the United Kingdom had over 25

million mobile banking customers who produce over 70% of the country's online community.

The study of behavioral profiling and application use for open authentication systems with mobile banking needs to be explored and researched to help with BI (Alotaibi et al., 2015). E-banking transaction used in mobile devices requires an interface to communicate with bank customers just like all other electronic transactions performed through some interface (Goyal et al., 2016). Using a theoretical framework incorporates critical elements of research and helps with understanding the theory of a research study. Online banking is one of the most requested tools by customers, and this feature allows banks to increase their profitability and increase their profitability client base (Abdullaev et al., 2019). Also, the International Telecommunication Union reported that more than 7 billion mobile customers and over 1 billion mobile customers use mobile banking (Abdullaev et al., 2019; Smith, 2016). For community banks, mobile banking has created a breakthrough for remote banking services; however, many customers have doubts about the new technology's security (Muñoz-Leiva et al., 2017). This study reviewed mobile banking literature through the lenses of customers adopting and accepting mobile banking risks because of the adoption of biometric technology with mobile banking. This theory helped develop the various factors that are revealed as antecedents to behaviors in previous research on the adoption of mobile banking application services.

In my investigation, I used the UTAUT and the extension of the UTAUT to examine the relationship between customer acceptance and the use of biometric technology with mobile banking apps in the Mid-Atlantic region. The UTAUT is an

information technology acceptance research with many competing models that focus on diverse acceptance determinants (Venkatesh et al., 2003). The UTAUT model was adopted because of the acceptance of research with new technology, which meets this study's objectives. Also, in the study, other intrinsic factors such as PC and TTF were added. In the security world, cyber-crime investigators talks about cyber-crimes and how to prevent them, and they even want a solution to minimize network penetration. Therefore, I added more relevant information to the massive security issues that have caused personal information from individuals and organizations. Security violations reported by the bank will change over time because of hackers' ability to find loopholes in the systems. Therefore, providing more research, data analysis helped with ways to strengthen security features to prevent security threats.

According to the UTAUT, PE, EE, SI, and FC were discovered to influence behaviors to use new technology, and behaviors and FC determine technology use (Al-Harby et al., 2010). UTAUT explained 77% of the variance in BI to use new technology and 52% of the workplace's technology (Al-Harby et al., 2010). To further support the UTAUT, Venkatesh et al. (2003) gathered information from two different organizations and add external validity to the preliminary test. Venkatesh et al. (2003) developed the UTAUT model as a comprehensive synthesis to determine user acceptance and use behavior of prior technology acceptance research. The UTAUT is a review and synthesis of eight theories of technology that predicted the critical factors and contingencies related to BI to use technology acceptance (Venkatesh et al., 2016). The UTAUT model is from four internal and external organizations. The model provides a creative tool for managers

needing to assess new technology and understand how to design interventions for customers. Venkatesh et al. (2003) explained how combining eight models were initially used to determine employee's technology acceptance and use. The eight models are the following:

- theory of reasoned action (TRA)
- technology acceptance model (TAM)
- motivational model (MM)
- theory of planned behavior (TPB)
- combined TAM and theory of planned behavior (CTAMTPB)
- model of personal computer utilization (MPCU)
- innovation diffusion theory (IDT)
- social cognitive theory (SCT)

The UTAUT has four key constructs that were valuable and valid research predictor tools of adoption behavior and BI. The UTAUT focuses on PE, EE, SI, and FC are direct determinants of user intent and behavior, and FC are a direct determinant of user behavior (Venkatesh et al., 2003). The research hypotheses measured reliability and validity with a theoretical framework based on the extended UTAUT with three moderating variables: age, gender, and education level. The UTAUT and extension of the UTAUT served as a comprehensive framework used to examine the components that contribute to the use and acceptance of biometric technology with mobile banking.

Theoretical Framework

The theoretical framework is the brains of the research study, and it gives structure to a theory (Dziak, 2018). The conceptual framework incorporates a working hypothesis to explored and theorizing with the theory evaluation framework (Venkatesh et al., 2016). Green (2014) explained how the conceptual framework draws on the concepts from different theories and findings, and the theoretical framework draws on research underpinned by one approach. Tarhini et al. (2016) created a conceptual framework by extending the UTAUT by assimilating two additional factors: PC and TTF theory. The theoretical framework for this study deals with biometric technology related to mobile banking for secure authentication. This study contributed to the research on biometric technology by looking at mobile banking adoption and how customers' BI affect their use and acceptance of mobile banking in the Mid-Atlantic region. Banks' many security violations increase because of hackers' ability to find loopholes in their systems. Therefore, providing more research data will help the decision-maker provide customers with preventive measures during bank transactions.

E-banking services for customers boosted the roles and significance of how banks impose e-business and e-services. Customers get more benefits from mobile banking because it provides more services, convenience, and 24-hour access for customers. Community bank reports show that an increase in mobile bank application security, and confidentiality is significant concerns for stakeholders. As previous studies have shown, PC and TTF offer a comprehensive theoretical perspective that further highlights the importance of security and privacy to customer's use of mobile bank apps. E-commerce is

the leading customer's service for banks to manage, and bank managers have implemented security protocols to strengthen mobile banking apps (Tassabehji & Kamala, 2012). Customers have increased their online mobile services for bank transactions, and e-banking has played a significant role in evolving e-business and e-services. Community banks have found that online mobile banking gives customers many options that offer cost savings and efficiency (Tassabehji & Kamala, 2012).

Mobile apps give customers more access to their bank accounts anywhere and anytime. Customers who use mobile bank apps can benefit from the way they provide them with more convenience and account access. However, because of the increasing security attacks and bank fraud, more customers accept and use mobile apps for convenience. Also, security issues are a concern for customers because of mobile banking security incidents. These security issues have caused customers to express their fears about using mobile bank apps when accessing their bank account. Since the evolution of online banking and mobile banking apps, online fraud has increased, causing banks to offer customers more strengthen security (Tassabehji & Kamala, 2012). Because of identity fraud and other security issues, customers have shown interest in using biometric technology to authenticate themselves during mobile bank transactions (Tassabehji & Kamala, 2012). When a customer chooses a bank, they rely on the bank to provide secure transactions when accessing their bank information or using other bank services.

Biometric technology is new to research, and bank customers are not aware of the benefit's biometric offers. Biometric technology offer enhances security to mobile bank apps, and it helps customers and stakeholder feel safer when accessing their accounts

(Tassabehji & Kamala, 2012). Management in the community banking industry is looking at a new process to help protect customers from different security breaches. Also, the government has offered their services to help with bank security issues. The government's primary goals were to use biometric technology with border control and national ID programs, in which the results showed they were satisfactory (Tassabehji & Kamala, 2012). Biometrics technology used with mobile bank apps can be a useful tool to authenticate customers and address concerns of customers. The System Usability Scale is the current system that measured community banks' security systems. During the SUS, a case study explains the natural and cost-efficient policy with more in-depth explanations of the bank's security system (Tassabehji & Kamala, 2012).

Mobile devices are becoming customer's first choice for mobile e-banking and banks are using multifactor identification methods to protect customers during transactions (Kaman et al., 2013). The community bank's management team's objective is to create services for customers to have safe and secure bank transactions. Customers are engaging in mobile banking because of the expansion of smart devices, and this has cause bank managers to understand the need for more enhance security protocols with their mobile apps. Previous research by Tarhini et al. (2016) examined the adoption and acceptance of Internet banking and how security and risk associated with PC and how well the technology will fit the customer's needs. Previous research findings suggest that PC is a strong determinant of customer satisfaction and behaviors to adopt mobile banking apps (Priya et al., 2018). In the adoption of mobile banking, this enables the

customers to have more control over their transactions, and security and trust issues (Tarhini et al., 2016) will dictate the decision.

Security and trust are the most critical factors motivating customers to implement any new technology (Priya et al., 2018). Previous studies show that customers have confidence in their banks, but their trust in technology is weak because of security issues resulting from using new technology (Tarhini et al., 2016). Therefore, adding PC will contribute to the factors of UTAUT and can improve the prediction of customer's acceptance of biometric technology with mobile banking. Integrating PC in the UTAUT is designed to help bank CEOs' look at the critical challenges of mobile bank's application security. Also, the previous study suggested the most critical need for new technology is to address customers' BI and their adoption of new technology (Tarhini et al., 2016). Also, there are not many studies that focus on the behaviors of how customers accept biometric technology with mobile banking apps in the Mid-Atlantic region with community banks. Therefore, by extending the UTAUT with the PC and TTF, a more comprehensive theoretical perspective of user technology acceptance in mobile banking was provided (Tarhini et al., 2016). In this study, gap was filled by expanding the UTAUT with PC and TTF.

Literature Review

An examination of the literature review reveals a comprehensive understanding of the UTAUT and the extension of the UTAUT model. Tarhini et al. (2016) explored how PE, SI, FC, PC, and TTF was significant predictors in influencing customer's BI to use

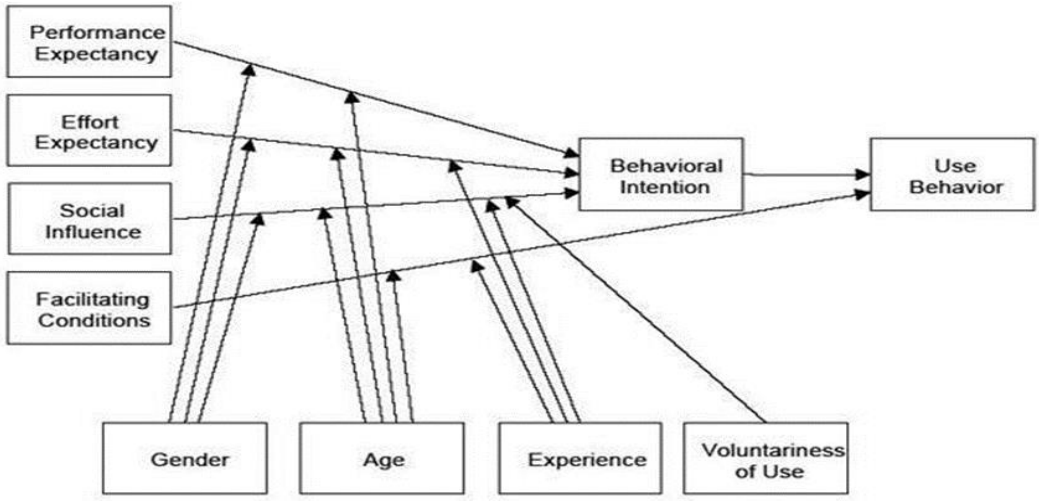
mobile banking. The literature review analyzed current research on UTAUT and the extension of UTAUT, mainly PC and TTF.

UTAUT

The UTAUT is a comprehensive technology model and has four key constructs; PE, EE, SI, and FC that influence behaviors to use technology (Venkatesh et al., 2016). The UTAUT was adopted because of the four key constructs and how prior research used customer technology acceptance and context. Venkatesh et al. (2016) explained how the UTAUT constructs influence technology and behaviors, and FC determine how customers use technology. The UTAUT model identifies user intentions and operates as the key-dependent variable, age, gender, experience, and voluntariness of use (Rajapakse (2011). At first, the UTAUT was developed to explain employee technology acceptance and use (Venkatesh et al., 2016). Figure 2 shows a diagram of the unified theory of acceptance and use of the technology model.

Figure 2

Unified Theory of Acceptance and Use of Technology (UTAUT)



Note. From Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology, by V.L. Venkatesh, J.Y., Thong, and X. Xu, 2012, 36(1), 157-178. Copyright 2012 by Venkatesh, Thong, Xu. Reprinted with permission (see Appendix D).

This study used the theory from Venkatesh et al. (2012) to use two pivot constructs to understand customer adoption and technology use. Once the constructs were identified, the original UTAUT will have new relationships. Previous research found that customers' behavior and information system found various constructs enabled a hedonic motivation, which is essential for customers' during new technology use (Venkatesh et al., 2012). The UTAUT is a base-model of technologies for various organizations and non-organizations (Tarhini et al., 2016). Since the original publications, many software applications and replications of the UTAUT model or part of the model in various

settings were used (Tarhini et al., 2016). Previous research using the UTAUT reported that 70% of the variance in intention and behavior explains individual acceptance and use decisions in organizations (Venkatesh et al., 2003). Previous theories and models have tried to describe the relationship between the user(s) beliefs, attitudes, and behaviors to use new technology (Tarhini et al., 2016).

Venkatesh et al. (2012) debated how the UTAUT constructs could be inadequate for showing a voluntary context for user acceptance of new technology. The original UTAUT study focuses on large organizations limiting the constructs' explanatory power (Tarhini et al., 2016). There are three types of UTAUT extensions and integrations: (1) extensions, and integration examined UTAUT in new contexts mainly, technology (2) the addition of new constructs to expand the theoretical mechanisms outlined in UTAUT (3) finally, exogenous predictors of the UTAUT variables are valuable in developing research of technology adoption and extending the boundaries of the theory (Tarhini et al., 2016). In this research, extending the UTAUT with two additional constructs, TTF and PC, is used to help understand the key factors that affect the customers' BI to use and adopt biometric technology with mobile banking in the Mid-Atlantic region.

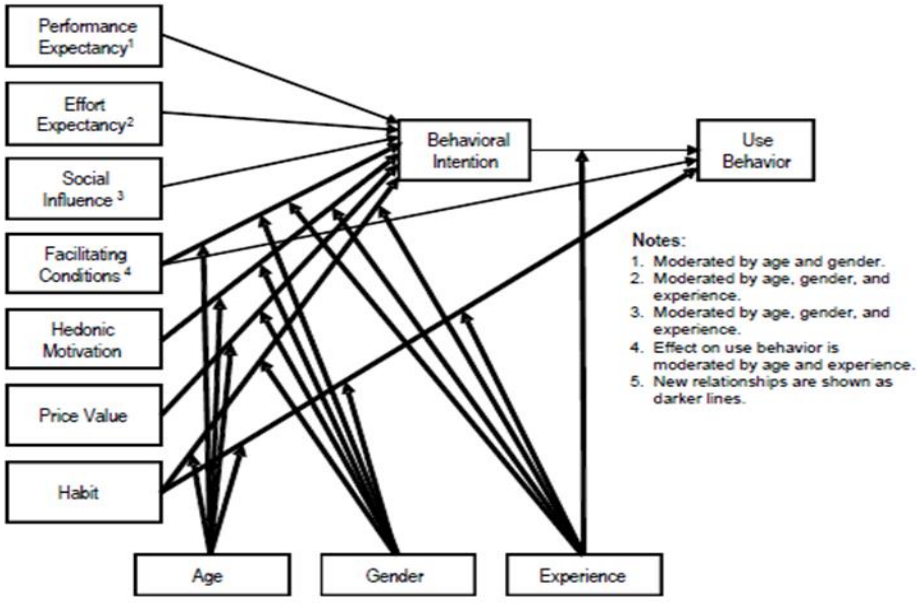
Extending the Unified Theory of Acceptance and Use of Technology

This paper will explore the UTAUT2 by focusing on critical additional constructs and relationships implemented into the UTAUT by tailoring it to the customer's use context. Tarhini et al. (2016) noted how the UTAUT is a proven valid research instrument and tool to predict the adoption behavior. Despite the proven research that has led many researchers to understand technology adoption. Tarhini et al. (2016) explained

how a systematic investigation is needed and theorizes the salient factors of customers' use of technology. Therefore, studying the adoption and acceptance of mobile banking and other factors can be considered because of bank apps' security and risk. Adding PC and TTF will show how the technology fits the customers' daily needs (Tarhini et al., 2016). By extending the UTAUT to including two more factors, PC and TTF, are a comprehensive theoretical perspective of customer" technology acceptance of mobile banking was provided (Tarhini et al., 2016). Figure 3 shows a diagram of the extended theory of acceptance and use of technology. The UTAUT2 model includes the UTAUT and the two more factors, PC, and TTF.

Figure 3

Extending the Unified Theory of Acceptance and Use of Technology (UTAUT2)



Note. From "Extending the UTAUT model to understand the customers' acceptance and use of Internet banking in Lebanon: A structural equation modeling approach," by A. Tarhini, M. El-Masri, M. Ali, and A. Serrano, 2016, 29(4), 834. Copyright 2016 by Tarhini, El-Masri, Ali, Serrano. Reprinted with permission (see Appendix E).

In previous research, TAM used PC and perceived ease of use to show that security and trust are the customers' direct BI (Oye et al., 2014). In an earlier study by Tarhini et al. (2016), they found that PC was a critical factor in explaining technology acceptance. The meaning behind PC is since customers cannot evaluate mobile banking the same way they assess a face-to-face bank transaction. For example, in a previous study, trust and security directly shape customers' intentions to accept new technology (Miltgen et al., 2013). Therefore, mobile devices' biometric technology system will

increase customers' disposition to take this technology, which trusts should influence BI directly (Miltgen et al., 2013). This study used PC constructs to measure customers' preferences to use mobile banking. The reason is that all customers fear losing data and especially money, using mobile banking transactions. Therefore, PC can be one of the most influential factors in customers' acceptance and adoption of biometric technology with mobile banking in the Mid-Atlantic region of the United States.

Banking research has shown that users who use services significantly positively affect traditional services (Tarhini et al., 2016). For example, TTF used within the UTAUT is beneficial to determine customers' BI from mobile banking. Evidence shows that users will not accept and use technology if it does not fit their needs and performance (Tarhini et al., 2016). In this study, the TTF model was used to propose a mobile banking user adoption model (Tarhini et al., 2016). TTF is a proven model that shows customers will adopt a technology to perform their daily tasks (Saputra et al., 2018). Therefore, the adoption of new technology significantly depends on the day-to-day functions of the customer. Previous studies revealed that providing customers with a good TTF would dramatically enhance the customer's experience (Tarhini et al., 2016). Banking research has shown that banks that support and promote security features for customers have positive impacts on use and adoption (Tarhini et al., 2016). Therefore, the TTF theory assisted and influence customers' behaviors to use biometric technology (Tarhini et al., 2016). Also, Suki and Suki (2017) found that behaviors are a significant and valid predictor of the behavior of new technology.

Chao (2019) revealed that BI is significantly and positively influenced by customers' satisfaction, trust, PE, and EE. In this study, the TTF was integrated with the UTAUT to understand customers' learned behavior. The TTF goal determined how customers will not accept and use technology if it does not fit their needs or improve their performance (Tarhini et al., 2016). Previous research suggested that TTF is a factor used to decide whether information technology systems and services by companies meet customer's needs (Al-Khafaji et al., 2018). Also, previous research showed that TTF is a theoretical model used to assess how information technology improves performance and use by customers (Al-Khafaji et al., 2018). According to Al-Khafaji et al. (2018), task characteristics and technology characteristics affect TTF, which is the determinant of customers' performance and utilization. The adoption of mobile banking was determined by customers' opinions toward technology and how the TTF their need.

The BI indicate how customers will act or respond to new products, which is an indicator of the customer's readiness to act on a specific behavior (Tarhini et al., 2016). The actual usage is the customer's behavior patterns and response to the organizations' target market (Tarhini et al., 2016). Venkatesh et al. (2003) explained how previous studies explained the effect of BI on actual usage in technology acceptance. PC as it deals with mobile device technology is where an individual believes that mobile technology will not precipitate any security or privacy threats (Palau-Saumell et al., 2019). In previous research, the PC construct was used to measure customers' security, privacy, and trust concerns that affected the customer's behaviors to use bank apps (Goyal et al., 2016). In the mobile environment, PC gets measured with two dimensions: security and

confidentiality (Palau-Saumell et al., 2019). Along with PC, the adoption of new technology will depend on the customers' daily activities (Saputra et al., 2018). Therefore, PE, EE, SI, PC, and TTF played critical roles in customer's behavior in accepting or rejecting MB apps in the Mid-Atlantic region.

Previous literature based on SEM analysis showed that PC has a significant relationship with trust and satisfaction (Masrek et al., 2018). In previous studies, the PC model was research to show the relationship between customer" beliefs, attitudes, and behaviors to use new technology (Tarhini et al., 2016). Also, Tarhini et al. (2016) argued that integrating PC into UTAUT will predict customer's BI towards using MB. In previous research, the PC construct was used to measure customers' security, privacy, and trust concerns that affected the customer's behaviors to use bank apps (Goyal et al., 2016). The rationale is since customers are afraid to lose money with mobile transactions because of the perceived subjective of MB. PC was an influential factor in deciding if customers will accept and adopt mobile banking in the Mid-Atlantic region. The TTF affected PE, initial trust, and customer adoption intention (Venkatesh et al., 2016).

Four Key Constructs of the UTAUT

The UTAUT is a proven valid research tool used as a predictor of behaviors and emphasizes PE (Tarhini et al., 2016). Voluntariness is the most salient driver of acceptance of new technology (Tarhini et al., 2016). Venkatesh et al. (2016) defined PE as using technology to benefit customers when performing certain services. PE is the extent to which an individual believes the system will help customers perform their activities better, whether business or personal (Oye et al., 2014). The predictive effect of

PE is mediated by age, gender, and experience. Venkatesh et al. (2016) defined PE as using technology to benefit customers when performing certain services. (Venkatesh et al., 2016).

- *Performance expectancy* is where the predictive effect gets mediated by age, gender, and experience. Previous literature found that PE significantly influenced the customers' BI to use a system (Tarhini et al., 2016). A similar study by Lee et al. (2019) revealed that PE and SI are the most significant new technology determinants. Also, PE, SI, Innovativeness, and perceived risk showed a significant effect on customers' acceptance of new technology (Lee et al., 2019). Tarhini et al. (2016) studied that perceived ease of use of the e-learning system was a significant predictor of customers' intention to adopt the system. Therefore, PE uses performed critical roles in customer's behavior in accepting or rejecting mobile banking apps in the Mid-Atlantic region.
- *Effort expectancy* is related to how comfortably a customer believes in the systems and how easily they can use them with ease (Oye et al., 2014). Venkatesh et al. (2016) defined EE as the measure of effort that customers deal with technology use. EE is how easy the customers can use the technology. In previous research by Tarhini et al. (2016), customers found banking with mobile devices a beneficial task, and it does not require much effort to use. Previous studies found that a significant relationship between EE and user intention confirmed customers' effort to adopt mobile banking (Buabeng-Andoh & Baah, 2019; Rahi et al., 2019). Evidence found that EE

has the full attention and awareness of FC and was a predictor of intention (Venkatesh et al., 2003). In connection with this study, if the customers find mobile banking services easy to use, they are more likely to use and adopt it. In contrast, if the customers find mobile banking services to be challenging, then they are less likely to embrace it.

- *Social influence* is defined as the extent where customers will perceive what is distinguished from other people, like family and friends, and think they should use a similar technology feature or device (Venkatesh et al., 2016). SI has an active behavioral element and adoption of new technology but may lack conviction or may occur after someone develops an intention to act without limitation (Oye et al., 2014). Venkatesh et al. (2016) defined SI as the extent to which customers will perceive what distinguished from other people, like family and friends, and think they should use a similar technology feature or device. Therefore, SI focuses on social pressure from an external environment where an individual's opinions and behaviors can get affected by engaging in specific actions by the views of friends and family (Tarhini et al., 2016). Previous research explained how groups are ready to adopt certain behaviors to impress a group because of SI on individual behavior (Tarhini et al. (2016). In previous studies, SI played a factor in influencing and supporting people who use new technology (Buabeng-Andoh & Baah, 2019; Rahi et al., 2019; Suki & Suki, 2017). The rationale is customers will get influenced by the doubt created by biometric technology with mobile banking; they will need

customers to interact with their trusted network of people to consult on their adoption decisions.

- *Facilitating conditions* is defined as something that refers to customers' perceptions of the resources and services available to perform a behavior (Venkatesh et al. (2016). Previous evidence by Venkatesh et al. (2003) showed that relationships between perceived behavioral, FC, and intentions. Perceived behavior is the customer's perception of internal and external constraints on behavior and includes self-efficacy, FC, and technology acceptance (Venkatesh et al., 2003). In previous research, PE, EE, and SI are three constructs that discovered the intention to use and FC determine the customers' usage behavior (Venkatesh et al., 2003). Venkatesh et al. (2016) explained how the UTAUT constructs, PE, EE, SI, and FC are theorized to influence behaviors for using technology and behaviors, and FC discover how customers use technology. The banks' support of systems FC that allow customers to accept and use the latest systems. Perceived usefulness and perceived ease of use was found to be a positive influence of FC within organizations (Peñarroja et al., 2019).

Previous literature also confirmed that FC had a variance in predicting customers' intention to adopt mobile banking (Rahi et al., 2018). In this study, FC were measured by the customer's perception of how they can use the systems and whether the banks support mobile banking services (Tarhini et al., 2016). Earlier studies by Venkatesh et al. (2012) revealed that FC refer to customers' perception of the resources and support provided to

perform a behavior. For performance to happen, mobile banking customers will need specific skills such as configuring and operating mobile devices and connecting to the Internet (Rahi et al., 2018).

Biometric Technology

Biometric technology is the result of security risks to e-commerce sites and information getting stolen on mobile devices. Biometrics authenticates individuals by discovering the personal characteristics of individuals giving some biological or behavioral traits. The physiological or behavioral symptoms can be one or more of the following: face, voice recognition, fingerprints, iris eye, hand-vein, signature, and other unique features (Vanian, 2015). Lasky (2014) explored the self-regulation of human physiological or behavioral characteristics during biometric authentication to confirm individuals. Previous literature by He et al. (2015) explained how security was a priority for many mobile banking customers. Previous studies found biometric technology reliable only if the performance rates are acceptable (Vila et al., 2014). For example, two conventional metrics used to evaluate biometrics' performance are i) false acceptance rates and ii) false rejection rates (Vila et al., 2014).

Multi-Modal Authentication

The multi-modal authentication process for community banks will need to include security policies, awareness, training, and knowledge transfer to have a secure protocol. Ivaturi and Janczewski (2013) noted that most security best practices include preventive measures for the users, but limited information is given, resulting in an ineffective way of presenting the information. Previous research from Gartner (2002) explored by Ivaturi

and Janczewski (2013) showed that community banks would need to examine their security policies, learn how customers access their accounts, and provide technical countermeasures to protect the bank's internal and external security protocols. Ivaturi and Janczewski explained that most of the research presented is invalid and only gives the banks general information, and the results need information. Ivaturi and Janczewski explored the gaps in their literature and found a framework to allow banks to assess reports and show the best security practices existing and emerging social engineering attacks.

Opara and Etnyre (2010) discussed the network enterprise systems and how they need to be reliable, flexible, and secure, so public and private information to users is secured and trusted. Identity thief affected 90 million Americans and cost roughly $173 billion in 2005, reported by the Federal Trade Commission (Opara & Etnyre, 2010). Opara and Etnyre (2010) surveyed access users' perception and understanding of the importance of a reliable authentication system. The survey was distributed randomly to Business Intelligence professionals at a symposium in Atlanta, Georgia. Out of 644 questionnaires distributed, 201 reviews were completed, and 17 rejected for lack of completion. The authors noted that participants did not get offered any incentives to complete the survey. The Australian Banks investigated 16 banks in the area and found deficiencies in Internet banking security (Subsorn & Limwiriyakul, 2012). The Australian banks' theory revealed the system was comprised because of affected customer's information getting stolen. Vanathi, Shanmugam, and Uthairaj (2016) discussed the advanced mobile security system for e-commerce and how users provide high-level

secure, friendly m-commerce transactions. Vanathi et al. analyzed different genders using the Neural Network that uses the m-commerce applications and forecasts the demand accordingly. Vanathi et al. used a quantitative method to analyze the multilayer backpropagation neural network for gender classification analysis.

Online Banking Systems

There is a strong need for secure systems, especially since banks have e-banking systems for clients and customers. The bank's online system needs to be protected during the initial login process and after the customers have login because e-banking systems depend on the overall opinion of the customer's perspective of their bank's system. Even though risks are involved with online banking, banks will need to grasp how the customer looks at the security and safety of the services they use from the bank. E-banking systems are not controllable and have less validity during bank transaction errors, especially when customers log in to bank transactions (Tassabehji & Kamala, 2012). A report by Experian explained how 88% of customers use mobile banking apps to perform banking transactions, and they believe banks are protecting their data (Gonzalez-Cotto, 2018). Strategies such as geolocation, Internet Protocol (IP) masking, biometric technology for authentication are just some of the mechanisms that are recommended to banks for security (Gonzalez-Cotto, 2018).

The 2016 Data Breaches and Customer Loyalty report revealed that customers focus on the organizations holding their data and not themselves (Sharma, 2017). A previous study showed that in many countries, 70% of customers felted that it was the companies' job to secure customer's data from cybersecurity threats (Sharma, 2017).

Previous research showed that over 51% of customers reuse the same password across different websites (Alhothaily et al., 2017). More than 77% of the customers either slightly changed or reuse the same existing passwords (Alhothaily et al., 2017). This common practice is a serious issue and can lead to security risks such as insider attacks. ThreatMetrix, a global cybersecurity company used by banks for the authenticity of digital transactions explained how 210 million attempted attacks were made on banks' networks during the first quarter of 2018 (Yurcan, 2018). There has been an increase of 211% of fake account attempts in 2017 through mobile device use (Yurcan, 2018).

The average U.S. customers choose to use biometric options over passwords, and over 79% stated they would only use biometrics to access their bank account (Biometric Technology Today, 2017). Also, 42% of customers said they would not use a bank or payment application that does not support biometric technology (Biometric Technology Today, 2017). According to Juniper Research, mobile payment using biometric technology will continue to rise by over 2 billion in 2017 compared to 600 million from the previous year (Biometric Technology Today, 2017). Over 4.8 billion data records were exposed since 2013, with identity theft being the top data breach situation, which accounted for 64% of the data breaches. A previous study showed fraudulent use of financial data that affected 21% of customers (Sharma, 2017). In contrast, 15% of customers has personal details taken, 14% had identity theft, and more than 36% was a victim of malicious attacks via online services, 34% experience clicking on a bad link, and 33% were phishing incidents (Sharma, 2017).

Online Trust with Customers

Mobile devices are becoming the first choice for customers to check their bank accounts. Since customers are using mobile apps to perform transactions, community banks work with mobile devices providers to provide biometric authentication as an option for account access. D'Arcy et al. (2014) used an online survey of 539 employees' users to learn about the SRS coping theory. To measure the responses, the authors used a series of questions designed to measure moral disengagement, perceived sanctions, and intention related to the Internet service provider issues depicted in the framework. For data analysis, the authors used SMARPLS as the primary statistical tool for measurement and structural models. Previous research showed the excellent withdrawal of customers mediates the relationship between customer's differences and improper behavior. D'Arcy et al. (2014) suggested they recognized potential connections between the customer's security-related stress (SRS) measurements and the multidisciplinary teams (MDT) categories. Security policies were researched by Ivaturi and Janczewski (2013), and they explored the best practices of online mobile banking by testing the security information on their software. Hackers use phishing attacks and social engineering methods to gain knowledge from people so they can potentially steal personal data and use their data to gain access to other people's accounts.

Biometric Technology Identification Methods

Since many customers are using mobile services, promoting biometric technology is essentials for community banks to compete with other banks to retain customers. In the early 2000s, banks had some issues with the first models of fingerprint technology

because of the separate hardware pieces with mobile devices. However, today's mobile devices have more reliable platforms where all data, including biometric features, can be integrated and accessible by applications (Crosman, 2014). Developers pointed out the agile approach of security features with mobile devices and biometrics was the main topic because of each transaction's trust and risk probabilities (Waggett, 2016). The customer's bank transactions determine how biometric data was used for risk purposes (Waggett, 2016). The U.S. National Science and Technology Council Subcommittee (NSTC) has classified biometric and two types: physiological and behavioral biometrics traits (Handa et al., 2018). Authentication gets classified into two types, which are static authentication, and continuous authentication, and they are essential for any trustworthy computing system of many security protocols (Handa et al., 2018). Continuous authentication is where the customers are continuously authenticated even after the login process is complete (Handa et al., 2018). It removes the requirement of frequent logout and logs in during transactions (Handa et al., 2018).

Information security services have five main processes that identify, authenticate, ensure confidentiality, and are nonrepudiation (Tait, 2019). After getting feedback from customers, MasterCard presented a new multi-factor authentication for customers using facial recognition and fingerprints to get into their accounts (Waggett, 2016). Because of competition, banks are provided benefits to their customers by offering online services, and this allows the bank to give the customers more convenience and assurance of their account (Yoon & Steege, 2013). Online use by customers expand because of online shopping, and customers wanted to check their accounts and apply for services online

(Yoon & Steege, 2013). Understanding customers' mindset is a critical part of achieving online and mobile safety of banks' apps. Internet crimes estimated that over 480 million dollars were lost, and the Crime Complaint Center (IC3) reported that in 2011, there was a 3.4% increase in security complaints. Despite security complaints, customers continue to use online and bank transactions regardless of security issues.

Kaman et al. (2013) explored the two-factor authentication (Two-FA) system with machines and devices (tokens and ATM), and this process has reduced customer's credentials. During mobile bank apps, the biometric scanning tools rely on three authentication features: things you know, stuff you have, and who you are. Kaman et al. discussed how banks use different measures so customers could access their systems. Kaman et al. used a literature survey to show how many efforts were put in place for security measures. Still, the authors proposed the Two-FA systems for banks to use a combination of security methods, like something you know and something you are. Kaman et al. showed that the authentication system is secure, and customers do not have to carry separate information like tokens and ATM cards for authentication. Crawford and Renaud (2014) used a quantitative research method, and the independent variable for the study is the extent of transparent authentication the user sees, whether high, moderate, or low-level. A survey by Crawford and Renaud's showed that 30% of participants used no security method on their mobile devices and over 90% of participants stated use transparent authentication methods.

Alotaibi et al. (2015) measured performance by the False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER) to show accurate and better

performing system's needs. Alotaibi et al. discussed previous literature and explained how some studies investigated the practicability of using behavioral characteristics as a transparent authentication method for mobile device security. Alotaibi et al. (2015) use a qualitative approach, and it was more of an informative research paper. The studies showed that behavioral characteristic is a practicable construct for customers' behavioral profiles during transparent and continuous authentication while the customer uses the mobile device. Alotaibi et al. discussed how research only finds suitable behavior patterns for the appropriate transparent authentication method. Alotaibi et al. explained a lack of investigation and study of behavioral profiling and application use for open authentication systems on mobile devices. Authentication is critical for online authentication and validating customer's identification through mobile devices. With constants, failures, and security breaches, biometrics and traditional authentication offer several benefits over the current authentication method.

Mobile Banking Gaps

Mobile banking is an emerging topic, but the understanding of mobile banking characteristics, such as information content and the impacts on customers' attitudes and transactions, are limited (Sreejesh et al., 2016). The acceptance rates between smaller banks and larger banks are major gaps in mobile banking (Thusi & Maduku, 2020). There is limited research on customer's evaluation of mobile banking perceived privacy concerns of how their attitude towards transaction intentions of mobile banking (Sreejesh et al., 2016). Because of the limited literature on mobile-banking, this poses challenges for bank managers who are trying to understand the intention of the transaction and

repeat use of mobile-banking (Sreejesh et al., 2016). Previous research examined the high demand mobile-banking solution and its advantages over other electronic mediums (Sreejesh et al., 2016). Over 92% of the top 25 banks are offering mobile banking, so smaller banks and credit unions risk losing customers, especially the customers who use mobile devices (Javelin Strategy & Research, 2012).

Previous research included technology acceptance, time of adoption, adopter categories, and innovation diffusion rate, which explained that mobile-banking represents the new-innovation of service delivery (Sreejesh et al., 2016). Providing mobile banking solutions offers many services for customers. Previous literature showed how innovations fall short in research areas: (a) like research in technology adoption and acceptance, (b) prior innovation overlooked service innovations, (c) previous literature disregards demographic roles in customer decisions relating to service innovation, and (d) prior studies stated that service type offered plays an important role in customers adoption decisions (Laukkanen, 2016). Attracting the right demographics is a crucial challenge for smaller community banks. The typical mobile banking customer is young, between the ages of 18 through 44, with an ethnic background of usually Asian, Latino, or African-American, and with over $75K in earnings (Javelin Strategy & Research, 2012). However, the regional and community banks and credit unions have different demographics with older, less wealthy, Caucasian, and less tech-savvy (Javelin Strategy & Research, 2012). Community banks must expand their services to appeal to a broader range of demographics to attract new customers if they want to compete and succeed in today's mobile banking market (Javelin Strategy & Research, 2012).

Summary and Conclusions

Throughout the literature review, I analyzed the UTAUT model, which was used to determine technology acceptance and use and is a valid research tool. Furthermore, I reviewed the UTAUT four constructs PE, EE, SI, and FC. I checked the UTAUT constructs' extension, PC, and TTF, highlighting the critical security and privacy of customers and stakeholders' assets. During my research, many previous works of literature work under the UTAUT, PC, TTF, survey approaches, Information assurance security theory, and biometric technology with mobile devices. Providing scholarly research to address biometric technology use and acceptance is necessary for community banks to provide a more secure transaction during mobile banking.

The method of biometric technology addressed many security issues occurring during e-banking security. Because of the rise of cyber-crimes electronic banking is changing, and bank managers decide to help prevent or stop hackers. Bank managers are trying to address the security issues by enhancing the bank's security system because of credit card or other security-related issues. Little information is known on customers' use and acceptance of biometric technology, so the baking industry is looking into new ways intruders attack their system. However, even though banks have integrated their banks' apps with other manufacturers' biometric scanning tools, some banks still do not have mobile apps to encrypt customers' information. The study used a research question based on the survey method, the UTAUT theoretical framework, and the extension of the UTAUT. The goal is to justify the benefit of biometric technology, the use and acceptance of customers, and the gaps in the related literature.

Chapter 3: Research Method

This quantitative questionnaire survey developed an understanding of the relationship between customers' acceptance and use of biometric technology with mobile banking. The specific problem is the lack of adoption of biometric technology by customers and bank managers do not understand the factors that influence mobile banking apps in the Mid-Atlantic region. Chapter 3 addresses the research question and present an overview of the research design, methodology, population, sampling procedures, measures, data collection process, and the research that I have completed.

Research Design and Rationale

The research design demonstrates how research incorporates different scientific goals and data collection and analysis (Ridder, 2017). Previous research explained how research designs primarily focus on the aims, uses, purposes, intentions, and plans of the researcher (Almalki, 2016). Rea and Parker (2014) explained how researchers must identify participants' critical characteristics by using focus groups to establish potential participants in research designs. Research designs deal with the approach, purposes, and methods of how researchers' knowledge and theoretical perspectives will reveal questions and collect and analyze data (Almalki, 2016). Having a research design helps researchers be cognizant of the bias they bring to the research and choose the tools they use to collect data (Almalki, 2016). There are three distinct approaches to presenting research: quantitative, qualitative, and mixed methods. Makrakis and Kostoulas-Makrakis (2016) explained how positivist and objectivist philosophies drive quantitative studies. Qualitative studies are conducted using phenomenological, social-constructivist, inter-

subjectivist, and interpretivism philosophy (Makrakis & Kostoulas-Makrakis, 2016). The combination of quantitative and qualitative methods addresses sustainability, and a wide range of data must be collected using mixed-method research methods (Makrakis & Kostoulas-Makrakis, 2016).

In quantitative research, researchers use a hypothesis statement to show independent and dependent relationships between two characteristics call variables that represent exhaustively and corresponding data (Frankfort-Nachmias & Leon-Guerrero, 2015). In the quantitative methods, hypotheses are tested, and statistical information is analyzed in the usual methodological foundation (Ridder, 2017). The research question guides the topic in a quantitative method, and when all the tangibles are selected, the stage is to figure out how to measure the variables and data collection (Guo & Yang, 2018). Statistics is the information used in many disciplines to interpret and learn the info gathers (call data), which is used as a statistical method to understand and learn from people's research. Statistics is a procedure used by social scientists to organize, summarize, and communicate data (Guo & Yang, 2018). While looking at statistical data, the visual presentation of quantitative evidence is an informative way to show data in a more readable and logical form: researchers' use statistical information in charts to teach organization, quick summary, and visual communication for data interpretation (Guo & Yang, 2018).

Quantitative methods use scientific samples as research surveys, and the sample survey results reveal more reliable results (Rea & Parker, 2014). However, qualitative focus group research is known to have an unknown degree of accuracy (Rea & Parker,

2014). When deciding on quantitative research, the researcher must understand the logic, rationale, and actions, which guide both study designs and how data are analyzed (Norris et al., 2015). In qualitative methods, the researcher is the instrument, and this is an advantage for some research projects because the information can be explained with more valid points. In qualitative approaches, the goal is to get a subjective meaning and multiple viewpoints (Hesse-Biber, 2016). Qualitative research uses interviews, observations from fieldwork, and documents in the data recording process. Qualitative research methods are use when researchers want to explore problems or issues and provide more meaning by directly involving the participants in data collection.

The distinction between quantitative and qualitative research is that qualitative methods are less confirmable, meaning they do not use or test a hypothesis but instead explore and discover participants' viewpoints (Hesse-Biber, 2016). Mixed methods designs are a combination of quantitative (numbers) and qualitative (nonnumerical) methods, where each is usually of equal status (Hesse-Biber, 2016). When using mixed methods, the researcher often aims to triangulate their findings by giving priority to both quantitative and qualitative data while collecting both types of data simultaneously but separately (Hesse-Biber, 2016). The primary goal of mixed-methods is to validate the findings by combining the discovery of quantitative and qualitative information to determine if the two different methods yield agreeable or disagreed results (Hesse-Biber, 2016). This study used a quantitative research approach to test the proposed research model so the research can be replicated and analyzed and compared with similar studies.

As risk mitigation for banks, training customers on biometric technology, like multimodal, continuous, two-factor, and additional encrypted authentication solutions, will help customers trust and use new technology. The goal is to make sure customers are comfortable using biometric technology to adjust to new security features. The first development for community banks is to roll out bank apps that have biometric technology capability. Early biometric technology events had some issues because the devices were purpose-built, cumbersome, and expensive to buy and operate (Waggett, 2016). However, current mobile devices have expanded with more high-quality biometric devices for customers (Waggett, 2016). The second development for biometrics is for banks to set up security protocols to detect and defeat spoofing attacks (Waggett, 2016). The third step is improving the capability to keep sensitive data, such as biometric data, safe and private, and the fourth is the big data solution for authentication approaches (Waggett, 2016).

Community banks learn from business analytics to improve operations and introduce new risk-based security approaches to help customers have frictionless login attempts. This study's research plan was quantitative research using a survey research design to measure before and after occurrences. The approach used a web-based questionnaire survey for examining community bank's customers' use of biometric technology with its bank application. The research question asked how customers view biometric technology with mobile devices, specifically mobile banking apps. In this study, I looked at several community banks and colleges to examine how participants use and accept biometric technology with mobile banking apps, as well as how community

banks used biometric technology to prevent unauthorized users from gaining access to a customer's bank account. I also explored the challenges, security, and difficulties and measure how banks use biometric scanning tools with their bank application. The demographic data were collected from locations that use mobile devices and biometric scanning tools.

The purpose of biometrics scanning tools (used with the traditional login process) is to create multilayer security through physical or behavioral characteristics, minimizing security violations by unauthorized attackers. Therefore, banks making security systems require the highest safety, which are the traits of the individual accessing the account, which could reduce illegal attacks.

Methodology

I used similar research for the theoretical model in technology acceptance and behavior intentions (Tarhini et al., 2016) by deploying a quantitative research approach to test the proposed research model. A theoretical framework was developed by extending the UTAUT by incorporating two additional factors: PC and TTF. A web-based questionnaire containing 38 questions (see Appendix I) was used to collect a purposeful random sample from the current mobile banking customers in the Mid-Atlantic area. I collected data from bank customers from three colleges and three community banks in the Mid-Atlantic region from October through December 2020. The participants selected for the study were analyzed because they (a) are bank customers who use mobile banking at a community bank and (b) use biometric technology as an authentication method with their bank's application. In this study, collecting data from random sources (like

participants in coffee shops, malls, and grocery stores) was not plausible because it is logical to expect the experiences of the participants represent what most mobile banking customers would experience.

In web-based technology, some researchers proved that web-based applications are ready to adopt certain behaviors if they are easy to use (Maharani et al., 2017). Tarhini et al. (2016) found that PE, EE, SI, and FC to be a valuable and valid research tool that is a predictor of adoption behavior and BI. In a previous study, PE, EE, SI, and FC were discovered to influence behaviors to use new technology, and BI and FC determine technology use (Al-Harby et al., 2010). Other researchers prove that PE, SI, FC, PC, and TTF are significant predictors in influencing customers' BI to use technology (Tarhini et al., 2016); Venkatesh et al., 2016). Venkatesh et al.'s (2003) research proved that PE, EE, SI, and FC are useful predictor tools of adoption behavior and BI. Also, PE, EE, SI, and FC are direct determinants of use intention and behavior, and FC are direct determinants of user behavior (Venkatesh et al., 2003). A self-report questionnaire will measure the AU because it was not feasible to capture the system's AU through the customers' logfile.

A questionnaire survey was suitable for this study to collect a sample of bank customers who use or intend to use biometric technology with mobile banking. Therefore, a questionnaire survey was appropriate because it was used for a portion of the total population. The web-based questionnaire survey had open-ended and closed-ended questions for the study. The web-based survey used a Likert scale format, with some open-ended questions where the participant could supply their answers. Closed-ended

questions can be presented in multiple forms, like true or false, yes or no, or multiple-choice formats (Hahn, 2018). Open-ended questions want the participants to provide their answers by filling in a blank section or writing a statement (Hahn, 2018). The information collected from the questionnaire can be multiple-choice, fill-in-the-blank, rating scales, or open-ended questions combined and analyzed by researchers to create a better understanding of a large group or population (Hahn, 2018).

I used analysis of variance (ANOVA) to test the significance and the correlation ratio E^2 and the measure of association Eta to measure the associations of the independent variable on the nominal scale and the dependent variable on the interval scale. The Eta is a correct measure of association when the independent variable is on the nominal scale, and the dependent variable is on the interval scale (Rea & Parker, 2014). ANOVA, developed by Ronald Fisher in the 1950s, is a method for testing the statistical significance of different means in three or more groups (Webster & Lark, 2018). The association's measure reflects the strength of the relationship; between two or more variables and is very descriptive to indicate the power of a relationship (Rea & Parker, 2014). Therefore, showing UTAUT constructs' connection helped understand if a relationship may or may not exist. Thus, a questionnaire survey was suitable for exploring the independent and dependent variables (see Table 2) associated with adopting biometric technology with the bank's mobile application. I used multiple linear regression analysis to understand the relationship between the variables by fitting them in a linear equation to observe the data. The use of multiple regression analysis evaluates the

consequences of two or more other variables against the variance that exists in the data (Rea & Parker, 2014).

No control group was used in this study, so an experimental or quasi-experimental design is not suitable. As explained by Pattison et al. (2019), experimental and quasi-experimental designs are used with studies that focused on cause-and-effect relationships rather than how or why some effect occurs in a relationship. An experimental or quasi-experimental design aims to control the potential causes in an environment to reduce or remove alternative explanations for an observed result (Pattison et al., 2019). A control mechanism for the independent variable significant threats to validity is alternate in experimental and quasi-experimental designs (Osborn, 2019). Researchers use a quasi-experimental design to examine the effects of social phenomena that experiments cannot investigate (Osborn, 2019). Therefore, a quasi-experimental was not appropriate because the investigation did not use control and experimental groups.

A correlation design was not appropriate due to some validity weakness when controlling plausible rival alternative hypotheses (Osborn, 2019). A true experiment is where random assignments are made in the project, and participants get put into a group, so no systematic bias in assigning individuals (Abidah et al., 2017). Since a true experiment is randomly assigned, it's was not appropriate because the participants are not assigned to a control group. However, while exploring the research problem, I looked at millennium college students to help the investigation give the best results. Also, critical thinking played a significant role in the approach to the research strategy. The audience

of this study was community bank customers with mobile banking accounts who use biometric technology.

Population

The United States has nearly 5,000 community banks with active charters across all 50 states (Bostic & Johnson, 2020). The participants were customers from over 500 local community banks within the Mid-Atlantic area of the United States (Bank Strategist, 2020). The general population was from community banks in the Mid-Atlantic region that use biometric technology with their mobile bank apps. The population used biometric technology to access many technologies related devices to access community bank's apps key to customers and stakeholders who need access to daily information. Incorporating feedback from customers and stakeholders throughout the design process ensures that biometric technologies have the best chance of achieving success (Lappi & Mole, 2018). The population that used biometric technology is from community banks that use biometric technology to access their banking information. The target population of this study included bank customers of different genders, ages, marital status, education level, employment status, and income. Also, the goal was to give bank customers more information on the benefits of using biometric technology with mobile banking.

I explored community banks for this study due to customers requiring less physical interaction with bank branches, payment methods, and point-of-sale (POS) terminals. Community banks face more challenges in growing deposits compared to larger banks (Schuld, 2020). By combining with strong technology partners, community banks can simplify support and operations to narrow the deposit gap while expanding

their customer relationships (Schuld, 2020). The evolution of mobile banking is perceived as slow but is estimated to continue to grow due to the vast revenue opportunities of this fast-growing segment (Evon & Leby Lau, 2016). In this study, my goal was to help community banks expand their mobile network and collaboration with customers virtually. Also, I wanted to give bank customers more information on the benefits of using biometric technology with mobile banking.

Sampling and Sampling Procedures

I used a purposeful random sample of participants who meet the following criteria: (a) over the age of 18, (b) have a banking account, (c) use a bank with a mobile application, (d) the bank has biometric technology set up with their application, (e) participant must use mobile devices, and (f) participants must use biometric technology. A purposeful sample is designed to help the researcher understand the problem, the research question and reduced judgment (Benoot, Hannes, & Bilsen, 2016). In quantitative methods, the objective is to protect information obtained from a delineation population from which the sample was drawn to avoid Type I and Type II errors (Palinkas et al., 2015). Purposeful random sampling methods are intended to increase efficiency and increase validity (Palinkas et al., 2015). Reaching many participants can be challenging during the sampling, so purposeful sampling makes reaching participants easier with technology. Gathering data from every member of a population is challenging; therefore, using samples of individuals from a population of interest will help with research studies (Zhang et al., 2019). A link was sent to the participants using an anonymous self-administered online survey.

In this study, I used a purposeful random strategy to increase the results' credibility (Palinkas et al., 2015). In previous research, purposeful sampling attempts to reduce judgment within a purposeful category (Benoot et al., 2016). A key argument with purposeful sampling approach is how it screens all potential participants' responses and examines the complexity of different conceptualizations and not just the correct answer (Benoot et al., 2016). Previous studies have shown that demographic trends show young adults increased differentiation from older adults, and they are more adaptive to the changing environment and urban settings (BouMjahed & Mahmassani, 2018). Purposeful random sampling was an excellent strategy for this exploratory investigation on biometric technology with mobile banks. Purposeful random sampling is a good strategy for this investigation because of millennium adults buying power, security demands, and their technology adoption (Enam & Konduri, 2018). Additional sampling methods were considered but were not selected were convenience sampling and stratified sampling.

The convenience sampling strategy gets used to collect information from participants who provided easy access to the researcher (Palinkas et al., 2015). Stratified sampling gets used to capture a major of participants rather than identify a more influential group (Palinkas et al., 2015). Convenience or stratified sampling was not appropriate because the investigation needs to have selected groups to validate the study. The samples were drawn from mobile banking customers through a web-based survey questionnaire. Using a vast and diverse data collection investigating biometrics enables the advancement of technology and the science of biometrics authentication. The results provided a guide for decision-makers on how to use biometric systems in the field (Yang

et al., 2018). I used the G*Power software version 3.0.10 to calculate sample size using a priori power analysis using alpha, statistical power, and effect size. The G*Power is an open-source power analysis program for a variety of statistical tests. A priori analysis is used for sample sizes computed as a function of user-specified values for the required sample level alpha, the statistical power 1- B, and the predicted population effect size (Faul, Erdfelder, Buchner, & Lang, 2009). The test family was an f-tests, and the statistical test was a linear multiple regression fixed model r^2 increase correlation point biserial model. A priori analysis with this effect size revealed that we needed a sample size of $N = 228$ to achieve a power of .95 in a test based on alpha = .05. See Appendix G and H for the G*Power illustrations of sample sizes using the power analyses process.

Procedures for Recruitment, Participation, and Data Collection (Primary Data)

I collected data using a survey questionnaire created in a web-based format. I will use closed questions for the Likert scale to measure how customers feel about the technology, services, or experiences with biometric technology with mobile banking. For closed questions, I used the 5-point Likert scale in which 1means "*strongly agree*, 2 means "*agree*," 3 means "*neutral*', 4 means "*disagree*," and 5 means "*strongly disagree*." Using software tools like LimeSurvey, SPSS, and other similar software types were used for data analysis and organization of data. Demographic data were collected through the local colleges and the Independent Community Bankers of America (ICBA) website to evaluate the bank's mobile banking application security features in the Mid-Atlantic region.

The participant recruitment and data collection process involved the following eight steps:

1. I used LimeSurvey to host the survey instrument that will use for purposeful random sampling.
2. Cint software was used to contact potential participants.
3. Cint software was used as an email invitation to potential respondents to participate. A link to the survey was provided in the email for the potential participants to select.
4. Participants who clicked on the provided link was able to access the survey's service agreement.
5. Participants was provided a consent form for their voluntary participation in the survey.
6. Respondents who continue had the choice to disagree or agree. If the respondents agreed they consent by clicking the agreement button and by completing the survey.
7. I checked for inaccuracies in the survey responses by looking at the member's replies.
8. Participants use the Cint to show a member checking process before submission of the final survey responses.

Pilot Study

A pilot study was conducted to ensure the questionnaire's content validity because the survey was adapted and adjusted in previous studies. The web-based questionnaire

was created in English and reviewed for content validity. The questionnaire was adopted from previous research for validity and reliability from the well-developed UTAUT model with two more constructs, the PC, and the TTF questions (see Appendix I). The Walden University Institutional Review Board (IRB) approval number for this study is 07-28-20-0409920, approved on July 28th, 2020, and valid for one year from the approval date. The Walden's IRB approval process was critical to ensure the university's ethical standards and U.S. Federal regulations are being upheld to protect human research participants and their data. The items were tested for validity and reliability, and the questions were modified to fit my specific study (see Appendix D, E, and F for author permission to use models).

Referring to Tarhini et al (2016), Oye et al. (2014), Venkatesh et al. (2016) this research in operationalized performance as the extent to which an individual believes that adopting mobile banking using biometric technology will benefits them when performing bank services, operationalized effort expectance as the measure of effort that customers deal with technology use, operationalized SI as the extent where customers will perceive what is distinguished from other people who think they should use similar technology, and think they should use a similar technology feature or device, operationalized FC as the extent to where customers' perceptions of the resources and services available to perform a service, operationalized PC as the extent to where a person believe that security and trust are the measures a person behavior to use mobile banking, and TTF as the extent to where a person believes how the technology fits their daily needs.

To ensure the content validity of the web-based survey questionnaire used in this study to assess each construct (see Appendix I). All items regarding the constructs' measurement were adapted from the well-developed UTAUT model and two more constructs, the PC and the TTF questions. The questions were carefully selected and reworded to fit mobile banking adoption using biometric technology in the U.S Mid-Atlantic region. The questions were adopted from the UTAUT model, and two additional constructs PC and TTF (see Appendix I). A pre-test was conducted, and three modifications of the survey were created because of visual errors, grammar, and content validity. A pilot test was conducted with five customers randomly chosen, so revisions and modifications of the questionnaire content could be established for validity and reliability. Therefore, some of the adopted question items were reviewed and modified based on the pilot-test results. See Appendix J for a summary report of the pilot study questions for evaluation.

Instrumentation and Operationalization of Constructs

In the study, I used a self-administered web-based questionnaire containing 38 questions (see Appendix I) for a purposely random sample from customers who use mobile banking in the Mid-Atlantic region of the United States for data collection. All scales from this study were adopted from the existing studies related to the UTAUT and previous empirical studies related to the TTF and PC to preserve those items' validity and reliability. Specifically, PE, EE, SI, FC, and BI were measured using four items. PE, EE, SI, FC, and BI corresponding items were adapted from Venkatesh et al. (2003) and related work (Tarhini et al., 2016; Venkatesh et al., 2012). Also, five items for the AU

were adapted to show customers' use (Venkatesh et al., 2003, 2012). Also, the TTF was measured using six items, and the scale was adapted from the work of Tarhini et al. (2016). Finally, seven items were adapted from Tarhini et al. (2016) to measure the PC. A pilot study was conducted using a web-based questionnaire of 42 bank customers; however, they were not included in the final survey.

A five-point Likert scale was used, ranging from strongly disagree to strongly agree, and measured the items that represent each construct within the proposed research model. A web-based questionnaire containing 38 questions (see Appendix I) was used to collect a purposeful random sample from the mobile banking customers in the Mid-Atlantic region of the United States. In previous studies by Tarhini et al. (2016) and Chao (2019), a pilot study was done, and it took the participant 10-15 minutes to complete the 38 question survey questionnaire. The second section of the survey contained demographic information presented on a nominal scale. The questionnaire collected necessary information about the respondent's characteristics, including age, gender, education, employment and experience with mobile banking with biometric technology.

The UTAUT model Venkatesh et al. (2003) instrument was used to determine the strength of predictors for mobile bank customer's intention to accept and use biometric technology with mobile banking apps for security. Also, Tarhini et al. (2016), extending the UTAUT instrument, was used to understand the customer's acceptance and use of biometric technology with mobile banking (see Appendix A). In previous research, Venkatesh et al. used the same UTAUT instrument to collect data in their study on information technology acceptance models. Also, Tarhini et al. used the same instrument

by extending the UTAUT to collect data in Lebanon's Internet banking research. Earlier studies showed acceptance determinants for information technology (Venkatesh et al., 2003). Venkatesh et al. used eight prominent models (TRA, TAM, MM, TPB, PC, IDT, Combined TAM, and TPB and the SCT) to explore over four organizations, and the eight models explained 17% and 53% of the variance of user intentions to use information technology. Even with the success of the eight models, Venkatesh et al. established the UTAUT, focusing on intention and use, and the UTAUT outperform the eight individual models of r2 of 69%. The UTAUT model confirmed again with two other organizations with similar results of r2 of 70% (Venkatesh et al., 2003).

I explored the relationship between the acceptance and use of biometric technology within the mobile banking application and PE, EE, SI, FC, PC, and TTF. The variable was measured separately with a specific hypothesis.

Research Question: To what extent do performance expectancy, effort expectancy, social influence, perceived credibility, task-technology fit, and facilitating conditions affect the BI of customers to adopt biometric technology with mobile banking?

$H1_0$: Performance expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H1_1$: Performance expectancy will affect customers' behavioral intention to use biometric technology with mobile banking.

$H2_0$: Effort expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H2_1$: Effort expectancy will affect customers' behavioral intention to use biometric technology with mobile banking.

$H3_0$: Social influence will not influence customers' behavioral intention to use biometric technology with mobile banking.

$H3_1$: Social influence will influence customers' behavioral intention to use biometric technology with mobile banking.

$H4_0$: Perceived credibility will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H4_1$: Perceived credibility will affect customers' behavioral intention to use biometric technology with mobile banking.

$H5_0$: Task-technology fit will not influence customers' behavioral intention to use biometric technology with mobile banking.

$H5_1$: Task-technology fit will influence customers' behavioral intention to use biometric technology with mobile banking.

$H6_0$: Facilitating conditions will not influence the actual usage of biometric technology with mobile banking.

$H6_1$: Facilitating conditions will influence the actual usage of biometric technology with mobile banking.

Hypotheses 1 through 6 will get tested by running the following multiple regression model:

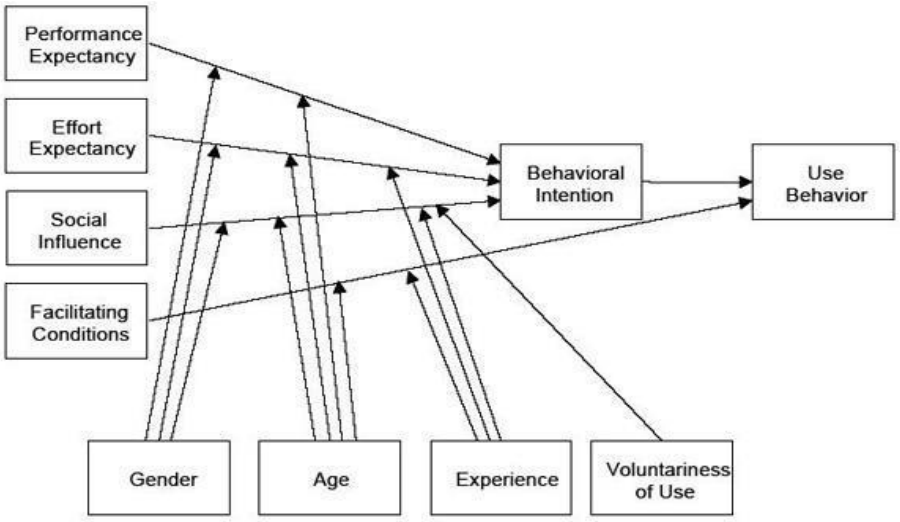
$$BI = \beta_0 + \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 PC + \beta_5 TTF + \beta_6 FC + €. \quad (1)$$

Where:

- BI is the dependent variable
- β_0, β_1, β_2, β_3, β_4, β_5, β_6 are the regression coefficients
- PE, EE, SI, PC, TTF, and FC are the independent or predictor variables
- € is the error term
- See Table 1 for independent and dependent constructs.
- See Table 2 for the constructs' roles
- See Table 3 for the constructs' hypotheses and directionality of the constructs

Figure 4

Research Model



Note. From Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology, by V.L. Venkatesh, J.Y., Thong, and X. Xu, 2012, 36(1), 157-178. Copyright 2012 by Venkatesh, Thong, Xu. Reprinted with permission.

I outlined the UTAUT and extension of the UTAUT instrument in Appendix A. Also, I presented the invitational email in Appendix C. I will use the UTAUT and expansion of the UTAUT instrument to assess the following aspects of biometric technology with mobile banking.

- Barriers and obstacles to biometric technology adoption
- Potential benefits of biometric technology adoption
- Prevalence and status of biometric technology in commercial banks
- Conditions that facilitate biometric technology adoption.

I asked bank customers to respond to items in each of the above areas by using a 5-point Likert scale that recommends acceptance of the statements.

Data Analysis Plan

Using different biometric scanning tools on how the data gets collected can reveal needed information to advance technology and science (Yang et al., 2018). The data collected results provided a road map for decision-makers on how to proceed with implementing biometric scanning tools (Yang et al., 2018). Using a sample database for large and unbalanced samples is recommended for a research study (Mehrotra et al., 2016). Collecting biometric scanning tool samples in the United States was approved by the IRB for human subjects' agreements (Yang et al., 2018). Sampling a population can be valuable to community banks and other financial institutions because it can provide up-to-date information on issues and help banks make financial decisions on security technology (Adapa & Roy, 2017). The banking industry goal is to share data and

consolidate while bank managers must give details on new trends and provide accurate and valid data to stakeholders (Adapa & Roy, 2017).

The bank customer was 18 or over who use mobile banking conversant with biometric technology from the Mid-Atlantic region. The general population consisted of two-hundred twenty-eight to two-hundred-fifty participants, and this was a reasonable number of participants to make my research reach saturation. Data Collection was from mobile banking customers in the Mid-Atlantic region of the United States, and the data were collected using the web-based survey questionnaires. Obtaining data for an investigation is a critical component to the success of a study. I used the electronic questionnaire to implement the survey with the volunteer participants. The electronic questionnaire survey was used to support the research's finding by focusing on specific information collected from participants. This study's goal was to achieved success by crucial observation of the participants, sources of data, and the type of data collected.

The data collection approach helped me achieved a valid and reliable finding to produce a quality study. I used the electronic questionnaire to implement the survey and data collection approach. I used the self-administered electronic survey to collect data from 228 participants. The survey was sent to over 1,000 customers to reach its sample goal of 228 participants. Data Collection was from mobile banking customers and the collected data through the electronic survey questionnaires created by a web-based survey. Software tools like SPSS, AMOS, LimeSurvey, Power BI, and Excel was used for data analysis and data organization of data.

Threats to Validity

External Validity

External validity explores whether the study findings can be generalized to other contexts (Andrade, 2018). Random samples used distinct populations in previous investigations to overcome facility-based experiments' apparent validity limitations (Barnighausen et al., 2017). The validity of the information collected from bank customers is dependent on the quality of the questions presented in the survey instrument. The questionnaire was modified to be more relevant to mobile bank customers' experiences and biometric technology for this study. See Appendix J for a summary report of the pilot study questions for evaluation. Modifying the survey questions to fit the study helps answer how customers adopt mobile banking using biometric technology. The modifications of the survey questions related to the real-world instances of how customers access their mobile bank application.

Many researchers studied the relationship between customers' age and their probability of using new technology, but no consensus on the mobile devices' phenomenon (Mosquera et al., 2018). Accessibility is advantageous for mobile banking customers; being susceptible to security risks may inhibit success (Shareef et al., 2018). Mobile banking lacks confidentiality between banks and customers for privacy, integrity, trust, reliable identification, and service availability because of external interruption during mobile bank transactions (Shareef et al., 2018). When framing a question, the random allocation of alternative approaches can show whether the age, sexuality, or race

of a person presents a specific behavior, which will dictate the participant evaluation of that behavior (Barnighausen et al., 2017).

I used the member checking feature to present survey responses to the accuracy checking participants in the replies. Member checking is where the researcher compares their interpretations and understanding obtained from the data analysis with participants' viewpoints to increase the accuracy and consistency of results (Santos et al., 2017). The participant uses the online survey questionnaire to answer the member checking process before submitting their results. Population-based experiments were commonly used to eliminate threats to external validity that facility-based study' usually suffer (Barnighausen et al., 2017). Previous research explicated that member checking was useful for validating important information not observed in the data analysis process, especially with different participants (Santos et al., 2017). The survey delivery mechanism can change the context in which the intervention effect is measurable (Barnighausen et al., 2017). By reducing the strength of the belief that the intervention will have the same impact in real life that established in the experiment (Barnighausen et al., 2017). In this study, community bank customers from the U.S Mid-Atlantic region who use mobile banking apps with biometric technology were chosen as the target population. Community banks offer fewer services and technology than larger banks, but the process of using mobile banking with biometric is the same. Therefore, no internal or external validity was affected because of the target group. Community banks face the same issues as large banks, like cyber-attacks, bank frauds, which is why all types of small and large banks are moving to biometric technology for more secure transactions.

Internal Validity

Internal validity examines whether the manner of a study designed, conduct, and analyzed without systematic bias is present (Andrade, 2018). For example, improper data collection from specific groups in the survey can undermine the results' fidelity and conclusion of proper randomization. An advantage of this study is the ability to collect data from mobile bank customers because of their frequent use and acceptance of the technology. Using internal validity is based on judgment and not computed statistics, just like external validity, and can improve by modifying the analysis plan (Andrade, 2018). Previous research showed that researchers who have one theory make more inadequate predictions, and those who have many methods find the one that can be applied the best to the situation (Profeta & Turvey, 2018). Researchers identified four types of questions for developing a theory (a) what works, (b) what it is and what does it look like, (c) visions of the possible, and (d) the theory-building questions (Profeta & Turvey, 2018).

I looked at visions of the possible and the theory-building questions. Biometric technology with mobile devices is growing with customers, and the idea of banks is to build trust with customers (Adapa & Roy, 2017). The theory-building questions and specific groups helped developed more clarity and validity in the study.

Construct Validity

Construct validity tells how well a test or experiment measures up to its claims and refers to whether the operational variable reflects the true theoretical meaning of a concept (Shuttleworth, 2009). Construct validity established in a study shows the relevant and consistent relationship with multiple measures in a large and diverse study population

(Loftfield et al., 2015). Testing the construct's validity is to gather evidence about how far the measurement results give the measured variables' constructs (Sumarni et al., 2018). For example, a test designed to measure biometric technology use with mobile banking must only measure the construct, not closely related ideas such as traditional password and username authentication. The Likert scale is an important instrument used to avoid redundancy and assessment fatigue to obtain quality data, which produces significant reliability (Sumarni et al., 2018). It may reduce the acquiesce bias when measuring positive psychological constructs (Sumarni et al., 2018). The validity of the construct's is to find out how the extent to which the measurement scores can illustrate the theoretical constructs underlying the measuring instrument (Sumarni et al., 2018). Validity is defined as a composite indicator of the extent to which an instrument measures the attribute it was designed to measure and the extent to their inferences and interpretations were made from participants' scores (Thapa & Cohen, 2017).

The advantages and disadvantages of using mobile banking can get viewed from the bank's standpoint and the customer's point of view as the primary stakeholders of the business (Milić et al., 2017). Mobile banking from the bank's side improves reputation, reduced transaction costs, faster and continuous service, greater market penetration, and e-banking to offer new financial products (Milić et al., 2017). Also, using e-banking helps banks manage customer relations better since they provide a wide range of services 24 hours a day. The banks can offer more services at a lower cost, which is an advantage to customers. However, a disadvantage for banks would be they would not have any personal contact (face-to-face) with customers who have different or more demanding

needs. Also, another disadvantage could be through bank transactions; there could be mistakes in the software. Thus, the loss of data could occur, and the bank may not provide 100% guarantee security for the e-banking transaction (Milić et al., 2017).

Two types of construct validity are convergent validity and divergent validity (also known as discriminant). Convergent validity tests construct expected to be related and determine no questions about the construct (Shuttleworth, 2009). Whereas divergent validity tests construct, that has no relationship and make sure the relationship does not exist (Shuttleworth, 2009). A purposeful random survey using bank customers can help achieve high internal validity for mobile device use with biometric technology for security. In construct validity, items on a questionnaire can cover the construct studied, and whereas internal validity measures the real-world events they are intended to measure. The purposeful random sample must make intuitive sense to the research; otherwise, the questionnaire has low factorial validity (Palinkas et al., 2015).

Ethical Procedures

The data associated with this study may be sensitive to community banks managing mobile banking apps. The privacy-related to biometric technology deployment is a critical factor for banks to protect their copyrighted information (Sanjith, 2017). Therefore, according to Walden University's Institutional Review Board guidelines, this study was conducted in an ethical standard. This study included only participants who voluntarily agreed to take the survey. Participants taking the survey were volunteering, and every participant was provided a consent form for their voluntary participation in the survey. Respondents who continue to take the survey had the choice to disagree or agree.

If the respondents agreed, they consent by clicking the agreement button and by completing the survey. The participants were provided with the Research Participant Advocate (RPA) phone number and email address at Walden University.

Furthermore, I informed the participants that the survey was voluntary, and no compensation was provided for taking the survey. Also, the participants were informed that no negative consequences were involved if they decided not to take or finish the survey. The participants were informed they could change their minds and stop the survey at any time. I ensured that the participants' responses were completely anonymous, and no personal identifying information (PII) or Internet Protocol (IP) addresses were collected. Also, I informed the participants that any data collected will not be used outside of the research project. I only published and reported general findings based on the analysis of the data. To ensure the anonymity of the commercial banks represented in this study, I employed a robust coding framework so no entity could use the reported results to identify any participant and their data collected. I ensured that the survey data was kept secure and stored on a password-protected external hard drive, only accessible to the researcher. The data will be kept for at least five years, as required by the University.

Summary

Chapter 3 discussed the quantitative methodology used to investigate the key research question of the current investigation. Bank customers from community banks in the Mid-Atlantic region are the primary target population of the research study. In the study, I targeted mobile banking customers to obtain a sample. For a survey and

questionnaire, I used LimeSurvey for a centralized organization. The participants who responded were selected based on purposive random sampling. The study was designed to gather valuable information from an online survey questionnaire from a minimum of 228 respondents. The primary instrumentation for the research was biometric technology with mobile devices during the bank transactions survey.

Approval was granted by Walden's IRB for human subjects. I used the approved UTAUT instrument by Venkatesh et al. (2003). The UTAUT model was used to determine the strength of predictors for mobile bank customers' intention to accept and use biometric technology with mobile banking apps for security. I used the approved instrument by Tarhini et al. (2016), who extends the UTAUT instrument to understand the customer's acceptance and use of biometric technology with mobile banking. My study looked at participants from the Mid-Atlantic region to examine how biometric scanning tools work with the bank's mobile security systems. The study discussed the challenges, security, difficulties and measure how banks that use biometric scanning tools with their bank's application security system. This study evaluated the integration of PC and TTF with UTAUT and determine if it is a useful theoretical model for examining the adoption of biometric technology within mobile banking. The general population was from community bank customers conversant with biometric scanning tools from the Mid-Atlantic region. I used a self-administered web-based questionnaire instrument for data collection. Data collection was from mobile banking customers through a web-based survey to analyze the data results.

The participants were provided information about the study and sent an invitation utilizing email through Cint, where they clicked on a link that took them to a secure website. If the participants did not want to continue the survey, they could opt-out before the survey was started. The secure webpage allowed participants to view the online survey questionnaire's consent documentation, and they could opt-out at any time during the survey. If the participant chose not to continue the survey, there would be no penalty or violation. I also informed the participants that a summary of the study was provided to them on ResearchGate. I used the following software tools for data analysis and organization of data:

- SPSS version 23
    - Multiple linear regressions
    - Factor analysis
    - Analysis of Variance (ANOVA)
- SPSS AMOS version 23
    - Structural Equation Model (SEM)
- Web-based Survey
    - Microsoft Forms
    - LimeSurvey
- Microsoft Excel
- G*Power software
- Microsoft Power BI

The research question was used to analyze a sample population of bank customers in the Mid-Atlantic region of the United States to establish an association between variables. During the purposeful random sample, I informed potential participants about the voluntary nature of the investigation. Also, I told the potential participants about all pertinent information concerning access to the survey instruments. The participants who volunteer choose of their free will and no penalties happen if they did not want to do the survey or back out of the survey.

In this chapter, I analyzed and developed the research design in the investigation. In Chapter 4, I present study results and analysis for the research question. Chapter 5 includes the (a) results interpretations, (b) limitations of the study, (c) scope and delimitations, (d) implication of social change, (e) future recommendations, and (f) and a conclusion of the study.

Chapter 4: Results

The purpose of this quantitative study was to develop a conceptual model that would have a conceivably more eminent explanatory power about the adoption of biometric technology with mobile banking. A conceptual framework was developed by extending the UTAUT by incorporating two more factors: PC and TTF. A quantitative approach based on a web-based questionnaire survey was used to collect data from 228 mobile banking customers in the U.S. Mid-Atlantic region. The specific problem is customers' lack of adoption of biometric technology, and bank managers do not understand the reasons that influence mobile banking adoption in the Mid-Atlantic region. Chapter 4 includes a detailed description of how I conducted the study, collected data, and analyzed the data. Chapter 4 also provides the data analysis results and a discussion of how I used the finding to test the hypotheses and answer the research question.

Pilot Study

The questions in Appendix I were used by the well-developed UTAUT model and two more constructs, the PC and the TTF questions. The questions were tested by previous research for validity and reliability. However, the questions were modified to fit my specific study. A pilot study was conducted after the Walden University IRB approval.

Based on the collected responses, I made several minor modifications in the survey, such as the survey introduction, consent information, the wording of questions, and sequence of items. Also, I asked for additional demographic information, such as

age, gender, race, income, marital status, employment status, and nationality. The demographic information (see Appendix L) was used for the study's inclusion criteria. The questions were tested by previous research for validity and reliability (Tarhini et al., 2016; Venkatesh et al., 2012; Yu, 2012). However, the questions were modified to fit my specific study. See Appendix J for a summary report of the pilot study questions for evaluation.

The pilot study used a random sample for the pretest and posttest design. See Appendix J for the summary report of the pilot study. Once the pilot study was set up and complete, I used the pilot study format for the final study. The only change from the pilot study to the final study was the data collection instrument. The pilot study used Microsoft Forms, and the final study used LimeSurvey to collect data. I asked participants to complete a preassessment of their mobile banking application use and biometric technology using a web-based survey using Microsoft Forms. Participants were recruited through social media sites, like Facebook, Instagram, Twitter, and LinkedIn. The Participants had 1 week to complete the pilot study survey. I emailed the survey link to participants, instead of directing them to a web-based survey, to ensure anonymity. Once the participants clicked on the link, they were directed to the survey by Microsoft Forms, which consisted of eight demographic questions (see Appendix L). The Microsoft Forms survey design was made to be taken on a personal computer, laptop, tablet, or smartphone to make sure participants could take the survey anytime and anyplace during the pilot test. No identifying information was collected. An email reminder was sent to all participants (even if they completed the survey) to complete the survey on Day 3 of the

survey's 1-week deadline. After Day 3, an email blast was sent to all participants every day to encourage new participants to take the survey.

The web-based survey was published 1 day before the survey was released to potential participants. The web-based survey included an implied consent form to all participants before proceeding with the survey. I also included an introduction and opinion statement in the survey for instructional purposes. Of the 42 possible participants, all 42 (100%) completed the pretest survey. The survey was titled "Biometric Authentication Usage and Acceptance with Mobile Banking Survey Pilot Study." Measured on the 5-point Likert scale in which 1 means *strongly disagree*, 2 means *disagree*, 3 means *neutral*, 4 means *agree*, and 5 means *strongly agree*. Higher scores indicated that the participants were more engaged, and lower scores meant the participants were less engaged in biometric technology with mobile banking. The participants received follow-up emails reminding them about the survey every 2 days from the initial email. The data collection lasted 1 week, and one response was set per person. After 1 month of the actual survey timeline, the participants received an email with a link to the survey post assessment of their mobile banking and biometric technology use and acceptance level. Participants who did not take the test within the allotted time frame could not attempt the test because the survey had a start and finish date. The survey was made unavailable on Microsoft Forms after a week of initiation.

The web-based survey was anonymous, and no personally identifiable information was asked during the pilot test. A brief introduction to the web-based survey was used to help participants understand the topic and get an emotional attachment to the

study, so the best possible answer would be given. A content agreement was added to ensure that participants knew they were volunteers, there was no compensation, and they could opt-out of the survey. A brief explanation of how the questions would be measured and definitions of key words were explained for the participants. Also, after the web-based survey was completed, participants were redirected to a note thanking them for participating. The modified questionnaire items were adjusted to ensure no bias, irrelevant or missing questions, and duplicate responses were removed. The web-based questionnaire was pilot tested among 42 bank customers, who were not included in the primary survey. The data were analyzed with Microsoft forms question-wise analysis and Microsoft Power BI. Also, data were extracted to Microsoft Excel and ran in SPSS 23 for data analysis. I found preliminary evidence that the scales were reliable and valid (Tarhini et al., 2016; Venkatesh et al., 2012; Yu, 2012).

The data were elicited from 42 people who were randomly selected from social medial sites. The participants live in the Mid-Atlantic region of the United States, and they use mobile banking and had biometric technology tools capabilities. The participants receive an e-mail welcoming and thanking them for their participation in the survey. Participants used a hyperlink to gain access to the web-based survey between August 3, 2020, through August 9, 2020. The survey was set so all the participants would answer every item. On the introduction page of the survey, the participants were told the survey was anonymous. The introduction explained that participants would take part in a research study about biometric technology use and acceptance for customers' security during mobile banking transactions. No incentives were given to the participants for their

responses, and all 42 participants responded and finished the survey; 42 participants have usable data sets for analysis, yielding a response rate of 100%. Nonparticipants resulted in invalid e-mail addresses, time constraints, or noncompletion of survey.

Data Collection

For the final study, I used a random sample technique, which is used when a diverse sample is necessary or the opinion of people who used a mobile device. When researchers use the data collection process, it is for gathering and measuring information on variables of interest, using an established systematic format that enables researchers to answer stated research questions, test hypotheses, and evaluate outcomes (Palacios Martínez, 2020). The target population of the final study was the Mid-Atlantic region of the United States, which is estimated at 41 million, according to the 2019 U.S. Census. According to the Global System for Mobile Communications, more than 5 billion people have mobile devices in the world (Wolfe, 2017). Sample sizes are defined as a finite part or subset of participants drawn from the target population (Martínez-Mesa et al., 2016). The final study's appropriate sample size with a confidence level of .95% and a margin of error of .5% was 228 participants. In the final study, I used purposeful random sampling to collect data on a web-based survey through the LimeSurvey website. The data obtained for this study were from a sample representative of the target population. The final study target population included adults living in the Mid-Atlantic region of the United States of different genders, age groups, ethnic backgrounds, marital status, education levels, income levels, and bank used.

In the final study, the participants included bank customers who use biometric technology when using their mobile bank apps. The survey link was posted to social media sites to direct a web-based survey to ensure anonymity. Once the participants clicked on the link, they were directed to the survey utilizing LimeSurvey. Participants were recruited through social media sites such as Facebook, Instagram, Twitter, and LinkedIn. The participants had 2 months to complete the web-based survey. LimeSurvey, which consisted of eight demographic questions (see Appendix L). The LimeSurvey design was made to be taken on a personal computer, laptop, tablet, or smartphone to make sure participants could take the survey anytime and anyplace during the survey. No identifying information was collected. An updated post on social media sites was done once a week as a reminder and to encourage new participants to take the survey.

Data Collection Process

The instrument in the final study consisted of nine groups in the questionnaire. The first group contained eight questions on demographics. The other group had 38 items used to measure the independent variables for using and accepting biometric technology with mobile banking in the U.S. Mid-Atlantic region. Tarhini et al.'s (2016) instrument had a 5-point Likert-type scale with Cronbach's alpha scores, and they were over 0.8 except FC and AU, which were over .75 respectfully. The item used to measure the independent variables derived from Tarhini et al.'s validated survey instrument used in a previous peer-reviewed study. The web-based survey was available for participants to complete for two months. The participants in this study included adults over the age of 18 from any (a) gender, (b) age, (c) marital status, (d) educational level, (e) race or ethnicity

background, (f) employment status, (g) income level, (h) technology level, and (i) mobile device owned. All participants used community banks or credit unions. Participants did not have to be affiliated with LimeSurvey to take the survey, but the participants did live in the Mid-Atlantic region of the United States.

Reliability of the Instrument

The Cronbach's alpha is used to determine whether the items of a scale measure the same underlying dimension. Therefore, Cronbach alpha is used when the construct comprises multiple items measured on an interval scale to see if the construct is reliable and consistent. The Cronbach's alpha ranges from 0 to 1, so if alpha is greater than .90, there is a great internal consistency. If Cronbach's alpha is between .80 and .90, there is a very good internal consistency and, if it's between .70 and .80, there is a good internal consistency. Cronbach's scores between .60 and .70 are acceptable, and values between .50 and .60 are poor, and anything below .50 is unacceptable. Therefore, the Cronbach's alpha should be over .70 and ideally over .80 or .90 for best internal consistency. The items used in this study were based on a validated instrument. However, a pilot study was needed to test for validity and reliability, and the questions were modified to fit my specific study.

In this study, a Cronbach's alpha for the instrument was analyzed to confirm the instrument's validity and reliability. The Cronbach's alpha showed a value of .949 ($\alpha \geq 0.90$). Cronbach's alpha is the most common statistic used to display items' internal consistency reliability. See Table 4 for reliability statistics for the whole instrument.

Table 4

Reliability Statistics

Cronbach's alpha	Cronbach's alpha based on standardized items	N of items
.949	.952	31

The measurement model (see Appendix M for descriptive of constructs) was first used to analyze and assess the instrument's reliability and validity before testing the study's research hypotheses. Cronbach's alpha for the scales was calculated (see Table 5) and showed a high level of internal consistency for the instrument used in this study. The first column (Mean) shows most of the items are over 4.36, meaning that most participants expressed positive responses to the constructs measured in the study. The second column (Standard Deviation) of the sample shows a high standard deviation meaning the values are spread out over a wider range. The third column (Corrected Item Total Correlation) is the correlation between an item and the sum of the rest of the items and how well they go with each other. The highest item-total correlation is BI[BIB] (r = .755) and the item with the lowest item-total correlation is FCD (r = .285). If the item-total correlation is close to zero, removing the item from the scale is recommended because it does not measure the same thing as the rest of the items. The fourth column (Cronbach's Alpha if Item Deleted) is a critical column because it estimates the Cronbach's alpha if you remove an item. For example, PE[PEA] (Cronbach's Alpha if Item Deleted) is .947, so that means the scale would drop from .949 to .947. Therefore, as shown in Table 5, removing any item would not change the instrument's best internal consistency. Therefore, the constructs were shown to have great reliability for the next step of the analysis.

Table 5

Descriptive Statistics of the Constructs

Construct	Mean	Std. *d*eviation	Corrected item total correlation	Cronbach's alpha if item deleted
PE[PEA]	4.53	.542	.618	.947
PE[PEB]	4.71	.462	.527	.948
PE[PEC]	4.69	.526	.615	.947
PE[PED]	4.69	.473	.648	.947
EEA	4.58	.537	.602	.947
EEB	4.60	.518	.662	.947
EEC	4.55	.557	.588	.947
EED	4.58	.569	.622	.947
SIA	3.88	.773	.589	.947
SIB	3.85	.765	.614	.947
SIC	3.89	.843	.643	.947
SIDA	4.06	.821	.546	.948
FCC	4.52	.612	.520	.948
FCD	3.62	.714	.285	.950
PCA[PCAA]	3.96	.614	.553	.948
PCA[PCAB]	4.21	.631	.580	.947
PCA[PCAC]	3.66	.731	.468	.949
PCA[PCAD]	4.04	.592	.580	.947
PCA[PCAE]	4.36	.617	.686	.946
PCA[PCAF]	4.36	.603	.662	.947
PCA[PCAG]	4.07	.526	.541	.948
TTF[TTFA]	4.68	.585	.606	.947
TTF[TTFB]	4.72	.563	.563	.947
TTF[TTFC]	4.18	.640	.621	.947
TTF[TTFD]	4.55	.722	.674	.946
TTF[TTFE]	4.61	.665	.639	.947
TTF[TTFF]	4.33	.716	.689	.946
BI[BIA]	4.54	.747	.667	.946
BI[BIB]	4.69	.501	.755	.946
BI[BIC]	4.70	.479	.747	.946
BI[BID]	4.69	.551	.729	.946

Note. The last column of Table 5 shows the value of Cronbach's alpha if an item was deleted from the scale. If an item is removed it would not affect the reliability of the instrument.

Study Results

I used SEM based on SPSS AMOS for data analysis. SEM was used as a general multivariate framework for identifying and examining a system of linear models that involve observed and latent variables (Sarstedt & Hwang, 2020). I conducted an exploratory factor analysis to reduce the variable to a manageable and relevant set of variables that could affect biometric technology implementation during mobile banking transactions.

The SPSS descriptive and SEM were used to measure statistical procedures for data analysis and test the hypotheses. The data were analyzed by using SPSS version 23 and presented in four stages (a) descriptive statistics report, (b) Principal axis factoring, (c) Chi-square for the goodness of fit, and (d) Principal component analysis. To test the research questions and hypothesis, I analyzed the data using AMOS version 23 to run a confirmatory factor analysis SEM fit model and path analysis to investigate the appropriate model. Also, I used SPSS (Version 23) to run multiple linear regressions and ANOVA to identify factors to determine the extent of influence of the factors on intentions to adopt biometric technology with mobile banking.

I used a web-based questionnaire survey as the data collection instrument, which focused on examining the adoption and operation of biometric technology with mobile banking. Based on the research model and extension of the research model, I grouped the factors into the following six categories: (a) conducting banking affairs, (b) learning to use (c) influence (d) environment (e) using mobile banking and (f) using biometric technology.

- Conducting Banking Affairs [PE] – benefits (2 variables) and service (2 variables).
- Learning to Use [EE] – ease of system (2 variables), ease of technology (1 variable) and beneficial tasks (1 variable).
- Influence [SI] – influence and support (3 variables) and trusted network (1 variable).
- Environment [FC] – behavior internal and external constraints (3 variables) and resources and support (1 variable).
- Using mobile banking (MB) [PC] – security and trust (7 variables)
- Using biometric technology [TTF] - needs and performance (2 variables), security features (1 variable), performance and utilization (3 variables).

The web-based questionnaire data was exported from LimeSurvey in a Microsoft Excel spreadsheet format. Once the data was extracted, I uploaded the Excel spreadsheet file into SPSS version 23 for analysis. The variables were grouped into factors and measured using the 5-point Likert-scale (extending from 1 = *strongly disagree*, to 5 = *strongly agree*). I reported the analysis in the following order (a) descriptive statistics report (b) principal factor axis factor (c) Chi-Square goodness-of-fit test, (d) principal component analysis, (e) exploratory factor analysis, (f) data analysis and results (g) research question, and (h) Hypotheses'.

Descriptive Statistics

Descriptive statistics summarize the data in a study by providing the basic features of the data, such as the standard deviation (SD) and the mean (Mishra et al.,

2019). Descriptive statistics were used in this study to interpret every quantitative analysis of data in a more meaningful way. The collected data was exported from LimeSurvey.com as a Microsoft Excel file to SPSS 23 for further data analyses.

The survey was titled "Biometric Authentication Usage and Acceptance with Mobile Banking Survey," and the responses used in SPSS were entered as 1 = *strongly disagree,* 2 = *disagree,* 3 = *neutral,* 4 = *agree,* and 5 = *strongly agree* for the biometric technology use with mobile banking. The higher the score meant, the more engaged, and the lower the score meant, the participants were less involved in biometric technology with mobile banking. I used closed questions for the Likert scale to measure how customers feel about the technology, services, or experiences with biometric technology with mobile banking.

The web-based survey was published one day before the survey was released to potential participants. A consent form, an introduction, and an opinion statement were included in introducing the survey for instructional purposes to the participants. Of the 234 possible participants, 228 participants (97.4%) completed the survey. From the 234 responses, six surveys were not fully completed and could not be included in the analysis. The survey was active from August 2020 to October 2020, and I collected data until I reach saturation of 228 participants. According to G*Power calculation, a sample size of $N = 228$ would achieve a power of .95 in a test based on alpha = .05. If the full sample were not received, the G*Power calculated a sample size of $N = 184$ would achieve a power of .90% in a test based on alpha = .05%. However, the full sample was received, so the .90% sample size was not needed.

Survey Returns

The data collections generated 234 responses, including six incomplete survey responses. Only surveys that were fully completed were used in the data analysis. After going through the survey summary, six incomplete responses were not included in the data analysis. Therefore, 228 complete responses were used for this study. Table 6 describes the descriptive statistics of the demographic data of the participants.

Table 6

Demographics

No.	Frequency	Male or Female	Age	Marital status	Education level	Employment status	Total income	Bank use
N	Valid	228	228	228	228	228	228	228
	Missing	0	0	0	0	0	0	0

Comparison of Demographics Between Population and Sample

The characteristics of the target Mid-Atlantic region of the United States and its sample were like each other. The comparison was conducted between the last U.S. Census (2019) data and the data collected for this study. According to the U.S. Census report (2019), among the 41 million Mid-Atlantic region populations, 52.8% were females, and 47.2% were men. In the sample used in this study, 54.4% were women, and 45.6% were men that participant in the study.

One large gap in the target population and the sample population was 18 - 39 - year represented groups. The target population gap was due to the millennial demographic buying power and how millennials are the future bank account holders. Therefore, the millennial generation will help guide the next generation of bank

customers into new technology. The comparison of demographics between the sample size and population size are listed in Table 7.

Table 7

Comparison of Demographics Between Population and Sample

Demographics	% of Mid-Atlantic Population	% of Sample
Male	47.2	45.6
Female	52.8	54.4
18 – 21	5.57%	17.5
22 – 39	23.8%	48.2
40 – 64	33.8%	19.7
65+	15.3%	14.9
Employed 40+ hours	58.8	64.9
Unemployed	4.8	6.6

Gender Report

The data were collected using a web-based survey randomly sent to participants living in the Mid-Atlantic region of the United States. Data were collected from 228 participants, which included 54.4% of females and 45.6% of men. Table 8 lists the gender statistics of the sample population. In this study, the sample population and demographics population were similar.

Table 8

Gender Statistics

Frequency	Sex	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	124	54.4	54.4	54.4
	Male	104	45.6	45.6	100
	Total	228	100.0	100.0	

Age Distribution Report

The sample in this study used all age groups. However, out of the 228 participants, the majority were between the ages of 21 and 29 (48.2%). The next age group with the highest participants was 18 – 20 (17.5%). The third majority group was

the age group of 40 – 49 (14.9%). However, the age group of 50 – 60 plus was under 8%. The age distribution of the participants in the study is presented in Table 9.

Table 9

Age Distribution

Frequency	Ages	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-20	40	17.5	17.5	17.5
	21-29	110	48.2	48.2	65.8
	30-39	27	11.8	11.8	77.6
	40-49	34	14.9	14.9	92.5
	50-59	11	4.8	4.8	97.4
	60 or older	6	2.6	2.6	100.0
	Total	228	100.0	100.0	

Marital Status Report

The participants in this study were married, separated, divorced, widowed, and single, and represented the Mid-Atlantic region of the United States. As listed in Table 9, most participants were single or married. Among the 228 participants of this study, 32.9% were married, 61.8% single, 3.1% divorced, 4% separated, and 1.8% widowed (see Table 10).

Table 10

Martial Status

Frequency	Marital Status	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Divorced	7	3.1	3.1	3.1
	Married	75	32.9	32.9	36.0
	Separated	1	.4	.4	36.4
	Single	141	61.8	61.8	98.2
	Widowed	4	1.8	1.8	100.0
	Total	228	100.0	100.0	

Educational Level

The sample of this study included participants of all educational backgrounds. Many of the participants had some college (24.1%) background. Among them, 23.2% had a bachelor's degree, 21.1% had an associate degree, 20.6% had a high school diploma, and 11% were college graduates. The educational level statistics of the participants in the study are presented in Table 11.

Table 11

Educational Level

Frequency	Degree	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Associate degree	48	21.1	21.1	21.1
	Bachelor's degree	53	23.2	23.2	44.3
	Graduate degree	25	11.0	11.0	55.3
	High School Degree	47	20.6	20.6	75.9
	Some College	55	24.1	24.1	100.0
	Total	228	100.0	100.0	

Income Levels Statistics

The income level report showed participants with many different total family income values. Most participants were in the $25,000 - $49,000 with 29.8%. Other high participants income level ranges were $50,000 - $74,000 with 27.2%, and $10,000 - $24,000 with 16.2%. The other income level groups in this study were under 10% (see table 11). The lowest income level group was the $150,000 - $1999,000, with 3.1% and a 4% group, which preferred not to comment on this area. See Table 12 for the complete list of total family income levels for this study.

Table 12

Income Level

Frequency	Salary range	Frequency	Percent	Valid percent	Cumulative percent
Valid	$0 - $9,999	10	4.4	4.4	4.4
	$10,000 - $24,000	37	16.2	16.2	20.6
	$25,000 - $49,000	68	29.8	29.8	50.4
	$50,000 - $74,000	62	27.2	27.2	77.6
	$75,000 - $99,000	16	7.0	7.0	84.6
	$100,000 - $149,000	19	8.3	8.3	93.0
	$150,000 - $199,000	7	3.1	3.1	96.1
	$200,00 and up	8	3.5	3.5	99.6
	Prefer not to say	1	.4	.4	100.0
	Total	228	100.0	100.0	

Bank Statistics

In this study, all participants use mobile banking on a mobile device while implementing biometric technology. Also, the sample participants of the Mid-Atlantic region of the United States used local community banks, whether commercial or credit unions. Table 13 lists the bank statistics of the participants in this study. The commercial bank (78.5%) was the most used bank by the participants. The credit union used by the participants of this study was at 21.5%.

Table 13

Bank Statistics

Frequency	Bank type	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Commercial Bank	179	78.5	78.5	78.5
	Credit Union	49	21.5	21.5	100.0
	Total	228	100.0	100.0	

Test of Normality

Most statistical procedures want research to verify at least two assumptions, the normality assumption and the absence of outliers. There are two categories of methods used to check the normality assumption: numerical methods and graphical methods. The numerical way is safer because it shows the number for verification. The most used numerical methods are the Skewness and Kurtosis indicators, the Shapiro-Wilk normality test, and the Kolmogorov-Smirnov test. The graphical techniques that are used to test normality are the histogram and the Q-Q plot. Table 14 shows the distribution of the Skewness and Kurtosis test.

Table 14

Skewness and Kurtosis Statistics

Variable	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
MBActualUse2	228	-1.505	.845	2.387	1.741
Valid N (listwise)	228				

To compute the values of the Skewness and Kurtosis test I used the following equations:

z = Skewness/Std. error = -1.78

z = Kurtosis/Std. error = 1.37

The scores show the values lie between the interval (-2.58, 258), and the variable is normally distributed with a 99% confidence level. The tests of normality show data for the Kolmogorov-Smirnov test and the Shapiro-Wilk test. The results can be shown in Table 15, and both the p-value of each test is greater than .05, so we conclude that the variable weight is normally distributed.

Table 15

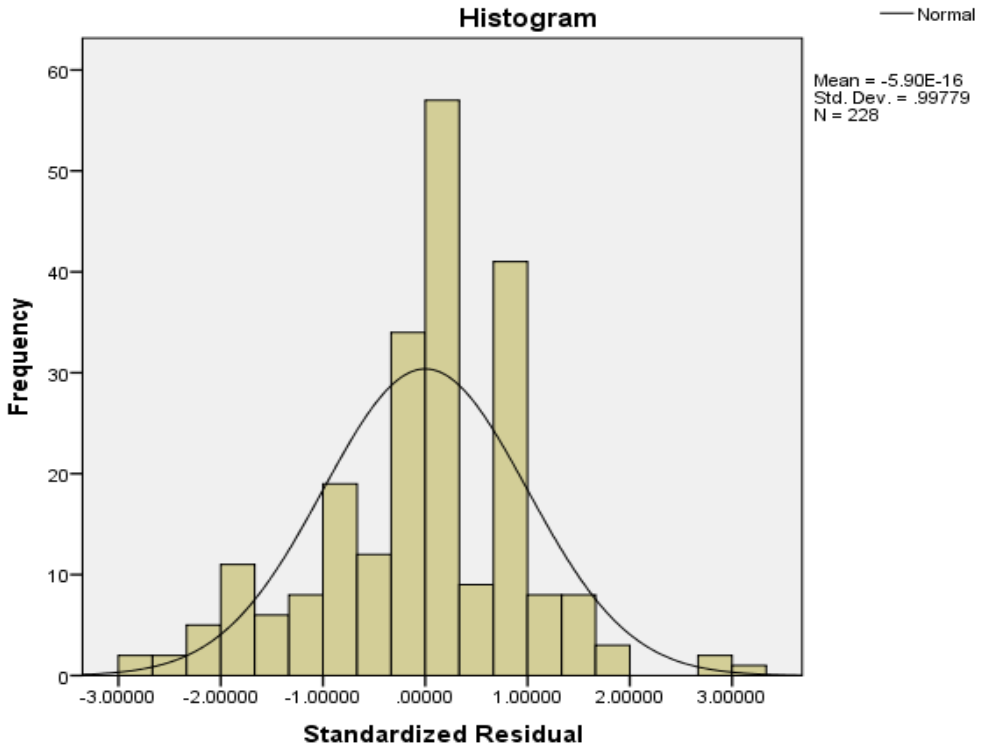
Tests of Normality

Variable	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
MB Actual Use	.233	228	.200*	.858	218	.182

Figure 5 displays the standardized residual, showing a normal distributed variable. This confirmed the normality test in Table 15, and we can consider that the distribution is normal.

Figure 5

Histogram of Regression Standardized Residual

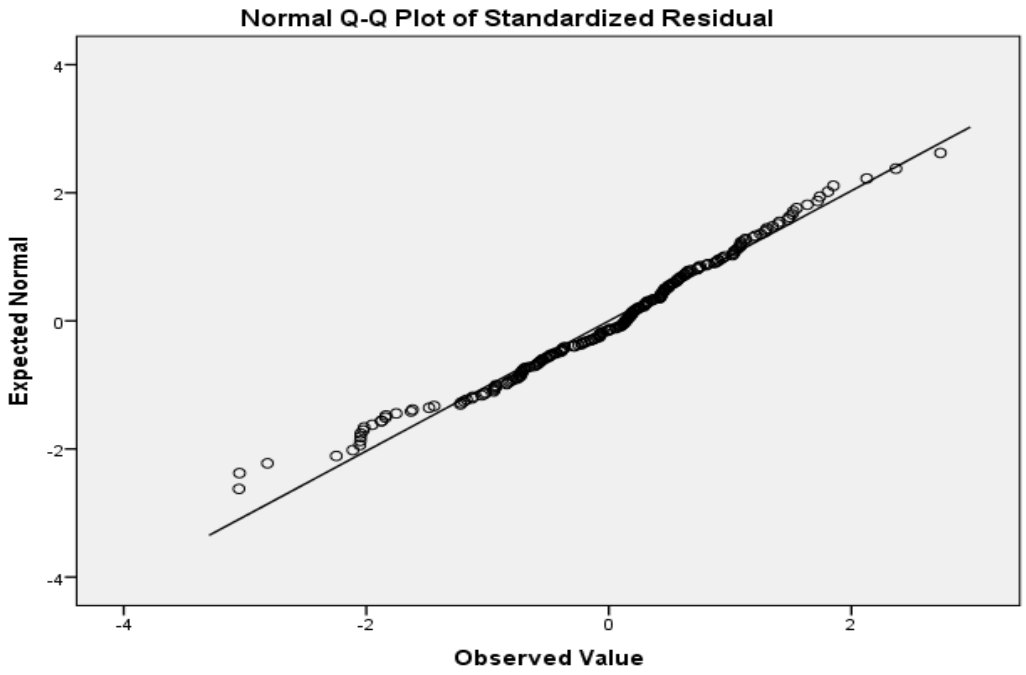


Note. The data was analyzed using IBM SPSS Statistics (Version 23) predictive analytics software.

The second graphical method for normality checking is the quantile-quantile (Q-Q) plot. The Q-Q plot diagram is included with the normality plots with the test in SPSS. Figure 6 shows the q size of all distribution (dots) and the q size of normal distribution (straight line). If the dots are close or follow the line, the distribution is normal, and according to Figure 6, the dots follow the line, so we can state the weight variable is normally distributed.

Figure 6

Normal Probability Plot



Note. The data was analyzed using IBM SPSS Statistics (Version 23) predictive analytics software.

Principal Factor Axis Factoring Test

I used SPSS version 23 to run the Pearson Correlation test using the principal factor axis extraction method. These multivariate statistics, exploratory factor analysis (EFA) with principal axis extraction method, and varimax rotation was used to assess the construct validity. This model is used to generalize to the population.

The factors were extracted with the Eigenvalue and were defaulted at 1. In the correlation matrix, the goal was to look for high correlations, and any correlations that had an absolute value above .8 was a concern. However, the correlation matrix presented in Table 16 shows most of the absolute values below .8%, so the items are considered highly correlated. The determinant is equal to 1.96, and the value needs to be greater than .001. The total variance explained tables show the Eigenvalues, and they are greater than 1. The exploratory factor analysis started with 27 variables relating to biometric technology use and acceptance with mobile banking and calculated four distinct factors. Appendix N and Appendix O shows all the extractable factors from the data analysis. Principal axis factor analysis shows the percentage of contributions to the variability of data, eigenvalues, and the Cronbach's α values for the extracted factors. All extracted factors show the Cronbach αvalue greater than 0.05, which means the data's reliability and internal consistency. The extracted factors were considered useful for analysis included:

- Using biometric technology [TTF] - Helps customers perform their daily tasks efficiently; security features for customers positively impact usage and

adoption. Six variables were extracted on this factor, which contributed 39.2% to data variability, internal consistency of 0.809.

- Learning to Use [EE] – Measure the customers' beliefs in the systems and how easily they can use it. Also, how easy the customers can use the technology. Four variables were extracted on this factor, which contributed 9.45% to data variability, internal consistency of 0.813.
- Using mobile banking (MB) [PC] – Measure customers' security, privacy, and trust concerns that affected the customer's behaviors to use bank apps. Six variables were extracted on this factor, which contributed 8.46% to data variability, internal consistency of 0.804.
- Conducting Banking Affairs [PE] – Mediated by age, gender, and experience. The use of technology provides benefits to customers when using services. Four variables were extracted on this factor, which contributed 5.6% to data variability, internal consistency of 0.813.
- Influence [SI] – Perceived what is distinguished from other people, like family and friends, and think they should use a similar technology feature or device. Four variables were extracted on this factor, which contributed 4.9% to data variability, internal consistency of 0.805.
- Environment [FC] – Perceptions of the resources and services are available to perform a behavior and include self-efficacy. Three variables were extracted on this factor, which contributed 4.06% to data variability, internal consistency of 0.811.

Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test

The KMO and Bartlett's Test is used to measure sampling adequacy for each variable to see how well your data is for factor analysis (see Table 17 for results). The KMO is between 0.80 and 0.90 (.896); therefore, the data indicate good sampling adequacy. Bartlett's Test of Sphericity *p* is <0.5%; therefore, the correlation is are significant. The KMO is high, and Bartlett's Test of Sphericity is significant, and the model is appropriate.

Table 16

Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test

Kaiser-Meyer-Olkin measure of sampling adequacy		.896
Bartlett's test of sphericity	Approx. chi-square	5030.753
	df	406
	Sig.	.000

Correlation Matrix

The correlation matrix shows the correlation coefficients between variables by summarizing the data. The correlation matrix goal is to show the patterns that all the variables positively correlate with each other. The covariance of the variables is banking using biometric technology [TTF], learning to use [EE], using mobile banking [PC], influence [SI], conducting banking affairs [PE], and environment [FC]. The correlation matrix illustrated in Table 18 was used to examine how the variables correlate with each other.

Table 17

Correlation Matrix

Factor	1	2	3	4	5	6
1	.518	.427	.428	.375	.359	.311
2	.187	-.616	.553	-.465	.250	.046
3	-.713	.163	.067	-.122	.474	.470
4	-.298	.424	.657	-.159	-.426	-.305
5	-.285	-.482	.274	.747	-.208	.099
6	.136	-.005	-.022	-.211	-.600	.760

Goodness-of-Fit Test

The Chi-square test for goodness-of-fit is used when the variable is nominal with at least three categories. The goal is to compare an observed distribution with a theoretical distribution. The value of the Chi-Square with 14 degrees of freedom (df) is 225, and the *p* is < .005; therefore, the data (see Table 19) shows there is a significant difference between the observed and the theoretical distribution and the model is a good fit for the data.

Table 18

Goodness-of-fit Test

Chi-square	225.816 [a]
df	14
Asymp. Sig.	.000

[a] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 15.2.

Communalities of Variables

The principal component analysis (PCA) is used to reduce a broad set of variables into a smaller set of principal components (or factors). The initial variable is grouped based on the correlations between them. The principal components synthesize the information contained in those variables. It's a data reduction technique like factor analysis. The goal is to identify several essential factors and then give an analytical interpretation of the relevant factors. The communalities of variables (see Appendix P) was extracted using the principal axis factoring analysis.

Factor Analysis

The parameters used in the component matrix included all 29 factors from the individual variables, which were group together to form groups. PE (4 variables), EE (4 variables), SI (4 variables), FC (4 variables), PC (7 variables), and TTF (6 variables) were the 29 parameters used to measure the factors affecting biometric technology with mobile banking in the Mid-Atlantic region of the United States. Appendix Q (unrotated factor matrix) shows the Principal Axis Factoring extraction method were six factors extracted and seven interactions required in the factor matrix before further data reduction is needed to clarify the factor solution. In the unrotated factor matrix (see Appendix Q), PCA and FCD was removed because the absolute value extraction with scores was above 0.4%.

The unrotated factor matrix (see Appendix Q) had many parameters belonging to more than one factor or several belonging to the same factor. Therefore, further data reduction was needed to show the specific rotation needed to be applied to this study

factor solution. Using the Principal Axis factoring extraction method and the Varimax with Kaiser Normalization rotation method (see Appendix R), displayed six factors that belong to one group and the items that remain after data extraction. All 29 parameters were included and grouped in the six different factors.

Descriptive Statistics for the Independent and Dependent Variables

Descriptive statistics are shown in Table 19 for the variables conducting banking affairs (PE), learning to use (EE), influence (SI), environment (FC), using mobile banking (PC), using biometric technology (TTF), banking affairs (BI), and mobile banking usage (AU). The variables conducting banking affairs (M = 4.6, SD = .438), learning to use (M = 4.5, SD = .504), using biometric technology (M = 4.5, SD = .531), and banking affairs (M = 4.6, SD = 4.6) observations ranged from 3.00 to 5.00. The variables environment (M = 4.1, SD = .547), using mobile banking (M = 4.09, SD = .473) observations ranged from 2.25 to 5.75. The variable influence observations ranged from 1.25 to 5.0, with a mean observation of 3.9 and a standard deviation of .687. Table 19 presents the means and standard deviations for continuous variables.

Table 19

Independent and Dependent Descriptive Statistics (N=228)

Variable	Mean	Std. deviation	Min	Max
Conducting Banking Affairs [PE]	4.6557	.43887	3.50	5.00
Learning to Use [EE]	4.5779	.50408	3.00	5.00
Influence [SI]	3.9221	.68754	1.25	5.00
Environment [FC]	4.1086	.54783	2.50	5.00
Using MB [PC]	4.0946	.47380	2.57	5.00
Using BioTech [TTF]	4.5110	.53144	3.00	5.00
Banking Affairs [BI]	4.6524	.51632	3.00	5.00
MB Usage [AU]	4.3333	.69387	2.25	5.75

SEM Fit and Modification

In the SEM, the model fit can be evaluated from two different global and local (Goodboy & Kline, 2017). The global fit looks at the sample variances, covariances, or the model's means to the data and local concentrates on the residuals (Goodboy & Kline, 2017). The model X2, with its degrees of freedom and p-value, tests the null hypothesis of exact or perfect fit and will be rejected if the p-value is less than the significance level, $\alpha = .05$. Common reported approximate fit indexes to include the Steiger-Lind Root Mean Square Error of Approximation (RMSEA) with a 90% confidence interval, the Bentler Comparative Fit index (CF)), and the Standardized Root Mean Square Residual (SRMR) (Gooboy & Kline, 2017). Also, Chi-Square is a global fit statistic; however, its little statistical or logical foundation has no role in the global fit assessment and should

not be reported (Goodboy & Kline, 2017). According to Kline (2016), the minimal set of global fit statistics sufficient to report are the X2, RMSEA with 90% CI, CFI, and the SRMR (Kline, 2016). Table 20 shows the SEM Fit statistics for the study model.

Table 20

SEM Fit Statistics

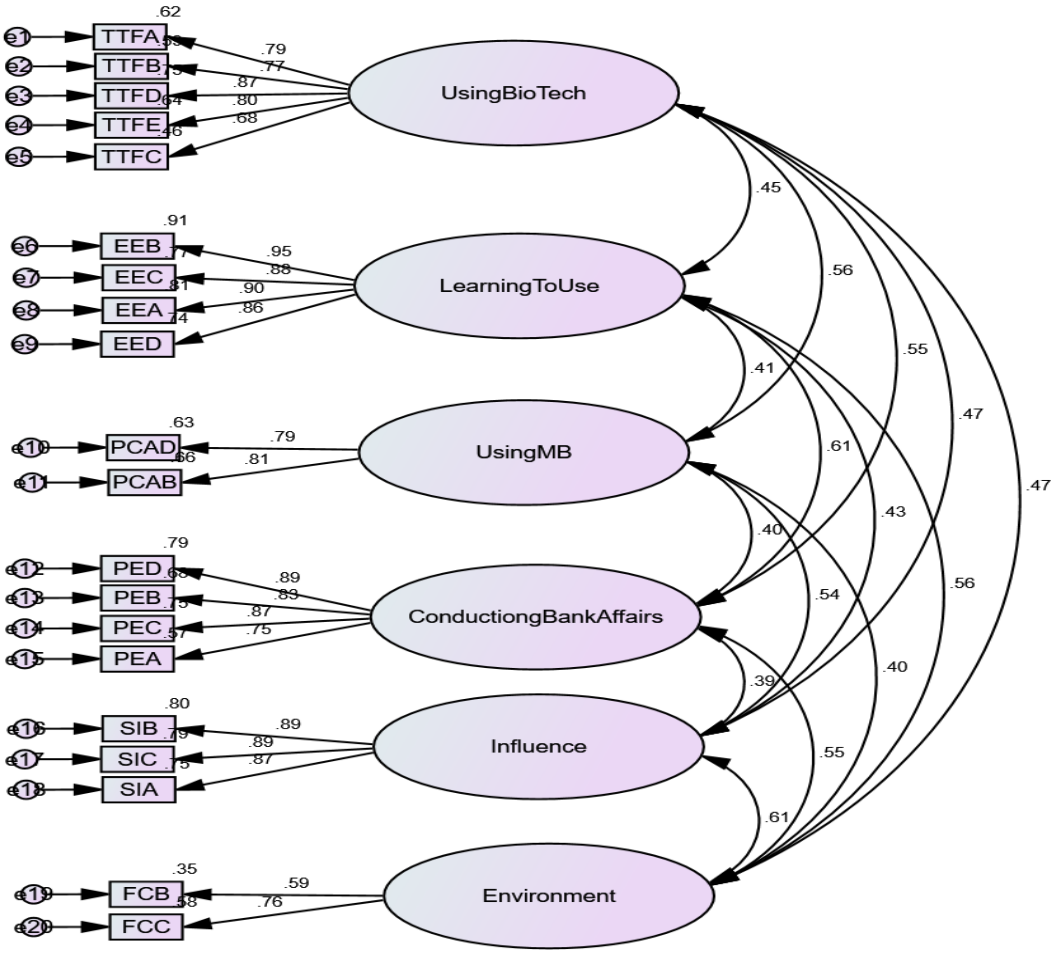
X^2	Degrees of freedom	# of distinct sample moments	# of distinct parameters to be estimated	RMSEA	CFI	SRMR	GFI	AGFI
473.76	156	210	54	.061	.906	.023	.951	.903

The confirmatory factor analysis SEM fit model (see Figure 7) was used with SPSS AMOS (Version 23). In the SEM fit model, I used 20 constructs of indicator variables, and six latent factors were presumed to account for variations in a set of measured variables. The regression weights showed that the indicators were loading significantly. The SEM fit statistics for the study (see Table 20) showed that the X2 (Chi-Square) had a value of 473.76, the RMSEA had a value of 0.061, the CFI had a value of .906, and the SRMR had a value of .023. Also, the Goodness-of-Fit Index (GFI) had a value of .951, and the Adjusted Goodness-of-Fit Index (AGFI) had a value of .903. The evidence suggest the model is a good fit.

The measurement model fit is shown in Figure 7, showing the parameters after deletion, and a model fit was generated. Only composite variables were used to estimate the model fit. TTFF, PCAA, PCAC, PCAG, PCAE, and FCD were removed and not included in the SEM. Standardized estimate for the SEM model are shown in Table 20 and offers the degrees of freedom at 156, number of distinct sample moments at 210, number of distinct parameters to be estimated at 54, and the probability level at .000.

Figure 7

SEM Model Fit based on Composite Variables



Note. The data was analyzed using IBM SPSS AMOS (Version 23) structural equation model (SEM) software.

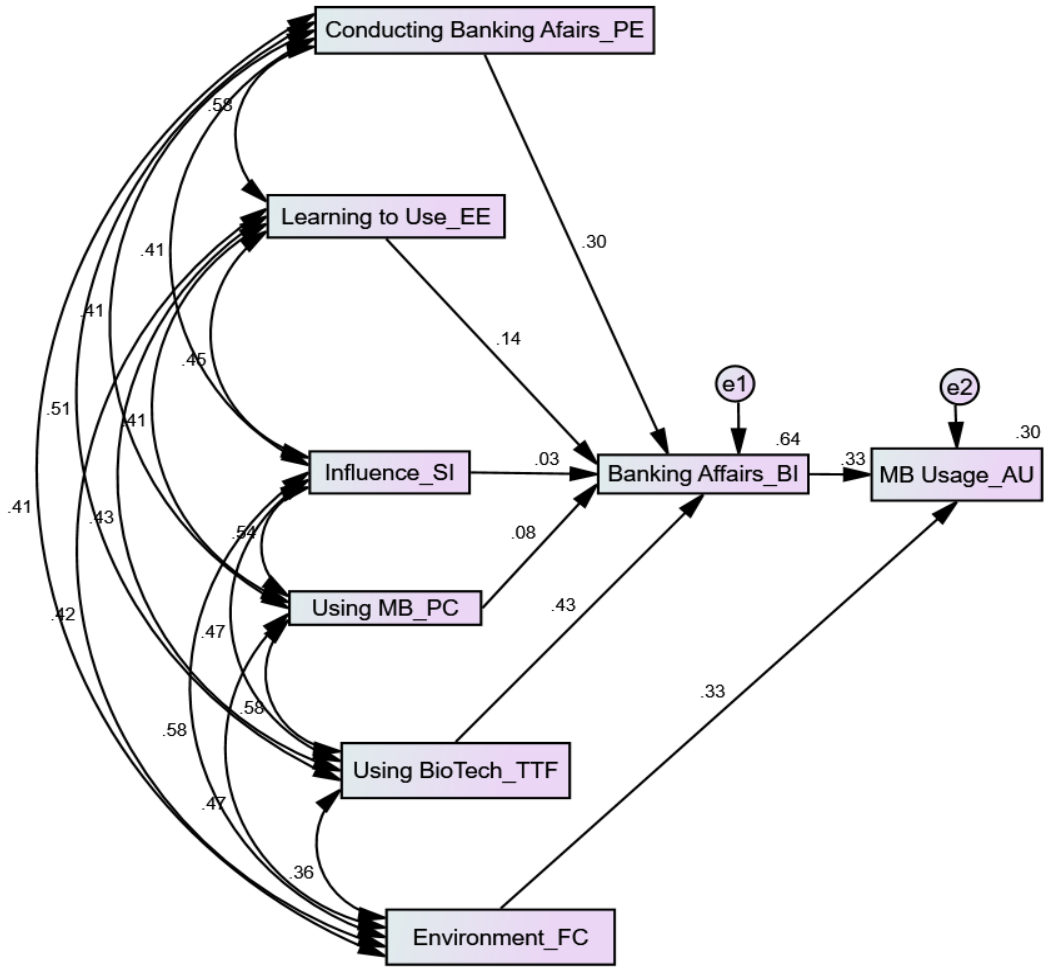
Path Analysis

The SEM analysis and statistics results were used to help answer the research question and this study's hypotheses. To test the SEM; theoretically, the path analysis is

used to investigate the appropriate model and combine the measurement error in both latent and observed variables (Uslu, 2018). SEM is a regression-based multivariable method that is combined with path analysis to determine the validity of the research and analyze the linkage of different sets of factors (Elhajjar & Ouaida, 2020). In the SEM path analysis, the observed endogenous variables were banking affairs (behavioral intentions) and mobile banking (actual usage). The observed exogenous variables were conducting banking affairs (PE), learning to use (EE), influence (SI), environment (FC), using mobile banking (PC), and using biometric technology (TTF). The results of path analysis involving regression coefficients and their significances are listed in Figure 8.

Figure 8

Conceptual Model with Standardized Regression Estimates



Note. The data was analyzed using IBM SPSS AMOS (Version 23) structural equation model (SEM) software.

The SEM path analysis findings showed that conducting banking affairs, learning to use, influence, influence, using mobile banking, and using biometric technology had a positive correlation with biometric technology use and acceptance with mobile banking in the Mid-Atlantic region. The SEM path analysis showed that TTF and PE with biometric technology use and acceptance were significant. Also, BI and FC with mobile banking actual usage had a positive correlation, and they were significant. The results in Figure 8 displays a visual of the SEM path analysis of biometric technology use and acceptance with mobile banking in the Mid-Atlantic region based on the six constructs.

Regression Analysis

The standardized regression weights in Table 21 displayed the coefficient estimates of the constructs. The SI had a coefficient estimate of .030, EE with .144, PC with .083, TTF with .431, PE (.297), BI (.329), and FC (.328) had a positive correlation with biometric technology use and acceptance with mobile banking in the Mid-Atlantic region of the United States.

Table 21

Standardized Regression Weights from SEM Path Analysis

Dependent variable	LISREL	Independent variable	Estimate
BehaviorInt	<---	Social Influence	.030
BehaviorInt	<---	EffortExp	.144
BehaviorInt	<---	PerceivedCred	.083
BehaviorInt	<---	TaskTechFit	.431
BehaviorInt	<---	PerformanceExp	.297
ActualUse	<---	BehaviorInt	.329
ActualUse	<---	FacilitatingCon	.328

The results of the Regression Weights in Table 22 displayed the different p-values of each correlation. All the constructs positively correlated with biometric technology use and acceptance with mobile banking in the Mid-Atlantic region of the United States. However, the results showed that TTF, PE, EE, BI, and FC were significant with *p* values <.05. SI and PC had a positive correction with biometric technology use and acceptance with mobile banking in the Mid-Atlantic region of the U.S, but their *p* value was > .05.

Table 22

Regression Weights from SEM Path Analysis

Dep. variable	LISREL	Ind. variable	Estimate	S.E.	C.R.	P
BehaviorInt	<---	SocialInfluence	.023	.038	.597	.551
BehaviorInt	<---	EffortExp	.148	.053	2.791	.005
BehaviorInt	<---	PerceivedCred	.091	.058	1.557	.119
BehaviorInt	<---	TaskTechFit	.419	.052	8.001	***
BehaviorInt	<---	PerformanceExp	.349	.062	5.604	***
ActualUse	<---	BehaviorInt	.441	.081	5.440	***
ActualUse	<---	FacilitatingCon	.414	.076	5.427	***

The multiple regression table (see Table 23) was created by using AMOS (Version 23). It displayed similar results with standard error and p-values with the regression weight for the SEM Path Analysis in Table 22. The two tables were similar, and from the data, it was clear that TTF, PE, EE, BI, and FC had the strongest effect on biometric technology use and acceptance with mobile banking in the Mid-Atlantic region of the United States.

Table 23

Multiple Regression Analysis

Variable	Unstandardized coefficients		Standardized coefficients			Collinearity statistics	
Model	B	Std. Error	Beta	*T*	Sig.	Tolerance	VIF
(Constant)	-.002	.253		-.008	.994		
Conducting Banking Affairs [PE]	.349	.063	.297	5.542	.000	.573	1.746
Learning to Use [EE]	.148	.054	.144	2.760	.005	.599	1.669
Influence [SI]	.023	.038	.030	.590	.556	.626	1.598
Using MB [PC]	.091	.059	.083	1.540	.125	.562	1.778
Using BioTech [TTF]	.419	.053	.431	7.912	.000	.552	1.811
Environment [FC]	.414	.078	.327	5.342	.000	.823	1.214
Banking Affairs [BI]	.441	.082	.328	5.354	.000	.823	1.214

The relationship was linear for all independent variables according to the partial regression plot; therefore, the linear assumption is met for all independent variables. The dependent variable and independent variables were linear according to the scatterplot figure; therefore, the linear assumptions are met overall. Also, homoscedasticity was met due to the scatterplot dots were uniformly spread on the chart. The Durbin-Watson test in the model summary (see Table 24) is 1.733, so it is between 1.50 and 2.50; therefore, the model's errors are independent. To examine the outliners in the data series, I used the casewise diagnostics, which had 209 case numbers. The standardized residual was 3.2, just above the standard deviations of 3.0; therefore, the data is considered a moderate outliner. I used the coefficients table to measure multicollinearity assumptions, which should not be strongly correlated. In the coefficients table, there adicators, the tolerance

and the variance inflation factor (VIF). The tolerance should be higher than 0.001, and the VIF should be below 10, and the closer to 1, the better. In the study, the collinearity statistics showed the tolerance at .823 and the VIF at 1.214; therefore, we do not have problems with multicollinearity.

Using BI as a dependent variable and conducting banking affairs (PE), learning to use (EE), using mobile banking (PC), environment (FC) as predictors, the results showed the r^2 at .635, the adjusted r^2 at .627, the F Change at 77.3, the significance at .000 and the Durbin-Watson at 1.73**.** In addition, based on Table 28, the results explained that any of the UTAUT constructs could explain r^2. Therefore, based on Tables 22 and 23, 63.5% of the biometric technology use and acceptance with mobile banking in the Mid-Atlantic was described by the four-strong UTAUT predictors. The model summary in Table 24 displayed the predictors' values for the model.

Table 24

Model Summary

Model summary predictors										
					Change statistics					
Model	R	R square	Adjusted R square	Std. Error of the estimate	R square change	F change	df1	df2	Sig. F change	Durbin-Watson
1	.797	.635	.627	.31526	.635	77.373	5	222	.000	1.733

ANOVA

In this study, the ANOVA was used to test the significance and correlation ratio E^2 and the measure of association Eta to measure the associations of the independent and dependent variables (see Table 2). The ANOVA analysis was used to measure the effect

size of the statistical test. Even though the study already showed significant and nonsignificant data (see Table 23). The E^2 was used to show the strength of the association. Eta Squared (η2) is the percentage of variance in the dependent variable accounted for by the independent variable and was interpreted the same way as r2. However, since E^2 can be biased and overestimates the true effect size, partial E^2 should be reported. Therefore, the strength of the most reported association in an ANOVA is a Partial Eta Squared. Partial Eta Squared (η2) was interpreted the same as r2, and the percentage of variance is the dependent variable accounted for by the independent variable.

The results in Table 25 showed that PE partial η^2 = 45%, EE partial η^2 = 37%, SI partial η^2 = 29%, PC partial η^2 = 36%, TTF partial η^2 = 56%, and FC partial η^2 = 24% showed a respective percentage of the variability of BI of customers biometric technology use with mobile banking in the Mid-Atlantic region of the United States.

Table 25

ANOVA and Eta Analysis

Variable	Eta	Eta squared	Partial eta squared
Banking Affairs [BI] * Conducting Banking Affairs [PE]	.667	.445	.445
Banking Affairs [BI] * Learning to Use [EE]	.604	.365	.365
Banking Affairs [BI] * Influence [SI]	.535	.287	.287
Banking Affairs [BI] * Using MB [PC]	.603	.363	.363
Banking Affairs [BI] * Using BioTech [TTF]	.749	.560	.560
MB Usage [AU] * Environment [FC]	.493	.243	.243

Data Analysis and Results

The research question and hypotheses were tested with the SEM path analysis and regression analysis statistics results using SPSS AMOS (Version 23) and SPSS (Version 23). The p-value is used in a test of significance to report the incompatibility between a set of data and a proposed model for the data constructed under the set of assumptions with a null hypothesis (Peskun, 2020). Therefore, the p-value measures how much evidence you have against the null hypothesis. If the value calculated is small, there is more evidence against the null hypothesis, and if the value is larger, there is less evidence against the null hypothesis. If the *p* value or significance value is < .05, I rejected the null hypothesis. However, if the *p* value is >.05, I accepted that the constructs will not significantly affect customers' BI to use biometric technology with mobile banking. The next sections are the results of the research questions and hypothesis explained by r^2 and based on the SEM path analysis using SPSS AMOS version 23.

Research Question 1 and Hypotheses 1 - 6

Research Question 1: To what extent do performance expectancy, effort expectancy, social influence, perceived credibility, task-technology fit, and facilitating conditions affect the behavioral intentions of customers to adopt biometric technology with mobile banking?

Hypothesis 1:

$H1_0$: Performance expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H1_1$: Performance expectancy will affect customers' behavioral intention to use biometric technology with mobile banking.

Results: PE was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States based on the standardized regression coefficient estimate $\beta = .30$ and explained by $r^2 = .635$. The correlation was significant with the $p = 0.00 < .05$. Therefore, $H1_0$ was rejected in consideration of the alternate hypothesis, $H1_1$.

Hypothesis 2:

$H2_0$: Effort expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H2_1$: Effort expectancy will affect customers' behavioral intention to use biometric technology with mobile banking.

Results: EE was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States based on the standardized regression coefficient estimate $\beta = .144$ and explained by $r^2 = .635$. The correlation was significant with the $p = 0.005 < .05$. Therefore, $H2_0$ was rejected in consideration of the alternate hypothesis, $H2_1$.

Hypothesis 3:

$H3_0$: Social influence will not influence customers' behavioral intention to use biometric technology with mobile banking.

$H3_1$: Social influence will influence customers' behavioral intention to use biometric technology with mobile banking.

Results: SI was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States based on the standardized regression coefficient estimate $\beta = .30$ and explained by $r^2 = .635$. However, the relationship was nonsignificant based on the $p = 0.551 > .05$. Therefore, $H3_0$ was not rejected, conversely $H3_1$ was rejected.

Hypothesis 4:

$H4_0$: Perceived credibility will not affect customers' behavioral intention to use biometric technology with mobile banking.

$H4_1$: Perceived credibility will affect customers' behavioral intention to use biometric technology with mobile banking.

Results: PC was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States based on the standardized regression coefficient estimate $\beta = .083$ and explained by $r^2 = .635$. However, the relationship was nonsignificant based on the $p = 0.119 > .05$. Therefore, $H4_0$ was not rejected, conversely $H4_1$ was rejected.

Hypothesis 5:

$H5_0$: Task-technology fit will not influence customers’ behavioral intention to use biometric technology with mobile banking.

$H5_1$: Task-technology fit will influence customers’ behavioral intention to use biometric technology with mobile banking.

Results: TTF was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States based on the standardized regression coefficient

estimate β = .431 and explained by r^2 = .635. The correlation was significant with the p = 0.00 < .05. Therefore, $H5_0$ was rejected in consideration of the alternate hypothesis, $H5_1$.

Hypothesis 6:

$H6_0$: Facilitating conditions will not influence the actual usage of biometric technology with mobile banking.

$H6_1$: Facilitating conditions will influence the actual usage of biometric technology with mobile banking.

Results: FC was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States based on the standardized regression coefficient estimate β = .327 and explained by r^2 = .635. The correlation was significant with the p = 0.00 < .05. Therefore, $H6_0$ was rejected in consideration of the alternate hypothesis, $H6_1$.

Summary

In Chapter 4, I discussed the results of the data collected for this study. Data was collected from mobile banking customers living in the Mid-Atlantic region of the United States through a web-based survey through LimeSurvey. I used a purposeful random sample of participants who will meet the following criteria: (a) participants over the age of 18 (b) have a banking account (c) use a bank with a mobile application (d) the bank has biometric technology implemented with their application (e) participant must use mobile devices (f) participants must use biometric technology. A total of 234 responses were collected; however, six (6) responses were invalid and discarded, and the remaining valid 238 survey responses were used for data analysis. SPSS version 23 and SPSS

AMOS version 23 was the software used to conduct an empirical analysis of the data in this study.

The results showed that PE compatibility (β = .30), EE (β = .144), SI (β = .30), PC (β = .083), TTF (β = .431), and FC (β = .327) variables were all positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States. The data analysis revealed that PE compatibility (β = .30, $p < .05$), EE (β = .144, $p < .05$), TTF (β = .431, $p < .05$), and FC (β = .327, $p < .05$) were the significant factors to positively affect biometric technology with mobile banking in the Mid-Atlantic region of the United States. Conversely, SI (β = .30) and PC (β = .083) were not significant factors; they were positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States. Comparing the correlations' strengths of all the UTAUT constructs to biometric technology use and acceptance with mobile banking in the Mid-Atlantic region of the United States, TTF and FC were the strongest predictors, followed by PE and EE. Overall, the four predictors explain 63.5% of the variance of biometric technology use and acceptance with mobile banking in the Mid-Atlantic region of the United States. The interpretation and findings of Chapter 4 are further discussed in Chapter 5. In Chapter 5, I provided recommendations and conclusions of the study, understanding of the significant results, limitations of the study, and future recommendations of the study.

Chapter 5: Discussion, Conclusions, and Recommendations

The aim of this study was to understand the factors that affect customers' biometric technology use and acceptance of mobile banking in the Mid-Atlantic region of the United States, as well as to understand customers' perceptions of using biometric technology with mobile banking. I explored the relationships between the UTAUT constructs, PE, EE, SI, FC, and two additional constructs: PC and TTF based on a web-based survey of bank customers. Data were collected through a purposeful random web-based survey from customers in the Mid-Atlantic region of the United States through LimeSurvey. The appropriate sampling size of the study with a confidence level of 95% and a margin of error of 5% was 228 participants.

The data collected generated 234 responses, including six incomplete survey responses. After discrediting the vague responses, 228 participants completed responses (N = 228) used in the data analysis. The study's demographic showed that about 47% of the participants were men, and 52% were women. Among the participants, 66% were between the ages of 18 and 29 years of age, 32% were between the ages of 30 and 59 years of age, and 3% were over 60 years old. The sample showed that 62% were single, 33% were married, 3% were divorced, 2% were widowed, and less than 1% were separated. The participants' educational levels from this study were represented from all backgrounds. The majority was at 68% with some college experience or held an undergraduate degree, 11% had a graduate degree, and 21% had a high school diploma. The study sample also showed different ranges of income levels. Among them, 20% had an income between $0 and $24 999, 57% had an income between $25,000 and $74,499,

18% had an income between $75,000 and 199,000, 4% had an income over $200,000, and less than 1% preferred not to say give their salary information.

The aim of this quantitative study was to develop a conceptual model that would have a conceivably more eminent explanatory power concerning the adoption of mobile banking technology. I created a conceptual framework by extending the UTAUT by incorporating two additional factors: PC and TTF. A quantitative approach based on a web-based questionnaire survey collected data from 228 mobile banking customers in the Mid-Atlantic region. The specific problem is the lack of adoption of biometric technology by customers and bank managers do not understand the factors influencing mobile banking application adoption in the Mid-Atlantic region. Chapter 4 discussed how the study was conducted and how data were collected and analyzed. Chapter 4 shows the data analysis results, how I tested the hypotheses, and a review of the research questions. The data collected were analyzed using the SPSS AMOS (Version 23) and SPSS (Version 23).

Interpretation of Findings

Participants in the study included bank customers from the Mid-Atlantic region (N = 228), where data were collected through a web-based survey using Lime Survey. I tested the research question and all the hypotheses of this study using the SEM analysis and multiple regression statistics results. Based on the hypotheses testing results, $H3_0$, (β = .30, p = .551 > .05), and $H4_0$, (β = .083, p = .119 > .05) were nonsignificant and not rejected. However, based on the testing results, $H1_0$, (β = .30, p = < .05), and $H2_0$, (β = .144, p < .05), $H5_0$, (β = .431, p < .05), and $H6_0$, (β = .327, p < .05) were rejected in

consideration of the alternate hypotheses, $H1_1$, $H2_1$, $H5_1$, and $H6_1$. See Table 26 for all the hypotheses results.

Table 26

Hypotheses Results

Null hypothesis	Test results
$H1_0$: Performance expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.	Rejected
$H2_0$: Effort expectancy will not affect customers' behavioral intention to use biometric technology with mobile banking.	Rejected
$H3_0$: Social influence will not influence customers' behavioral intention to use biometric technology with mobile banking.	Not Rejected
$H4_0$: Perceived credibility will not affect customers' behavioral intention to use biometric technology with mobile banking.	Not Rejected
$H5_0$: Task-technology fit will not influence customers' behavioral intention to use biometric technology with mobile banking.	Rejected
$H6_0$: Facilitating conditions will not influence the actual usage of biometric technology with mobile banking.	Rejected

The results showed that PE ($\beta = .30$, $p = < .05$), EE ($\beta = .144$, $p < .05$), SI ($\beta = .30$, $p = .551 > .05$), PC ($\beta = .083$, $p = .119 > .05$), TTF ($\beta = .431$, $p < .05$), and FC ($\beta = .327$, $p < .05$) variables were all positively related to customer acceptance and use of biometric technology with mobile banking apps in the Mid-Atlantic region of the United States. In the study, PE ($\beta = .30$, $p = < .05$), EE ($\beta = .144$, $p < .05$), TTF ($\beta = .431$, $p < .05$), and FC ($\beta = .327$, $p < .05$) were the significant factors to positively affect customer acceptance and use of biometric technology with mobile banking apps in the Mid-Atlantic region of the United States. TTF and FC were the strongest predictors, followed by EE and PE to customers biometric technology use and acceptance with mobile

banking apps in the Mid-Atlantic region of the United States. The two nonsignificant constructs, SI (β = .30, p = .551 > .05), and PC (β = .083, p = .119 > .05) were low positive correlations for customers biometric technology use and acceptance with mobile banking apps in the Mid-Atlantic region of the United States. Overall, 63.5% of variance in customers' biometric technology use and acceptance with mobile banking apps in the Mid-Atlantic region of the United States was explained by four of the strongest predictors. See Appendix S for the hypotheses' summary of findings.

The data results indicated that PE, EE, TTF, and FC significantly affected customers' biometric technology use and acceptance with mobile banking apps in the Mid-Atlantic region of the United States. PE is defined as the extent to which an individual believes the system will help them perform their activities better, whether business or personal (Oye et al., 2014). Venkatesh et al. (2016) defined EE as the measure of effort that customers deal with and use technology. TTF is defined as the degree whereby the technology will fit the customer's needs and how it affects their PE, initial trust, and customer adoption intention (Venkatesh et al., 2016). FC is defined as something that refers to customer's perceptions of the resources and services available to perform a behavior and how the organization will support using the system (Venkatesh et al. (2016).

Unlike in previous research by (Buabeng-Andoh & Baah, 2019; Rahi et al., 2019; Suki & Suki, 2017), in this study, SI was not a significant factor to customers' biometric technology use and acceptance of mobile banking apps in the Mid-Atlantic region of the United States. However, a direct positive relationship of SI on customers' intention to use

the system was consistent with previous peer-reviewed studies on behavior intentions and mobile banking use (Tarhini et al., 2016). According to the research, the rationale is that since customers will get influenced by the skepticism created by biometric technology with mobile banking, trusted interaction with people they trust is critical to their adoption decisions. In contrast to other previous studies based on the SEM analysis, in this study, PC was not a significant factor with trust and satisfaction for customers biometric technology use and acceptance with mobile banking apps in the Mid-Atlantic region of the United States (Masrek et al., 2018). Also, in difference to previous studies by (Priya et al., 2018; Tarhini et al., 2016), in this study, PC did not further highlight the importance of security and privacy, nor was it a strong determinant of customer satisfaction and behaviors to adopt mobile banking apps. However, PC was consistent with previous research that found experience influenced PC utilization directly, and indirect influences were less evident (Thompson et al., 1994). According to the previous study, PC gets measured with two dimensions; security and confidentiality and having prior knowledge with information technology is a critical factor when developing, testing, or applying new information technology adoption and use (Palau-Saumell et al., 2019; Thompson et al., 1994).

The results of this study were consistent with previous peer-reviewed studies on mobile banking adoption (e.g., Al-Harby et al., 2010; He et al., 2015; Oye et al., 2014; Palau-Saumell et al., 2019; Rahi et al., 2018; Saputra et al., 2018; Tarhini et al., 2016; Tassabehji & Kamala, 2012; Thompson et al., 1994; Venkatesh et al., 2003; Zhou et al., 2010). Al-Harby et al. (2010) found that UTAUT constructs, PE, EE, SI, and FC were

discovered to influence BI to use new technology, and FC determine technology use. In contrast, out of the four primary constructs (PE, EE, SI, and FC), in my study, SI had no significant influence on customers' biometric technology adoption with mobile banking in the Mid-Atlantic region of the United States. Al-Harby et al. (2010) also found that UTAUT explained 77% of the variance in BI to use new technology and 52% of the workplace's technology. In my study, the UTAUT demonstrated 63% of the variance in BI to use new technology by mobile banking customers.

Venkatesh et al. (2003) found that EE has the full attention and awareness of FC and was a predictor of mobile banking adoption's BI. Rahi et al. (2018), Tarhini et al. (2016), Zhou et al. (2010) studied customers' intentions to adopt mobile banking in Pakistan, Lebanon, and China. Tarhini et al., Zhou et al. found that FC had a significant amount of variance in predicting Pakistan, Lebanese, and Chinese customers' intention to adopt mobile banking. Similarly, the results of this study showed that FC determine technology use. Saputra et al. researched customers' adoption of mobile banking technology and showed that TTF is a proven model that shows customers will adopt a technology to perform their daily tasks. Saputra et al. also showed that combining TTF and the UTAUT would determine a customer's perspective. TTF showed that banks who support and promote security features for customers would positively impact the use and adoption of biometric technology with mobile banking (Saputra et al., 2018). A previous study by Chao (2019) revealed that BI was significantly influenced by customers' satisfaction, trust, PE, and EE. Similarly, in this study, PE and EE were positive influences on customers trust, security, and customer satisfaction.

Limitations of the Study

The study alleviated limitations stated in Chapter 1: the millennial demographic's usability, e-banking, continuous authentication, transparent, and biometric technology. Looking at the generations, ranging from the traditionalists, baby boomers, Generation X (Gen X), millennials (Gen Y), and Generation Z (iGen), there could be differences in values, beliefs, and opinions from their respective generation. This study does not investigate the values and attitudes of the millennial generations or other generations. Another limitation of the study was the method of gathering participants randomly through an online web-based survey questionnaire. Even though a platform was put in place to target millennials and other generations, there is no guarantee that the respondents in this study covered the Mid-Atlantic region of the United States. Another limitation of the study was that the participants were experienced using biometric technology with mobile banking, which could cause a selection bias. Another limitation was the reports of security professional risk and cost-benefit analyses of their e-banking systems. Security professionals at banks only provided social engineering attacks and did not include other forms of attacks, and this could cause selection bias (Vila et al., 2014).

A limitation of the study is the focus on transparent and continuous authentication methods for mobile device security. This study highlights how transparent and continuous authentication help secure mobile devices for customers. Alotaibi et al. (2015) discussed how current research only finds suitable behavior patterns for the appropriate transparent authentication method. Alotaibi et al. and Crawford and Renaud's (2014) argued a lack of investigation and study of behavioral profiling and application use for

open authentication systems on mobile devices. Also, Alotaibi et al., Crawford and Renaud's, and (Handa et al., 2018) argued that current research only concentrates on finding suitable behavior patterns for the appropriate continuous and transparent authentication method. Consequently, banks focus more on the bank's application services using mobile banking versus the total mobile user authentication at entry authentication and post-log authentication stages simultaneously.

Lastly, another limitation is biometric technology with mobile banking. Many factors can affect biometric systems, like technology use, performance, and inadequate biometric technology devices. Also, biometric technology is not accepted by all customers as a universal fit for authentication. In this study, biometric technology was discussed as a complement to the traditional login method of username and password. There is no guarantee that all participant in the target population will have a minimum quality of biometric technology devices.

Recommendations

This study will help develop the various factors that were revealed as antecedents to behaviors in previous research on the adoption of mobile banking application services. In my investigation, I used the UTAUT and the extension of the UTAUT to examine the relationship between customer acceptance and use of biometric technology with mobile banking apps in the Mid-Atlantic region of the United States. Also, in the study, other intrinsic factors such as PC and TTF were added. In the security world, everyone talks about cyber-crimes and how to prevent them, and they even want a solution to minimize network penetration. Therefore, this study is an added step to add more pertinent

information to the massive phenomenon of security issues that have caused personal information from customers using mobile banking apps. In the Mid-Atlantic region, further study is needed in mobile banking services to understand customer's adoption behaviors and risk opinion with biometric technology adoption models. Therefore, it is critical to research on the millennials generation who are the future bank account holders, and this generation will help guide the next generation into new technology.

In a previous study, it showed that showed 31% of clients would pay for improved security features, 63% are ready to switch accounts for better security features, and 71% are eager to change bank accounts to a bank that guaranteed losses and reimbursed (He et al., 2015). In the United States, 65% of adults who use the internet have had cybercrime, computer scams, fraud, virus, and malware attacks against them (He et al., 2015). Crawford and Renaud (2014) explained that 30% of participants had no security process for accessing their mobile devices even though over 73% of participants felt that biometric technology was more secure than traditional methods. There are 4 billion mobile cellular subscriptions throughout the world, and mobile networks can offer mobile banking to over 61% of the world population (Yadav, 2016). As technology grows and develops, mobile devices are becoming more than just placing calls and texting people. This study aims to review mobile banking literature through the lenses of customers adopting and accepting mobile banking risks because of the adoption of biometric technology with mobile banking.

Previous studies from researchers have used several theoretical frameworks to study customers' use and acceptance of mobile banking apps. Among all the theories and

research models, the UTAUT was a more appropriate method due to the proven research instrument. The UAUT found to be a predictor of adoption and BI with a focus on PE, and EE can positively influence the BI of customers to use technology (Tarhini et al., 2016; Venkatesh et al. (2003). However, past research model has shown and identified distinct factors that significantly affected customers attitudes, behaviors and adoption of technology customers' perception and how they feel about a new service has shown the model like the (Boslaugh, 2013; Chang et al., 2015; Dziak, 2017; Marques et al., 2011; Petre, 2017; Procter et al., 2019; Tavallaee et al., 2017; Venkatesh et al., 2003). Using more than one theoretical framework can be useful to conduct a study on customers biometric technology use and acceptance with mobile banking apps.

In this study, I examined the factors affecting biometric technology with mobile banking in the Mid-Atlantic region of the United States using the UTAUT theoretical framework and two more constructs, PC, and task-technology. Therefore, future research could focus on other constructs and relationships implemented into the UTAUT by tailoring it to the customer's use context. Further research is suggested by examining how to categorize data classification of mobile apps at sensitive levels. Transparent authentication offers behind-the-scenes authentication and threat detection capabilities to protect against fraud attacks while improving the customers' experience. Continuous authentication comes into play because anyone can access your information after point-of-entry on mobile devices if they gain access. Also, future research should examine the use of different theoretical frameworks to conduct a similar study. Theories and models such as:

- TRA
- TAM
- C-TAM-TPB
- MM
- TPB
- MPCU
- IDT
- SCT can conduct a similar study on biometric technology adoption with mobile bank apps.

Finally, this study was based on a quantitative research approach. The research objectives and goals were met; however, this study would have more substantial findings if a mix-method approach were implemented.

Implications

The data from this study affect social change by providing bank CEOs' with critical information so decisions can be made on how to measure and implement a successful mobile banking application using biometric technology. Bank intuitions leaders can use the finding of this study to improve the security features of mobile banking. The core level of security features of mobile banking, bank CEOs', will have to look at are (a) mobile application layer, (b) security layer, and (c) customers' trust, which will help provide solutions and confirm trust with customers. This study's findings showed that PE was significantly positively correlated with biometric technology use with mobile banking in the Mid-Atlantic region of the United States. EE was significantly

positively correlated with biometric technology use with mobile banking in the Mid-Atlantic region of the United States. TTF was significantly positively correlated with biometric technology use with mobile banking in the U.S. Mid-Atlantic region. FC was significantly positively correlated with biometric technology use with mobile banking in the Mid-Atlantic region of the United States.

This study contributes to the banking industry by providing bank CEOs', leaders, and customers with the security measures it takes to create and work with other technologies about biometric technology with mobile banking apps. Having a mobile banking system is essential for banks to operate and sustain customer satisfaction. Therefore, creating a secure mobile application is necessary to keep mobile banking customers. The results of this study may help bank leaders understand the perception of bank customers, and therefore reach their customers by identifying the social and ethical concerns related to biometric technology deployment and the mitigating of risk associated with security attacks by identifying the person(s) participating in the operation.

Conclusions

This study was conducted to explore the factors affecting customers' biometric technology use and acceptance of mobile banking in the Mid-Atlantic region of the United States. The target population of this study was in the Mid-Atlantic region of the United States, which was estimated at 41 million according to the 2019 U.S. Census report. The appropriate sample size of this study was 228 participants to represent the target population. Using a purposeful random sample, the participants included adults who met the following criteria: (a) over the age of 18, (b) have a banking account, (c) use

a bank with a mobile application, (d) the bank has biometric technology implemented with their application, (e) participant use mobile devices, and (f) participants use biometric technology. The participants were contacted through social media sites, like Facebook, Instagram, Twitter, and LinkedIn. This study's theoretical base was the UTAUT. A conceptual framework was developed by extending the UTAUT by incorporating two additional factors: PC and TTF.

The web-based survey analysis revealed that three factors of the UTAUT and one factor of the theoretical framework by extending the UTAUT, TTF was significant factors influencing customer acceptance and use of biometric technology with mobile banking apps in the Mid-Atlantic region of the United States. TTF and FC were the strongest predictors, followed by PE and EE. The study results revealed that PE, EE, SI, and FC positively correlated with BI to use new technology, and FC determine technology use. However, SI and PC had no significant influence on customers biometric technology adoption with mobile banking in the Mid-Atlantic region of the United States.

There are many types of mobile devices like tablets, smartphones, tablet computers that customers use daily. Developing safe practices will help customers keep their information safe. This study explained how customers accept and use biometric technology with mobile banking in the Mid-Atlantic region of the United States. This study provided bank CEOs’ with knowledge of customers' opinions of biometric technology with mobile bank apps so decisions can improve mobile banking's security features. The finding of this study can be used to develop strategies to expand biometric

technology by mitigating the risk associated with security attacks by identifying the person(s) participating in the operation of the mobile bank application.

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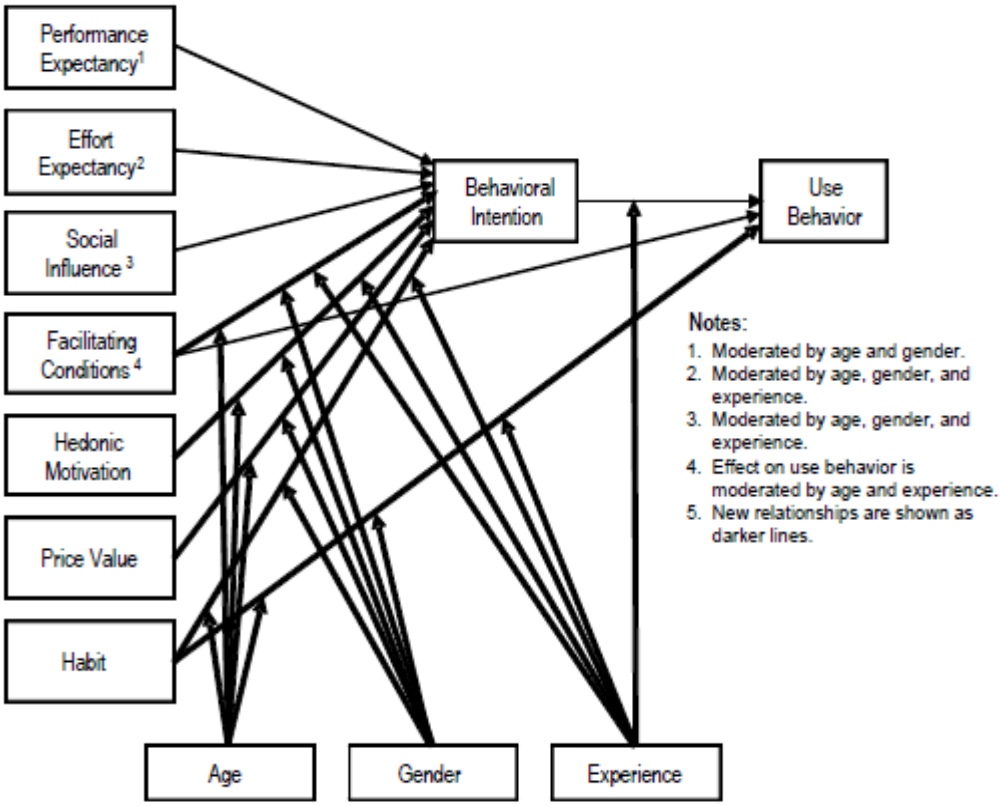
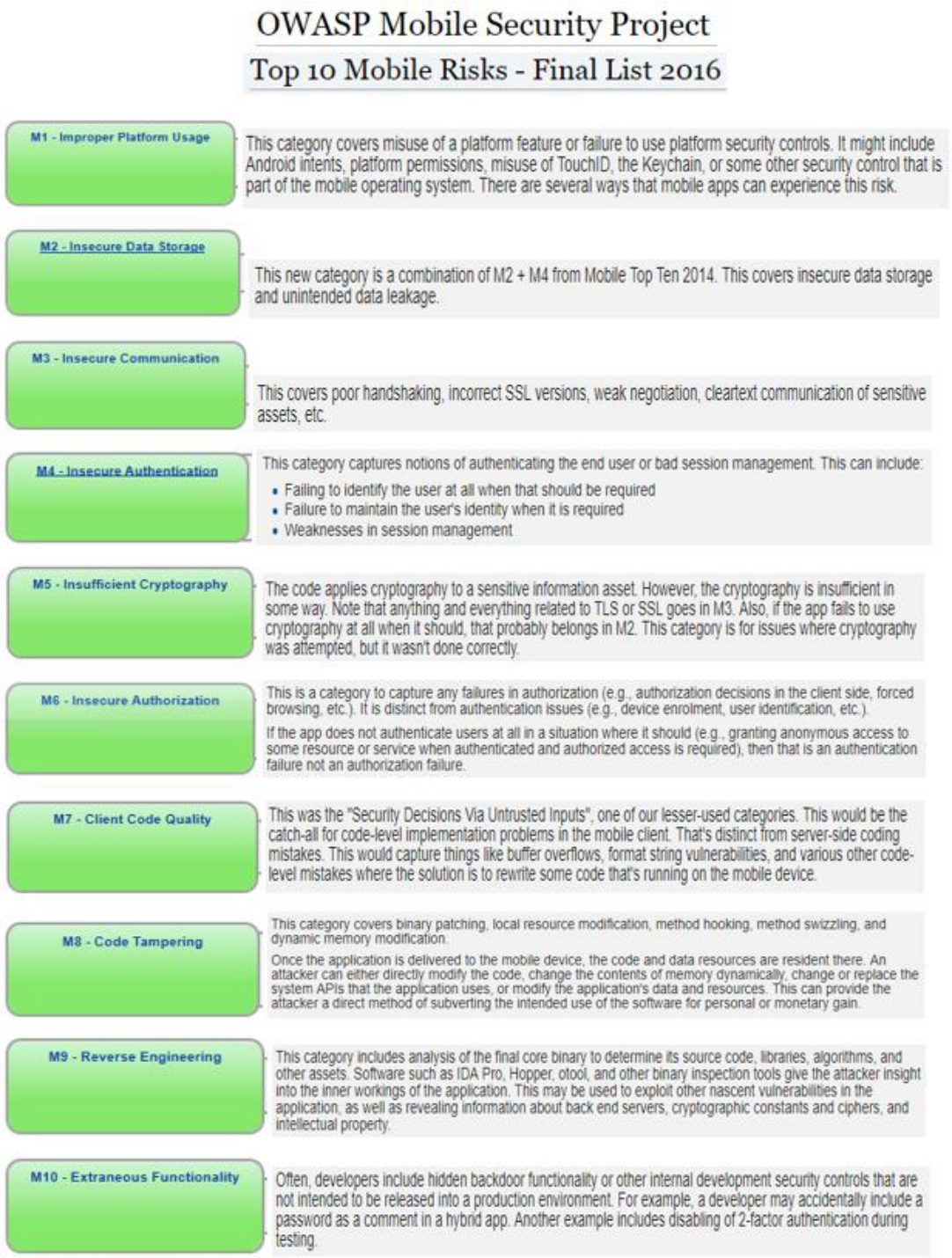
Appendix A: UTAUT2 Model



Appendix B: OWASP Top 10 2016-Top 10



Appendix C: Invitational email

Invitation to participate in the research dissertation titled:
"Examining Consumer's Perspectives Using Biometric Technology with Mobile Banking"

Dear Mobile Bank User,
Welcome to the Examining Consumer's Perspectives Using Biometric Technology with Mobile Banking Pilot Study

This study is being conducted by a researcher named Rodney A. Clark, MBA, MIM, who is a doctoral candidate in Information System Management at Walden University.

You are invited to take part in a research study about biometric authentication usage and acceptance for consumers' during mobile banking transactions. This voluntary survey asks about your current beliefs, attitudes, and experiences. There are no negative consequences if you don't want to take it. If you start the survey you can always change your mind and stop at any time. The information that you provide will help evaluate the actual usage of consumers' and can be used to predicted behavior intentions of consumers to help banks create a safe, and supportive mobile banking experience.
The survey will take you between 5 and 12 minutes to complete and is very informal. The goal is to capture your thoughts and perspectives on the benefits of using biometric technology when accessing your bank account with mobile devices. Your responses to the questions will be kept confidential. Each survey will be linked to a number to help ensure that one response is given per participate.
There is no compensation for participating in this study. However, your participation will be a valuable addition to my research and the finding could lead to a greater public understanding of biometric technology usage with mobile banking.
Best Regards,
Rodney A. Clark

Please click the following link to complete the survey.

START SURVEY

Or copy paste the URL below into your internet browser.
[[SurveyLink]]

This is a system generated email, please do not reply to it. The survey link in this email is unique to its recipient. Please do not forward this email. If you would like to unsubscribe and stop receiving these emails, click unsubscribe..

Appendix D: Permission to use the UTAUT model

Papers-Permissions/Download

WordPress

Mon 3/11/2019 4:26 PM

To: Rodney Clark <rodney.clark@waldenu.edu>

Thank you for your interest. Your permission to use content from the paper is granted. Please cite the work appropriately. Note that this permission does not exempt you from seeking the necessary permission from the copyright owner (typically, the publisher of the journal) for any reproduction of any materials contained in this paper.

Sincerely,
Viswanath Venkatesh
Distinguished Professor and George and Boyce Billingsley Chair in Information Systems
Email: vvenkatesh@vvenkatesh.us
Website: http://vvenkatesh.com

Appendix E: Permission to use the UTAUT2 model

Re: Letter Seeking Permission to Use Survey/Questionnaire Tool - Walden University

Ali Tarhini <ali.tarhini@hotmail.co.uk>
Tue 10/16/2018 1:17 AM
To: Rodney Clark <rodney.clark@waldenu.edu>

Dear Rodney

Thanks for your email. Please go ahead

Wish you all the best

Dr Ali Tarhini

On Fri, Oct 12, 2018 at 12:32 AM Rodney Clark <rodney.clark@waldenu.edu> wrote:

> Please see the attachment for official request to use the survey/questionnaire tool. If you have any questions or concerns, please let me know.
>
> Best,
> Rodney Clark
> Walden University
> rodney.clark@waldenu.edu
> raclark06@gmail.com
> 443-928-2052

--
Best Regards,

Ali Tarhini

Appendix F: Permission to use the UTAUT: Adopt Mobile Banking Questions

Letter Seeking Permission to Use Survey/Questionnaire Tool - Walden University

余強生 <csyu@g2.usc.edu.tw>
Thu 11/21/2019 8:03 AM
Rodney Clark

Hello Dr. Rodney Clark,

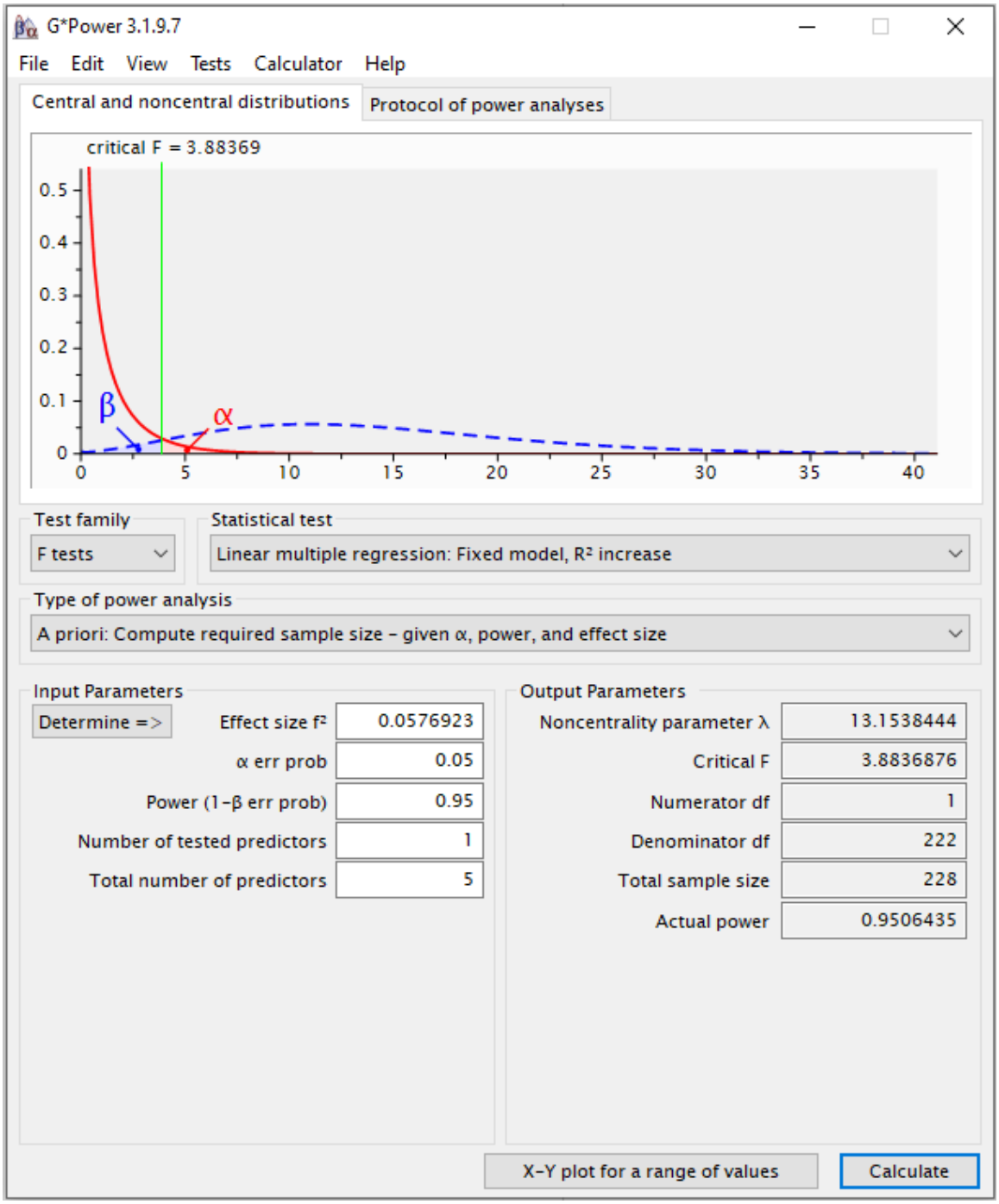
No problem.

Sincerely,

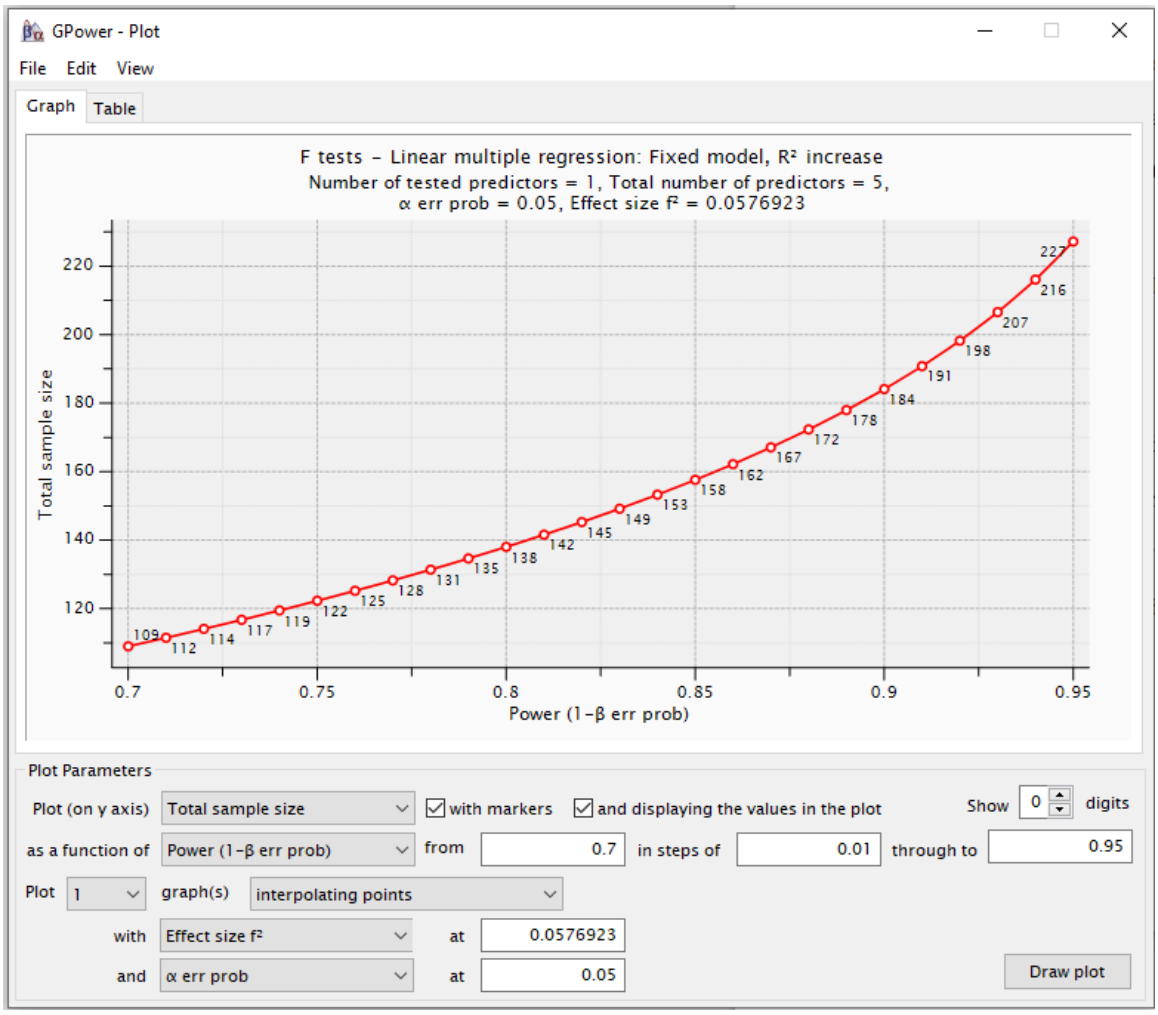
Chian-Son
=-=

Chian-Son Yu, Ph.D.
Member of Editorial Advisory Board, Internet Research (indexed in SSCI and SCI)
Member of Editorial Board, Journal of Information Management (indexed in TSSCI)
Member of Editorial Board, International Journal of Mobile Learning and Organization (indexed in Scopus and EI)
Member of Editorial Board, Contemporary Management Research (indexed in ABI/INFORM and EBSCO)
Member of Editorial Advisory Board, International Journal of Cyber Society and Education(indexed in ABI/INFORM and EBSCO)
Member of Committee Board, Electronic Commerce Studies
Committee Member, Information Management Association (IMA)
Committee Member, Chinese Society of Information Management (CSIM)
Committee Member, Academy of Taiwan Information System Research (ATISR)
Professor, Department of Information Technology and Management
Shih Chien University, Taipei, Taiwan
#70 Da-Zhi Street, Taipei 10497, Taiwan
Tel: 886-2-25381111 ext. 8921
Fax: 886-2-25333143

Appendix G: G*Power 3.0 using a linear multiple regression power analysis for sample size



Appendix H: G*Power 3.0 showing a range of sample sizes from 109 to 228



Appendix I: Constructs and Corresponding Items

Construct	Corresponding Items	Items Sources
Performance Expectance	In conducting banking affairs, (PE1): using mobile banking would improve my performance (PE2): using mobile banking would save my time (PE3): I would use mobile banking anyplace (PE4): I would find mobile banking useful	Performance expectancy (PE) - Adopted from Venkatesh et al., 2003; Tarhini et al., (2016); Yu, (2012)
Effort Expectancy	(EE1): Learning to use mobile banking is easy for me (EE2): Becoming skillful at using mobile banking is easy for me (EE3): Interaction with mobile banking is easy for me (EE4): I would find mobile banking is easy to use	Effort expectancy (EE) - Adopted from Venkatesh et al., 2003; Tarhini et al., (2016); Yu, (2012)
Social Influence	(SI1): People who are important to me think that I should use mobile banking (SI2): People who are familiar with me think that I should use mobile banking (SI3): People who influence my behavior think that I should use mobile banking (SI4): Most people surrounding with me use mobile banking	Social Influence (SI) - Adopted from Venkatesh et al., 2003; Tarhini et al., (2016); Yu, (2012) Venkatesh et al. [2003], Venkatesh and Zhang [2010], Foon and Fah [2011], Sripalawat et al. [2011]
Facilitating Conditions	(FC1): My living environment supports me to use mobile banking (FC2): My working environment supports me to use mobile banking (FC3): Using mobile banking is compatible with my life (FC4): Help is available when I get problem in using mobile banking	Facilitating Conditions (FC) - Adopted from Venkatesh et al., 2003; Tarhini et al., (2016); Yu, (2012) Venkatesh et al. [2003], Venkatesh and Zhang [2010], Sripalawat et al. [2011]
Perceived Credibility	When using mobile banking, (PC1): I believe my information is kept confidential (PC2): I believe my transactions are secured (PC3): I believe my privacy would not be divulged (PC4): I believe the banking environment is safe (PC5): I believe biometric technology will help protect my data (PC6): I feel safe when using biometric technology (PC7): Do you feel mobile banking applications are safe?	Perceived Credibility (PC) - Adopted from Tarhini et al., (2016); Yu, (2012)
Task Technology Fit	When using biometric for mobile banking, (TTF1): Do biometrics make logging into apps easier? (TTF2): Do you feel biometric technology will protect your data from being stolen more effectively than username and password? (TTF3): Do you trust biometric technology? (TTF4): Do you use biometric technology to sign into your bank application? (TTF5): Do you use banking apps more frequently? (TTF6): Does using biometric technology fully meet your security needs?	Task Technology Fit (TTF) - Adopted from Tarhini et al., (2016); Zhou, Lu, & Wang, (2010)
Behavioral Intention	When dealing with banking affairs, (BI1): I prefer to use mobile banking (BI2): I intend to use mobile banking (BI3): I would use mobile banking (BI4): I would use biometric (voice, face, fingerprint, etc.…) technology when using mobile banking	Behavioral Intention (BI) - Adopted from Venkatesh et al., 2003; Tarhini et al., (2016); Yu, (2012)
Actual Use	(AU1): I often use mobile banking to manage my account (AU2): I often use mobile banking to transfer and remit money (AU3): I often use mobile banking to make payments (AU4): What method of biometric do you use? Face, fingerprint, Iris, finger vein, voice, other, I do not use (AU5): How many months have you use biometric technology with mobile banking? <6, 6-12 months, 12-24 months, >24 months	Actual Use (AU) - Adopted from Venkatesh et al., 2003; Tarhini et al., (2016); Zhou, Lu, & Wang, (2010)

Appendix J: Summary Report of Pilot Study

The questions from PE, EE, SI, FC were the original questions with no modifications. PC and TTF, BI and AU were modified to fit the study (See Appendix I). PC questions (PC5, PC6 and PC7) were added with the words “biometric technology” and “mobile baking applications” to fit the study. TTF questions were from the previous studies; however, they were reworded using “biometric technology” and “banking apps” to fit the need of the study. The questions from BI were from previous studies except the question (BI4), which ask the customers what type of biometric technology they used during mobile banking transactions. Question BI4 was used to determine what method of biometric scanning tool was used by the customers or offer by the mobile devices.

The questions from actual use were from previous studies except for the question AU3 and AU4 (see Appendix I), which ask the participant what method of biometric technology they used when accessing their bank account. Question AU5 asks how many months the participant used biometric technology. The questions AU4 and AU5 were used to ensure that the survey participants use mobile banking with biometric technology. Also, questions AU4 and AU5 were exit questions in the survey. If the participants did not use any of the services, the survey responses would not be valid. No alternation or changes were made from the pilot study (Microsoft Forms) to the final analysis (LimeSurvey), except for the data collections instruments.

Appendix K: Demographic of the Pilot Test

Demographic Variable	Sample Composition (N = 42)
Gender	
Male	22 (52.38%)
Female	20 (47.62%)
Age	
18-20	9 (21.43%)
21-29	22 (52.38%)
30-39	3 (7.14%)
40-49	8 (19.05%)
50 or Older	n/a
Education	
High School Degree	9 (21.43%)
Some College but no Degree	11 (26.19%)
Associate Degree	1 (2.38%)
Bachelor's degree	13 (30.95%)
Graduate Degree	8 (19.05%)
Employment	
Employed 40 or more hours per week	24 (57.14%)
Employed 1-39 hours per week	13 (30.95%)
Not Employed	5 (11.90%)
Mobile Banking Use with Biometric	
< 6 Months	13 (30.95%)
6 - 12 Months	16 (38.10%)
12 - 24 Months	5 (11.90%)
24 Months	8 (19.05%)
Method of Biometric Technology	
Face	19 (45.24%)
Fingerprint	20 (47.62%)
Voice	3 (7.14%)
Bank	
Commercial Bank	34 (80.95%)
Credit Union	9 (21.43%)

Appendix L: Final Study Demographic Questions

*Are you male or female?

Female	Male

*Which category below includes your age?

	18-20	21-29	30-39	40-49	50-59	60 or older
	○	○	○	○	○	○

*What is your martial status?

	Divorced	Married	Separated	Single	Widowed
	○	○	○	○	○

*What is the highest level of school you have completed or the highest degree you have received

	Less than High School degree	High School Degree	GED	Some College	Associate degree	Bachelor degree	Graduate degree
	○	○	○	○	○	○	○

*What is your race or ethnicity?

	American Indian	Asian	Black or African American	Hispanic	Latino	White or Caucasian	Multiple races	Other
	○	○	○	○	○	○	○	○

*Which of the following categories best describes your employment status?

	Employed, working 1-39 hours per week	Employed, working 40 or more hours per week	Not employed, looking for work	Retired	Disabled, not able to work
	○	○	○	○	○

*How much total combined money did all members of your household earn last year?

	$0 - $9,999	$10,000 - $24,000	$25,000 - $49,000	$50,000 - $74,000	$75,000 - $99,000	$100,000 - $149,000	$150,000 - $199,000	$200,00 and up
	○	○	○	○	○	○	○	○

*What type of bank do you use?

	Commercial Bank	Credit Union
	○	○

Appendix M: Descriptive of the Constructs

Name	Question
PE[PEA]	In conducting banking affairs, [Using mobile banking would improve my performance?]
PE[PEB]	In conducting banking affairs, [Using mobile banking would save me time?]
PE[PEC]	In conducting banking affairs, [I would use mobile banking anyplace?]
PE[PED]	In conducting banking affairs, [I would find mobile banking useful?]
EEA	Learning to use mobile banking is easy for me?
EEB	Becoming skillful at using mobile banking is easy for me?
EEC	Interaction with mobile banking is easy for me?
EED	I would find mobile banking is easy to use?
SIA	People who are important to me think that I should use mobile banking?
SIB	People who are familiar with me think that I should use mobile banking?
SIC	People who influence my behavior think that I should use mobile banking?
SIDA	Most people surrounding me use mobile banking?
FCA	My living environment supports me to use mobile banking?
FCB	My working environment supports me to use mobile banking?
FCC	Using mobile banking is compatible with my life?
FCD	Help is available when I get problem in using mobile banking?
PCA[PCAA]	When using mobile banking, [I believe my information is kept confidential?]
PCA[PCAB]	When using mobile banking, [I believe my transactions are secured?]
PCA[PCAC]	When using mobile banking, [I believe my privacy would not be divulged?]
PCA[PCAD]	When using mobile banking, [I believe the banking environment is safe?]
PCA[PCAE]	When using mobile banking, [I believe biometric technology will help protect my data?]
PCA[PCAF]	When using mobile banking, [I feel safe when using biometric technology?]
PCA[PCAG]	When using mobile banking, [Do you feel mobile banking applications are safe?]
TTF[TTFA]	When using biometric for mobile banking, [Do biometrics make logging into apps easier?]
TTF[TTFB]	When using biometric for mobile banking, [Do you feel biometric technology will protect your data from being stolen more effectively than username and password?]
TTF[TTFC]	When using biometric for mobile banking, [Do you trust biometric technology?]
TTF[TTFD]	When using biometric for mobile banking, [Do you use biometric technology to sign into your bank application?]
TTF[TTFE]	When using biometric for mobile banking, [Do you use banking apps more frequently?]
TTF[TTFF]	When using biometric for mobile banking, [Does using biometric technology fully meet your security needs?]
BI[BIA]	When dealing with banking affairs, [I prefer to use mobile banking?]
BI[BIB]	When dealing with banking affairs, [I intend to use mobile banking?]
BI[BIC]	When dealing with banking affairs, [I would use mobile banking?]
BI[BID]	When dealing with banking affairs, [I would use biometric (5, 1, 2, etc.…) technology when using mobile banking?]
AUA	I often use mobile banking to manage my account?
AUB	I often use mobile banking to transfer and remit money?
AUC	I often use mobile banking to make payments?
AUE	How many months have you used biometric technology with mobile banking?

Appendix N: Principal Axis Factor Analysis

Factors	Variables	Factor loading	No. of Variables	Cronbach alpha	Eigen value	% of variance
Using biometric technology [TTF]	TTFA, TTFB, TTFD, TTFE, TTFF, TTFC		6	.809	11.38	39.2
	When using biometric for mobile banking, [Do biometrics make logging into apps easier?] TTFA	.799				
	When using biometric for mobile banking, [Do you feel biometric technology will protect your data from being stolen more effectively than username and password?] TTFB	.793				
	When using biometric for mobile banking, [Do you use biometric technology to sign into your bank application?] TTFD	.739				
	When using biometric for mobile banking, [Do you use banking apps more frequently?] TTFE	.660				
	When using biometric for mobile banking, [Does using biometric technology fully meet your security needs?] TTFF	.638				
	When using biometric for mobile banking, [Do you trust biometric technology?] EEB. Becoming skillful at using mobile banking is easy for me? TTFC	.561				
Learning to Use [EE]	EEB, EEC, EEA, EED		4	.813	2.74	9.45
	Becoming skillful at using mobile banking is easy for me? EEB	.871				
	Interaction with mobile banking is easy for me? EEC	.830				
	Learning to use mobile banking is easy for me? EEA	.801				
	I would find mobile banking is easy to use?	.762				
Using mobile banking (MB) [PC]	PCAD, PCAA, PCAC, PCAB, PCAG, PCAE		6	.804	2.45	8.46
	When using mobile banking, [I believe the banking environment is safe?] PCAD	.760				
	When using mobile banking, [I believe my information is kept confidential?] PCAA	.709				
	When using mobile banking, [I believe my privacy would not be divulged?] PCAC	.670				
	When using mobile banking, [I believe my transactions are secured?] PCAB	.670				
	When using mobile banking, [Do you feel mobile banking applications are safe?] PCAG	.528				
	When using mobile banking, [I believe biometric technology will help protect my data?] PCAE	.507				

Appendix O: Principal Axis Factor Analysis

Factors	Variables	Factor loading	No. of Variables	Cronbach alpha	Eigen value	% of variance
Conducting Banking Affairs [PE]	PED, PEB, PEC, PEA		4	.813	1.64	5.66
	When using mobile banking, [I believe the banking environment is safe?] PED	.774				
	In conducting banking affairs, [Using mobile banking would save me time?] PEB	.770				
	In conducting banking affairs, [I would use mobile banking anyplace?] PEC	.760				
	In conducting banking affairs, [Using mobile banking would improve my performance?] PEA	.618				
Influence [SI]	SIB, SIC, SIA		3	.805	1.44	4.96
	People who are familiar with me think that I should use mobile banking? SIB	.791				
	People who influence my behavior think that I should use mobile banking? SIC	.752				
	People who are important to me think that I should use mobile banking? SIA	.759				
Environment [FC]	FCB, FCA, FCC		3	.811	1.17	4.06
	My working environment supports me to use mobile banking? FCB	.690				
	My living environment supports me to use mobile banking?	.683				
	Using mobile banking is compatible with my life? FCC	.554				

Appendix P: Communalities of Variables

Correlation	Initial	Extraction
PE[PEA]	.620	.587
PE[PEB]	.681	.705
PE[PEC]	.764	.752
PE[PED]	.773	.789
EEA	.827	.785
EEB	.881	.911
EEC	.837	.831
EED	.809	.739
SIA	.706	.732
SIB	.737	.785
SIC	.777	.806
SIDA	.470	.434
FCA	.615	.662
FCB	.579	.617
FCC	.599	.512
FCD	.436	.352
PCA[PCAA]	.633	.614
PCA[PCAB]	.618	.583
PCA[PCAC]	.567	.539
PCA[PCAD]	.655	.707
PCA[PCAE]	.775	.614
PCA[PCAF]	.756	.583
PCA[PCAG]	.540	.499
TTF[TTFA]	.730	.720
TTF[TTFB]	.696	.673
TTF[TTFC].	.524	.471
TTF[TTFD]	.745	.686
TTF[TTFE].	.688	.583
TTF[TTFF]	.635	.613

Appendix Q: Unrotated Factor Matrix

	Factor					
	1	2	3	4	5	6
EEB	.716					
PCA[PCAE]	.712					
TTF[TTFF]	.692					
PCA[PCAF]	.683					
SIC	.683					
PE[PED]	.677					
TTF[TTFD]	.675					
EED	.669					
EEA	.656					
EEC	.649	-.536				
SIB	.647					
PE[PEC]	.644					
PE[PEA]	.635					
TTF[TTFA]	.633					
TTF[TTFE]	.627					
SIA	.627					
FCA	.616					
TTF[TTFC]	.611					
PCA[PCAB]	.608					
PCA[PCAD]	.598					
TTF[TTFB]	.586		-.497			
SIDA	.566					
PE[PEB]	.564					
FCC	.562					
PCA[PCAA]	.560					
PCA[PCAG]	.560					
FCB	.510					
PCA[PCAC]						
FCD						

Appendix R: Rotated Component Matrix

	Factor					
	1	2	3	4	5	6
TTF[TTFA]	.799					
TTF[TTFB]	.793					
TTF[TTFD]	.739					
TTF[TTFE]	.660					
TTF[TTFF]	.638					
TTF[TTFC]	.561					
PCA[PCAF]						
EEB		.871				
EEC		.830				
EEA		.801				
EED		.762				
PCA[PCAD]			.760			
PCA[PCAA]			.709			
PCA[PCAC]			.670			
PCA[PCAB]			.670			
PCA[PCAG]			.528			
PCA[PCAE]			.507			
PE[PED]				.774		
PE[PEB]				.770		
PE[PEC]				.760		
PE[PEA]				.618		
SIB					.791	
SIC					.759	
SIA					.752	
SIDA						
FCB						.690
FCA						.683
FCC						.554
FCD						

Appendix S: Summary of Findings

	Research Question	Research Hypothesis	Survey Questions	Type of Analysis	Results	Conclusion
RQ1	To what extent do performance expectancy, effort expectancy, social influence, perceived credibility, task-technology fit, and facilitating conditions affect the behavioral intentions of customers to adopt biometric technology with mobile banking?	Performance expectancy will affect customers' behavioral intention to use biometric technology with mobile banking	When using mobile banking, [I believe the banking environment is safe?] PED In conducting banking affairs, [Using mobile banking would save me time?] PEB In conducting banking affairs, [I would use mobile banking anyplace?] PEC In conducting banking affairs, [Using mobile banking would improve my performance?] PEA	IBM SPSS 23 IBM SPSS AMOS 23	β = .30, r^2 = .635 p< 0.00	Performance expectancy was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States.
	Research Question	Research Hypothesis	Survey Questions	Type of Analysis	Results	Conclusion
		Effort expectancy will affect customers' behavioral intention to use biometric technology with mobile banking	Becoming skillful at using mobile banking is easy for me? EEB Interaction with mobile banking is easy for me? EEC Learning to use mobile banking is easy for me? EEA I would find mobile banking is easy to use?	IBM SPSS 23 IBM SPSS AMOS 23	β =.144, r^2 =.635, p<.005	Effort expectancy was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States.
	Research Question	Research Hypothesis	Survey Questions	Type of Analysis	Results	Conclusion
		Social influence will not influence customers' behavioral intention to use biometric technology with mobile banking	People who are familiar with me think that I should use mobile banking? SIB People who influence my behavior think that I should use mobile banking? SIC People who are important to me think that I should use mobile banking? SIA	IBM SPSS 23 IBM SPSS AMOS 23	β = .30, r^2 =.635, p>.551	Social influence was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States.
	Research Question	Research Hypothesis	Survey Questions	Type of Analysis	Results	Conclusion
		Perceived credibility will affect customers' behavioral intention to use biometric technology with mobile banking	When using mobile banking, [I believe the banking environment is safe?] PCAD When using mobile banking, [I believe my information is kept confidential?] PCAA When using mobile banking, [I believe my privacy would not be divulged?] PCAC When using mobile banking, [I believe my transactions are secured?] PCAB When using mobile banking, [Do you feel mobile banking applications are safe?] PCAG When using mobile banking, [I believe biometric technology will help protect my data?] PCAE	IBM SPSS 23 IBM SPSS AMOS 23	β =.083, r^2 =.635, p>.119	Perceived credibility was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States.
	Research Question	Research Hypothesis	Survey Questions	Type of Analysis	Results	Conclusion
		Task-technology fit will influence customers' behavioral intention to use biometric technology with mobile banking	When using biometric for mobile banking, [Do biometrics make logging into apps easier?] TTFA When using biometric for mobile banking, [Do you feel biometric technology will protect your data from being stolen more effectively than username and password?] TTFB When using biometric for mobile banking, [Do you use biometric technology to sign into your bank application?] TTFD When using biometric for mobile banking, [Do you use banking apps more frequently?] TTFE When using biometric for mobile banking, [Does using biometric technology fully meet your security needs?] TTFF When using biometric for mobile banking, [Do you trust biometric technology?] EEB. Becoming skillful at using mobile banking is easy for me? TTFC	IBM SPSS 23 IBM SPSS AMOS 23	β =.431, r^2 =.635, p<.000	Task-technology fit was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States.
	Research Question	Research Hypothesis	Survey Questions	Type of Analysis	Results	Conclusion
		Facilitating conditions will influence the actual usage of biometric technology with mobile banking	My working environment supports me to use mobile banking? FCB My living environment supports me to use mobile banking? Using mobile banking is compatible with my life? FCC	IBM SPSS 23 IBM SPSS AMOS 23	β =.527, r^2 =.635, p<.000	Facilitating conditions was positively related to biometric technology with mobile banking in the Mid-Atlantic region of the United States.