TRUST IN CONSUMER ADOPTION OF ARTIFICIAL INTELLIGENCE-DRIVEN VIRTUAL FINANCE ASSISTANTS: A TECHNOLOGY ACCEPTANCE MODEL PERSPECTIVE

by

D. Blaine Nashold, Jr.

A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Business Administration

Charlotte, NC

2020

Approved by:

____
Dr. Justin W. Webb

____
Dr. Franz W. Kellermanns

____
Dr. Torsten M. Pieper

____
Dr. Ram L. Kumar

ABSTRACT

D. BLAINE NASHOLD, JR. Trust in Consumer Adoption of Artificial Intelligence-Driven Virtual Finance Assistants: A Technology Acceptance Model Perspective (Under the direction of DR. JUSTIN W. WEBB)

While numerous studies have investigated technology acceptance through the classical technology acceptance model (TAM), little empirical research has touched on the emerging technology trend of financial technology or “fintech”. More specifically, artificial intelligence-driven virtual finance assistants offered by many of today’s largest financial institutions and touted as innovative, analytic, and predictive applications that can help make everyday banking easier. In this dissertation, I examine what factors influence consumers to use artificial intelligence-driven virtual finance assistants and how these factors affect the technology’s perceived usefulness and perceived ease of use. I also examine the moderating influence of three established dimensions of trust – 1) contractual, 2) competence, and 3) goodwill. I randomly sampled 121 adults via a multi-stage survey approach which separated the measurement of independent and dependent variables over a one month time period. The hypotheses were tested using hierarchical moderated linear regression. By examining these relationships, the research here has attempted to enhance the understanding of the seminal technology acceptance model and is the first to investigate the trust dimensions of contractual, competence, and goodwill. I hope this research encourages other scholars to 1) continue to examine and expand the boundaries on technology acceptance specific to current fintech applications as this is a vastly underserved area of study and 2) continue to ride the wave of the ever-expanding technology revolution and drive the intersect between academia and practitioner.

DEDICATION

All glory to my Lord and Savior Jesus Christ, through whom all things are possible. And infinite love, gratitude, and admiration to the blessings of my life – Danielle, Trey, and Wells.

ACKNOWLEDGEMENTS

So many to acknowledge on this wonderful journey as it really does take a village… Most importantly, my family whose unwavering support, unyielding grace and guidance, and selfless sacrifice has anchored my upbringing and made me the man I am today. Next, my university family – Dr. Justin W. Webb who not only chaired my dissertation committee but shepherded me on this voyage with patience, encouragement, and tenacity. You've always been a mentor, but now I'm proud to also call you a friend. Dr. Franz W. Kellermanns, Dr. Torsten M. Pieper, and Dr. Ram L. Kumar – your scholarly support, responsiveness, and creativity as a committee not only made this dissertation the best manuscript it could be but, more notably, challenged me to be the best student I could be. And, cohort 1 – I look forward to shared successes, research, and recounting our time together with impeccable fondness. To all – from family, friends, faculty, and beyond mentioned here and implicitly – simply, thank you!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

TAM	Technology Acceptance Model
PEU	Perceived Ease of Use
PU	Perceived Usefulness

CHAPTER 1: INTRODUCTION

What drives a consumer's decision to use a financial technology ("fintech") and what potentially moderates a fintech's perceived usefulness in relation to a consumer's behavioral intention to use? This study examines this question by evaluating how individuals adopt services like artificial intelligence-driven virtual finance assistants such as Bank of America's Erica or Capital One's Eno offerings (e.g. conversational agents). This is an important question with the ever-growing advancement of technology and its increasing integration into users' personal financial lives yet one that remains largely unanswered regarding specific decisions to accept or reject a financial technology (Marangunić & Granić, 2015). In particular, whether consumers, who (1) have traditionally interacted face to face with bank employees, often transacting based on a level of trust, and (2) are potentially placing their financial wealth at risk by interfacing with technology (or at least have significant concerns of this risk, whether real or not), are willing to adopt fintech remains an important question for banks and other financial services seeking significant gains in efficiencies offered by reducing employee numbers and brick-and-mortar locations and increased market share by improving the quality and variety of banking services. With financial services of immense importance to society and the daily lives of consumers worldwide, much literature (Berger, 2003; Mareev, 2016; Shim & Shin, 2016) posits that a new era is being born for the financial services industry with the rise of fintechs (Milian, Spinola, & Carvalho, 2019). Specific to this study, artificial intelligence will dramatically change the business world across many industries, especially financial services and financial technology, as it can enhance customer service and customer experiences (Ransbotham, Kiron, Gerbert, & Reeves, 2017). However, while Ransbotham et al. (2017) offer that a majority of executives (85%) believe that artificial intelligence will facilitate competitive advantage (Ransbotham et al., 2017), consumers' use of chatbot services has been deemed slow (Jung, Dorner, Weinhardt, & Pusmaz, 2018, p. 367). This dissertation endeavors to investigate at least a small piece as to why this is.

Seminal technology acceptance literature distinguishes between perceived usefulness and perceived ease of use as factors affecting individual behavioral attitudes. Perceived usefulness (PU) refers to the extent to which individuals view the use of a given technology as potentially increasing their job performance, and perceived ease of use (PEU) refers to the extent to which individuals view using a technology as being relatively effort-free, and together PU and PEU influence the adoption of new technology (Davis, 1985, 1989). Potential users who believe in a technologies' ease of use and benefits will promote a consumer's willingness to actually use the new technology (Chau & Hu, 2002; Davis, 1985; Davis, Bagozzi, & Warshaw, 1989). However, there are a lack of studies that provide theoretical knowledge or systematic evidence about the underlying cognitive, affective, and behavioral mechanisms driving chatbot technology adoption (Cardona, Werth, Schönborn, & Breitner, 2019). Accordingly, a chatbot is defined as a conversational software interface or computer-based dialog system which, depending on degree of sophistication and design, a conversational interaction can be built on a decision-tree logic or can be activated through sophisticated natural language queries while learning from previous conversational interactions (Cardona et al., 2019). Specifically, chatbot adoption patterns in highly conservative and regulated contexts such as financial services may tend to change ambivalently in proportion to perceived advantages and the degree of perceived financial, social, and privacy risk concerns – risk concerns normally channeled through high levels of human interaction but in these digitized customer offerings rely on the trust of dialog systems to digitalize the human capacity and accurately imitate the human-agent interaction (Cardona et al., 2019). The role of trust within fintech is of critical importance due to the novelty of the technologies and the highly confidential nature of data involved in the provision of the service. Kesharwani and Bisht (2012) found that users' trust can influence their adoption-related actions, with trust formed by their inherent perceptions (e.g. perceived risks) of online banking in India (Kesharwani & Singh Bisht, 2012). And, considering the inherent aspects of fintech, its adoption presents certain risks with trust found to be closely related to brand image and perceived risks (e.g. the more trust in a service provider a user has, the more likely the user will adopt the service) (Z. Hu, Ding, Li, Chen, & Yang, 2019). To utilize artificial intelligence-driven virtual finance assistants, consumers need to provide a multitude of private personal information. Semuel and Lianto (2014) proposed that a quality brand can increase trust among users by effectively reducing risk (Semuel & Lianto, 2014).

Extant research on consumer adoption has examined the role of trust. Chaouali et al. (2016) investigated trust in customers' intention to adopt internet banking services in an emerging country, finding that internet banking adoption is influenced by trust and that trust in the physical bank has an indirect impact on internet banking adoption (Chaouali, Yahia, & Souiden, 2016). Lu et al. (2011) examined the influence that trust in one type of technology has on trust in other similar technologies, thereby influencing one's behavioral intention to use each of the technologies (Y. Lu, Yang, Chau, & Cao, 2011). Weerd et al. (2011) monitored individuals' intention to use protective measures during a flu pandemic, given government trust and perceived individual risk (van der Weerd, Timmermans, Beaujean, Oudhoff, & van Steenbergen, 2011) while Horst et al. (2007) looked at perceived usefulness, personal experiences, risk perception, and trust as determinants of adoption of e-government services also in the Netherlands (Horst, Kuttschreuter, & Gutteling, 2007).

While the aforementioned studies examine trust, general theory underlying trust (specifically finer-grained conceptualizations of different forms of trust), surface questions of whether all forms of trust are relevant and how organizations can engender the different forms of trust to encourage consumer adoption of technologies. Trust can be categorized in several ways (Barney & Hansen, 1994; Rousseau, Sitkin, Burt, & Camerer, 1998; Sako, 1992). For purposes of this dissertation, I use Sako's (1992) categorization which categorizes trust into three forms – 1) contractual, 2) competence, and 3) goodwill (Sako, 1992). As defined in Ireland and Webb (2007), "Contractual trust entails a mutual understanding by partners to adhere to a specified agreement; competence trust stems from the belief that a given partner has the managerial and technical capabilities to properly perform a given set of tasks; and, goodwill trust exists when partners are willing to act in ways exceeding stipulated contractual agreements" (Ireland & Webb, 2007, p. 484). For purposes of this dissertation, I focus on the relationship between a financial services firm and its consumers in lieu of the partnership amongst supply chain partners described above.

Herein, I integrate TAM with trust research to provide a more holistic understanding of how trust influences consumers' intentions to use / adopt chatbot services. More specifically, I examine the extent to which each form of trust – competence, contractual, and goodwill – moderates the relationships between perceived usefulness and perceived ease of use with consumer adoption of artificial intelligence-driven chatbots. Consumers' trust in the competence of a financial institution in general, and / or its technology, is expected to increase consumer comfort levels that chatbots can be effective replacements for interpersonal interactions with bank tellers and other representatives – accurately addressing consumer concerns in a timely manner without the risk of fraud / theft in an easy to use manner. Trust in the contract underlying the fintech solution can ease concerns that potential fraud would lead to ongoing problems for the consumer and that the risk lies with the bank. Goodwill trust between the consumer and the bank should ease consumer concerns for potentially unforeseen circumstances not covered by the contract or otherwise unexpected.

1.1 Research Objective

Over the last few decades, interest in both the research and clinical communities in understanding why individuals decide to accept or reject technology and its effective usage has stemmed both technology acceptance theory and model advances (Marangunić & Granić, 2015). The predominant model, which this study grounds on, is Fred Davis' technology acceptance model (TAM). Originally developed as part of Davis' (1985) doctoral dissertation while at the Massachusetts Institute of Technology, TAM proposes that two variables - perceived usefulness (PU) and perceived ease of use (PEU) – mediate the relationship between system characteristics (e.g. external variables) and potential technology usage (Davis, 1985). Davis derived TAM to mitigate the shortcomings from the theory of reasoned action (M. Fishbein & Ajzen, 1975) and theory of planned behavior (Ajzen, 1985) to better explain and predict actual behavior regarding technology adoption. Historically, the theory of reasoned action has largely served as a predictive model for behavior and intentions (and approaches to alter both) while the theory of planned behavior integrated perceived behavioral control as a precursor to behavioral intentions (Madden, Ellen, & Ajzen, 1992). Today, TAM is considered crucial in understanding what predicts technology acceptance or rejection. Regarded as the most utilized framework in predicting information technology adoption (Legris, Ingham, & Collerette, 2003) it has become so popular that it has been cited in the majority of research that studies user acceptance of technology (Y. Lee, Kozar, & Larsen, 2003). TAM is a valid and robust model with the potential for broad applicability as evidenced by the variety of fields of application included in academic literature (King & He, 2006).

Fintech, a derived contraction short for financial technology, is defined as “a new financial industry that applies technology to improve financial activities” (Schueffel, 2016, p. 45). Fintech is often a buzzword used in the press described as “an important phenomenon that should be observed by practitioners linked to the financial industry, information technology and innovation (incubators, venture capital, angels, among others)” (Milian et al., 2019, p. 1). At its core, fintech describes the connection of modern technologies (e.g. cloud computing, smart phones) with classical financial services business activities (e.g. loans, payments, transfers) with an aim of improved efficiency (Gomber, Koch, & Siering, 2017). This intersection of finance and technology has resulted in a continuously advancing service productivity, which simultaneously challenges and caters to the attitudes of consumers who are deciding whether to adopt new fintechs to gain market opportunities (Chuang, Liu, & Kao, 2016). Further, much fintech is adopted internally by banks, unbeknownst to consumers, to enhance their own efficiencies and effectiveness in areas such as regulatory reporting, compliance training, and workforce productivity. However, key fintechs are implemented at the critical interface of banks and their consumers, such as ATMs, online banking, customer service, and most recently, artificial intelligence-driven chatbots. Yet, despite the increasing hype surrounding fintech, there is a prominent deficiency of academic literature that deals with the topic systematically, a disparate research agenda for future directions, and a general lack of structure (Milian et al., 2019). Moreover, fintech has become the focus of new technological applications making the field a prime candidate for TAM application and evaluation (Y. Kim, Park, & Choi, 2016).

An expansive review of the above models and concepts, their evolution, and extant literature is provided below in the literature review contained in Chapter 2.

1.2 Research Goals of the Dissertation

The research goals of this dissertation are to investigate opportunities for extending and addressing gaps in the research of technology acceptance as applied to fintech. Specifically, leveraging TAM to examine trust in consumer adoption of artificial intelligence-driven virtual finance assistants.

From a TAM perspective, Lee et al. (2003) emphasized a necessity for variable expansion and boundary condition investigation of TAM as part of their literature review (Y. Lee et al., 2003) while King and He (2006) demonstrated TAM to be a valid and robust model, widely used, and implied its potential wider applicability (King & He, 2006). Hsiao and Yang (2011) identified three main trends in TAM application, one of which being e-commerce (fintech) systems (Hsiao & Yang, 2011).

From a general fintech perspective, research tends to be disparate with no intelligible research plan (Kavuri & Milne, 2019). Drilling down, Nguyen (2018) suggested that relationships between humans and chatbots need further considerations as human-computer interaction literature on its own is incomplete (Nguyen & Sidorova, 2018). And, according to Acemoglu and Restrepo (2017), the trend of unparalleled expansion of artificial intelligence and robotics across lines of business is having a key bearing on monetary, societal, and employment areas (Acemoglu & Restrepo, 2017).

Bridging the technology acceptance and fintech research streams, only Lucente (2002) in the context of e-commerce, Nguyen (2018) in the travel field, Belanche (2019) with robo-advisers, and Cardona (2019) in insurance have undertaken various levels of research (Belanche, Casaló, & Flavián, 2019; Cardona et al., 2019; Lucente, 2000; Nguyen & Sidorova, 2018). Further, most studies have concentrated on technical and / or legal issues (Glaser, Iliewa, Jung, & Weber, 2019; Ji, 2017). Therefore, due to the novelty of artificial intelligence-driven virtual finance assistants, there is currently a paucity of information about vital adoption factors by consumers. To the best of my knowledge, no study has examined trust in the acceptance of artificial intelligence-driven virtual finance assistants utilizing TAM.

To fill this gap, this study utilized TAM to examine consumers' trust, in its various forms, in banks and, more specifically, their AI-driven chatbot technologies that can then influence the consumers' adoption of these technologies – specifically, artificial intelligence-driven virtual finance assistants (e.g. Bank of America's Erica, Capital One's Eno, USAA's Clinc).

1.3 Organization of Dissertation

This dissertation is organized as follows. Chapter 1 (Introduction) attempts to "set the hook" for this research by answering three fundamental questions – 1) Who cares?, 2) What do we know, what do we not know, and so what?, and 3) What will the reader learn? (Grant & Pollock, 2011). Chapter 2 (Literature Review and Hypotheses Development) provides an exhaustive review of extant literature relating to technology acceptance and fintech. Then, I cultivate a novelty or gap in that oeuvre to develop and introduce my hypotheses with theoretical grounding that 1) positions those hypotheses in relation to related research, 2) conveys a clear, logical argument, and 3) creates a sense of coherence in the relationships contained within the proposed model (Sparrowe & Mayer, 2011). Next, Chapter 3 (Research Design and Methodology) explains the methods of analysis and how the data were collected and subsequently analyzed. Chapter 4 (Results) reports how the data were analyzed and what was found, with the examination of implications, limitations, and prospects for future research immediately following in Chapter 5 (Discussion and Conclusion). A concluding brief summation of the dissertation's key objectives and findings are also included in this chapter.

CHAPTER 2: LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Technology Acceptance Model

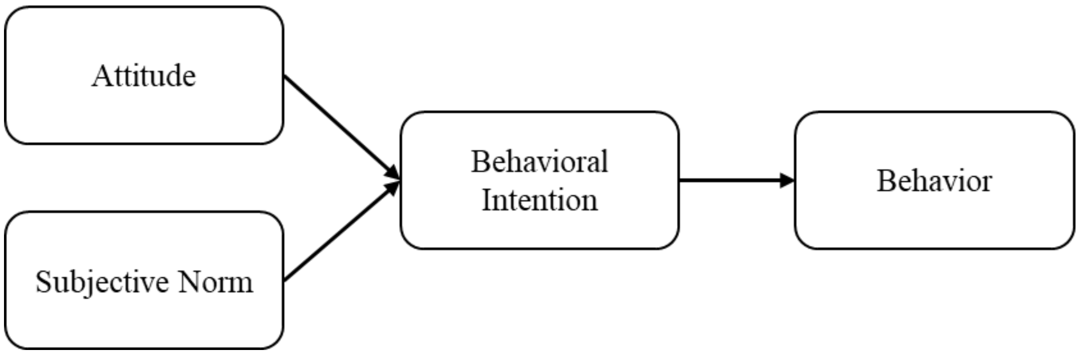
Davis' (1989) technology acceptance model (TAM) is one of the seminal models of technology acceptance. Established to predict organizational acceptance of information systems, it grounds with two chief mechanisms influencing the intention to utilize new technology: perceived usefulness (PU) and perceived ease of use (PEU) (Davis, 1989). With both the theory of reasoned action and the theory of planned behavior foundationally critical to the creation and evolution of TAM (this paper's selected theoretical framework), a brief description of these preceding and influencing theories is necessary.

Theory of Reasoned Action

Before technology was inextricably intertwined in our everyday lives, there was an increasing interest to understand why a technology was accepted or rejected. Initial theories attempting to explain and predict those decisions were not rooted in the yet to be created field of technology acceptance but in psychology via Fishbein and Ajzen's (1975) theory of reasoned action and Ajzen's (1985) theory of planned behavior. With the supposition that humans are rational and methodically leverage obtainable information, Fishbein and Ajzen (1975) developed the theory of reasoned action as a theory to predict and understand behavior and attitudes (M. Fishbein & Ajzen, 1975). The theory of reasoned action posited that "behavioral intentions, which are immediate antecedents to behavior, are a function of salient information or beliefs about the likelihood that performing a particular behavior will lead to a specific outcome" (Madden et al., 1992, p.

3). According to Ajzen and Fishbein (1980), complete volitional control of the behavior must be present for the theory of reasoned action to apply (Ajzen & Fishbein, 1980).

Figure 2.1 Theory of Reasoned Action – Fishbein & Ajzen (1975)



Fishbein and Ajzen (1975) divided the beliefs antecedent to behavioral intentions into two theoretically different sets: 1) behavioral – suggested to be the causal influence on one's attitude to executing the behavior and 2) normative – beliefs regarding the subjective norms about executing the behavior (M. Fishbein & Ajzen, 1975). Therefore, intentions and behavior can be affected by available information or salient beliefs via attitudes (e.g. mobile banking is convenient) and / or through subjective norms (e.g. my friends are using mobile banking). As further noted by Fishbein and Ajzen (1975), intentions can be affected by external variables but only to the degree that they influence attitudes or subjective norms (M. Fishbein & Ajzen, 1975). These external variables can include for example system architecture, user attributes (e.g. cognitive and personality), job traits, or otherwise that shape individuals' attitudes and their perceptions of subjective norms regarding a technology (or organization, or practice, etc.) and ultimately their intention to adopt the technology (or apply for a position, or utilize a given practice, respectively) (Davis et al., 1989). As Davis et al. (1989) suggested, this implies that the theory of reasoned action mediates the effect of irrepressible environmental changes and manageable interferences on user behavior, adding “If so, then the theory of reasoned action captures the internal psychological variables through which numerous external variables studied in information systems research achieve their influence on user acceptance, and may provide a common frame of reference within which to integrate various disparate lines of inquiry” (Davis et al., 1989, pp. 984-985).

Other inclusion and expansion variables have also been suggested for the theory of reasoned action. Fishbein (1967) included personal norms, finding an individual's intention to perform any behavior in a given situation and eventually the behavior itself is a function of his attitude toward performing the behavior in that situation, his perception of the norms governing the behavior in that situation, and his compliance with these norms (M. E. Fishbein, 1967). Gorsuch (1983) added a component measuring moral obligation to Ajzen and Fishbein's original model by experimenting with Baptist Sunday school classes who were exposed to two morally relevant and two not morally relevant hypothetical situations, finding moral considerations added significantly to prediction of behavioral intention and are necessary to predict behavioral intentions in moral situations (Gorsuch & Ortberg, 1983). Zuckerman and Reis (1978) also examined moral obligations by comparing three models for understanding altruistic behavior, investigating intention patterns in blood donations and demonstrating that intentions and attitudes best foretold of willingness to donate, while intentions were defined as a byproduct of attitudes and norms (both social and moral). These outcomes supported Fishbein’s model and added a direct attitude–behavior link (Zuckerman & Reis, 1978). And, competing attitudes (including elements of affect, cognition, and conation) were studied via couples’ contraceptive preferences reaffirming that individuals will be most likely to perform the behavior towards which they have the most positive attitude (Davidson & Morrison, 1983).

Fishbein and Ajzen (1975) additionally detailed three boundary conditions that can alter the relationship between intentions and behavior. First, intention measures and behavioral measures should specifically align and be recent – "measure of intention available to the investigator must reflect respondents' intentions as they exist just prior to performance of the behavior") (M. Fishbein & Ajzen, 1975, p. 18). In general, intentions and behavior should be assessed on the same time horizon and scope of objective activities. Second, intentions should remain consistent while being measured and while the behavior completed. Third, individuals should have volitional control of their intentions and behaviors (M. Fishbein & Ajzen, 1975). This boundary condition is extended by the subsequent theory of planned behavior as it entails a self-efficacy component where individuals who feel better equipped and more prepared for performing a specific behavior have increased perceived behavioral control over that behavior (Madden et al., 1992).

From a theoretical point of view, the theory of reasoned action is perceptive, parsimonious, and incisive in its behavior explanation capability (Bagozzi, 1982). And, as a predictive model, has been used in a variety of fields to predict individuals' actions based on certain criteria. Prestholdt et al. (1987) utilized the theory of reasoned action to build a model of nurse turnover, demonstrating its usefulness both from theoretical and practitioner perspectives, finding the significant predictors of differential intention (the difference between remaining or resigning) were differential attitude, differential subjective norm, and differential moral obligation (Prestholdt, Lane, & Mathews, 1987).

Prestholdt et al. (1987) found the theory of reasoned action relevant to process models of turnover as it “…(a) focused on the individual as the unit of analysis, (b) recognized the role of the individual's perception and evaluation of alternatives to the present job, and (c) consider[ed] the individual's intention as the immediate determinant of behavior” (Prestholdt et al., 1987, p. 1). In the field of education, Fredricks (1983) examined class attendance of 236 undergraduates as the behavioral measure and, consistent with the theory of reasoned action, did not find a significant direct path from attitude to subsequent behavior (Fredricks & Dossett, 1983). Drawing upon a sample of 134 women who imagined they had discovered a change in their breast, Timko (1987) presented a choice between two alternatives based on the theory of reasoned action – 1) contacting a doctor quickly (prompt behavior) or 2) self-examination and monitoring without professional intervention (delay behavior), finding that intentions to delay were positively related with favorable attitudes toward delay and with the social perception of pressure to delay. Further, intentions were more heavily influenced by attitude than social norms (Timko, 1987). Similarly, Huang examined the antecedents (destination image, subjective norms, constraints, and constraint negotiation) of behavioral intentions in the travel industry with results suggesting that behavioral intentions were positively impacted by destination image and subjective norm yet negatively affected by constraints (Y.-C. Huang, 2009). Lastly, Richardson et al. (2013) tested the applicability of the theory of reasoned action with potential informers within fraternity and sorority hazing with results indicating the theory has a thorough context for predicting informers’ intentions while the severity level of the proposed scenarios served as a moderator for behavioral intentions (Richardson, Wang, & Hall, 2012).

Attitude

In the theory of reasoned action, attitude is defined as “predispositions to respond in a particular way toward a specific class of objects” (Rosenberg, 1960, p. 1). As they are not able to be directly observed or measured, these predispositions are instead inferred by personal reactions to specific stimuli (Rosenberg, 1960). Attitude to a behavior alludes to what level an individual has a favorable or unfavorable assessment of said behavior. In the theory of reasoned action, attitude is suggested to be the initial and most crucial antecedent of behavioral intentions and is an individual’s belief, positive or negative, about completing a specific action (Y.-C. Huang, 2009). Once an attitude is established about an act or event, the attitude then forms behavioral intentions in relation to that act (Ajzen, 1985). An individual will intend to carry out a specific behavior they evaluate positively, and conversely, will not intend to carry out a behavior they evaluate negatively. As such, both the theory of reasoned action and the theory of planned behavior presume that attitudes have a direct effect on behavioral intentions (Y.-C. Huang, 2009).

As Ajzen (1991) offered, “The relative importance of attitude, subjective norm, and perceived behavioral control in the prediction of intention is expected to vary across behaviors and situations. Thus, in some applications it may be found that only attitudes have a significant impact on intentions, in others that attitudes and perceived behavioral control are sufficient to account for intentions, and in still others that all three predictors make independent contributions” (Ajzen, 1991, p. 188). Studies, including Marcoux and Shope (1997), have demonstrated that external variables such as peer pressure and friends’ experience in an activity (in this case underage alcohol consumption) is more important in predicting intention than attitude towards that behavior (Marcoux & Shope, 1997).

Subjective Norms

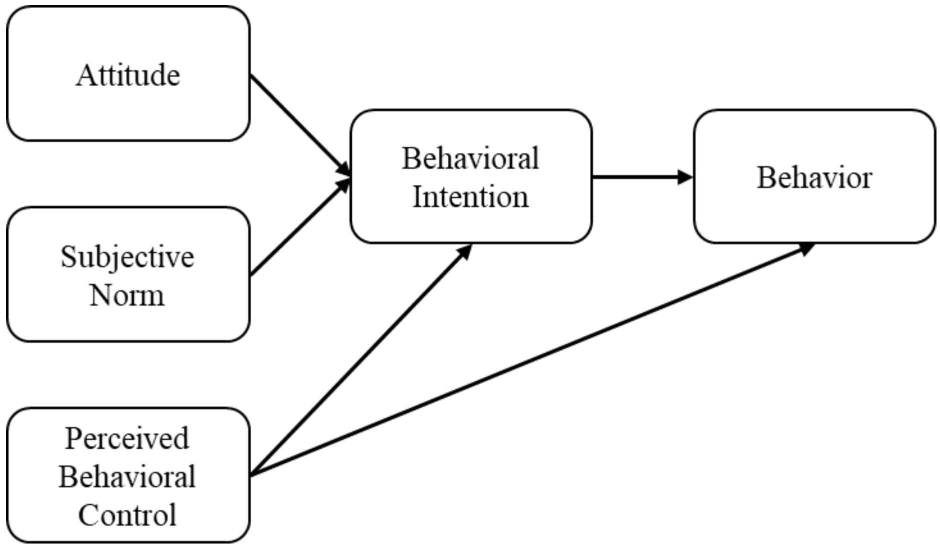
Subjective norms are defined as individuals' perceptions of how others who are valuable to that person believe the individual should or should not carry out the behavior being considered (e.g. apparent societal pressure to act on or not act on a behavior) (Chang, 1998). It is presumed that an individual will intend to carry out a certain behavior when they perceive that vital individuals (family, friends, colleagues) think they should (Ajzen, 1985). Subjective norms and behavioral intentions can be directly linked under the guise of compliance with the individual accepting influence in exchange for favorable feedback from another person or group (Venkatesh & Davis, 2000).

However, even as the theory of reasoned action gained prominence in social science, several inadequacies and limitations were discovered. Mainly, how does the theory of reasoned action apply to those individuals who have little behavioral or attitudinal control. Or as Ajzen described, the spectrum of behavior and attitudes with facets ranging from minimal control to maximal control (Ajzen, 1985). To mitigate these shortcomings, a third component was added to the original the theory of reasoned action – perceived behavioral control (e.g. will my phone support mobile banking and what are the requirements). This addition by Ajzen resulted in a new theory known as the theory of planned behavior.

Theory of Planned Behavior

As an extension of the theory of reasoned action, the theory of planned behavior extended the boundary condition of pure volitional control and addressed the original model's incapacity to deal with volitionally uncontrolled behaviors. At the core of the theory of planned behavior is the individual's intention to carry out a specific behavior (Marangunić & Granić, 2015). According to this theory, human action is directed by three types of considerations – 1) consequential beliefs about the behavior (behavioral beliefs), 2) beliefs about the normative hopes of others (normative beliefs), and 3) performance beliefs about the existence of helping or hindering factors (control beliefs) (M. Fishbein, Ajzen, Albarracin, & Hornik, 2007). Independently, behavioral beliefs produce a positive or negative attitude toward the behavior; normative beliefs lead to perceived societal tension or subjective norm; and control beliefs contribute to perceived behavioral control, the perceived ease or difficulty of behavioral performance (M. Fishbein et al., 2007). As with attitudes, subjective norms and perceptions of behavioral control are thought to occur freely and instinctually as individuals form normative and control beliefs autonomously (M. Fishbein et al., 2007). In sum, these factors lead to the creation of a behavioral intention (Y.-C. Huang, 2009). In the theory of planned behavior, perceived behavioral control directly effects behavior and indirectly effects behavior via intentions as an exogenous variable (Madden et al., 1992). Generally, the more attitude and subjective norm are favorable, combined with a greater perceived control, the stronger an individual's intention to perform the behavior in question (Ajzen & Madden, 1986).

Figure 2.2 Theory of Planned Behavior – Ajzen (1985)



Perceived behavioral control and behavioral achievement have a direct link in the theory of planned behavior. Ajzen (1985) suggested that when intention to engage is identical, an individual with higher confidence in their personal abilities is more likely to succeed in a given behavior than someone who has uncertainties (Ajzen, 1985). Intention is also a direct antecedent of behavior, assumed to direct behavior in a controlled and deliberate fashion. However, volitional control can be limited by certain behaviors and therefore perceived behavioral control should be considered in addition to intention (Y.-C. Huang, 2009). To the degree that people judge a behavior's difficulty accurately, perceived behavioral control measures may provide a proxy of actual control and help predict the behavior in question (Ajzen, 1985). The theory's key purpose is prediction and comprehension of behavioral motivating influences not under a person's volitional control and identification of focused strategies for altering the behavior (Marangunić & Granić, 2015). Both the theory of reasoned action and the theory of planned behavior allude to the same conclusion – that attitude is the main predictor of behavior. With its aim of not merely predicting but explaining human behavior, the theory of planned behavior employs attitudes, subjective norms, and perceived behavioral control as antecedents to support in the comprehension of intentions and actions (Madden et al., 1992).

Perceived Behavioral Control

Perceived behavioral control is defined as the degree to which an individual believes that they have control over personal or external factors that may enable or restrict behavior (Ajzen, 1985). When complete volitional control is non-existent, the individual must have the essential abilities and chances to carry out the behavior. The more abilities and chances an individual feels they possess, the more pronounced their perceived behavioral control should be on the behavior (Y.-C. Huang, 2009). Ajzen (1985) believed that individuals are unlikely to formulate a robust intention to perform a behavior if they think that they do not have enough abilities or chances to do so even if they carry positive attitudes about the behavior and think that personally valued individuals would approve of the behavior. Therefore, perceived behavioral control is believed to be positively and directly linked to behavioral intention (Ajzen, 1985). This assumption has been supported by myriad human behavior studies (Bamberg, Ajzen, & Schmidt, 2003; Conner, Martin, Silverdale, & Grogan, 1996; Hagger, Chatzisarantis, & Biddle, 2002; Hrubes, Ajzen, & Daigle, 2001).

A major limitation of the theory of planned behavior is that the theory only applies when some behavioral aspect is not under volitional control as it assumes that human beings are inherently rational and consistently make logical decisions based on available information. This is important as situations may arise that could hamper the volitional control of an individual in certain situations. And, where complete volitional control in not exhibited on the behavior, the individual must have the necessary attributes and chances to perform the behavior; thus, distinct predictive and explanative models are necessary for voluntary and involuntary behaviors (Kiriakidis, 2015). Hence, unconscious motives are not considered (Marangunić & Granić, 2015).

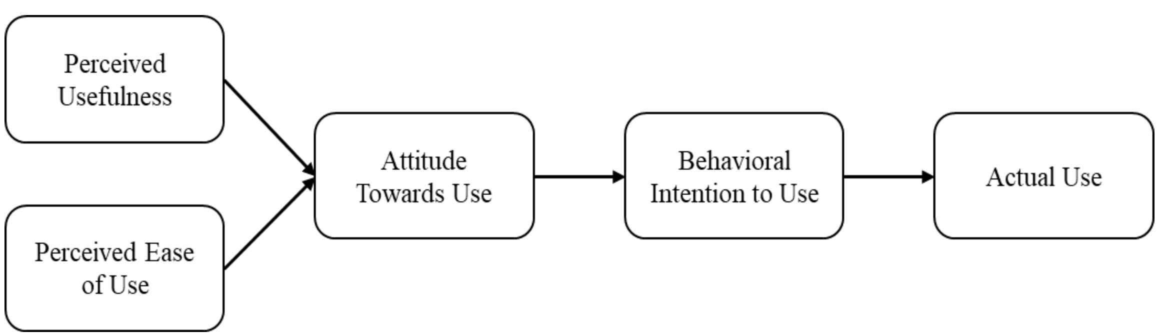
Other gaps in research based on the theory of planned behavior include not considering factors, such as personality differences between genders (e.g. hierarchy, independence, intimacy, solidarity) and use of e-mail as examined by Gefen (1997), who finds men and women vary in their views but not utility of e-mail (Gefen & Straub, 1997). Additionally, demographic characteristics such as internal and external control (abstracted as technology self-efficacy), intrinsic motivation (abstracted as technology playfulness), and emotion (abstracted as technology anxiety) are studied by Venkatesh (2000) as anchors that define a new technology's perceived ease of use of (Venkatesh, 2000). Likewise, Mathieson (1991) discovered that perceived behavioral control may not always predict actual behavioral control when comparing the theory of planned behavior and the technology acceptance model (Mathieson, 1991). This is pertinent as fintech solutions, as with all information systems, cannot be effective unless they are used. Yet, consumers sometimes do not use offerings that could potentially increase their performance. And, since it is impossible for unused solutions to be effective, regardless of their technological benefit, it is critically important to comprehend how individuals decide whether they will use a fintech or not.

Technology Acceptance Model Development

Davis (1985) believed despite their limitations, both the theory of reasoned action and theory of planned behavior provided valuable models that could potentially explain and predict the actual behavior of an individual. Though, quickly adaptation problems of these models to various environments (e.g. user acceptance of a technology) arose with most experiments failing to produce reliable measures that could explain system acceptance or rejection (Marangunić & Granić, 2015). To create a dependable predictive model that would address actual use of any technology, Davis (1985) modified these theories to form the technology acceptance model (TAM). To fit his needs, Davis (1985) considered the use of a technology as a behavior and made two core changes to the theory of reasoned action and the theory of planned behavior models – 1) he did not account for subjective norms in predicting an actual behavior, exclusively considering an individual's attitude toward it and 2) he identified two discrete beliefs, perceived usefulness (PU) and perceived ease of use (PEU), deemed adequate to predict an individual's attitude toward the use of a technology (Davis, 1985). With TAM originally intended to be employed in a laboratory setting during his dissertation, Davis (1985) omitted subjective norms as they are not likely to be operative in a laboratory setting (Davis, 1985). Davis (1985) further explained, "Recall that the objective of the model is to explain the causal mechanisms linking the design characteristics of systems to actual usage behavior. Thus, some theoretical concern centers around the possible role of subjective norm as an alternative mechanism by which differences in system features may affect usage. It is quite plausible that the characteristics of a system may affect a referent's opinion regarding whether a potential user should or should not use that system. If such an effect on subjective norm directly influences intention or behavior, then we should view subjective norm as a mediating construct apart from attitude. Conversely, if social norm influences behavior only indirectly through its effect on attitude, then subjective norm does not function as an independent mediator, its effects on behavior being mediated by attitude" (Davis, 1985, p. 227). Further, behavioral control, referring to the various resources and skills needed to use a technology, is treated differently between TAM and the theory of planned behavior with PEU the only such variable included in TAM (Mathieson, 1991). The theory of planned behavior identifies the important behavioral control variables for each situation independently and has a higher likelihood of capturing such situation-specific factors while TAM is unlikely to identify peculiar impediments to use (Mathieson, 1991). This is consistent with the stated objective of Davis et al. (1989) to create a model that is relevant across many conditions, but inadvertently will cause the model to overlook control issues that are critical in certain contexts (Davis et al., 1989; Mathieson, 1991).

Davis (1985) defined perceived usefulness as the extent to which individuals view the use of a given technology as potentially increasing their job performance, whereas perceived ease of use is defined as the extent to which individuals view using a technology as being relatively effort-free (Davis, 1985). Technological design characteristics were indicated to directly influence both beliefs.

Figure 2.3 Technology Acceptance Model (TAM) – Davis (1985)



Davis' original conceptual TAM, emerging from psychological research and theory, suggested that usage of technology is a response that can be predicted or explained by user motivation, which, subsequently, is directly influenced by an external stimulus consisting of the actual solution's features and functionalities (Marangunić & Granić, 2015). Following conceptual TAM refinements suggested that the user's motivation can be explained by three factors: PU, PEU, and attitude toward using. Davis (1985) hypothesized that the attitude of a user toward a specific technology was a major determinant of whether the user will actually use or reject the technology (Davis, 1985). Therefore, PU and PEU were found to influence user attitude with PEU having a direct influence on PU (e.g. the easier the technology is to use, the more useful the technology is deemed). Both beliefs subsequently were postulated to be influenced directly by system design characteristics (e.g. web interface, security). As Davis (1991) elaborated through a field study of 112 users regarding two end-user systems, the attitudes and behavioral intentions of TAM "fully mediated the effects of system characteristics on usage behavior, accounting for 36% of the variance in usage…and finding that perceived usefulness was 50% more influential than ease of use in determining usage, underscoring the importance of incorporating the appropriate functional capabilities in new systems" (Davis, 1993, p. 475). Academics and practitioners alike endeavor to better understand how to choose from the myriad of possibilities afforded by technology those particular system design features that will contribute most to user acceptance and performance (Goslar, 1986; Klein & Beck, 1987; Reimann & Waren, 1985). Further, TAM proposed that both PU and PEU influence a user's attitude toward the technology as well as regularly account for 40% of a user's intention to accept and adopt a technology (Gangwar & Date, 2016).

Later, Davis et al. (1989) discovered that attitude toward using did not fully mediate PU and PEU and, as such, suggested a parsimonious TAM where attitude toward using was removed as a construct (Davis, 1989). That same year, Davis et al. (1989), to more efficiently explain and accurately predict the user's behavior of information technology, modified the theoretical model to encompass the application of information systems context (Davis et al., 1989). This suggested there would be instances when a technology was perceived as useful, and a user may develop a compelling behavioral intention to use that technology but without forming any attitudinal connection, necessitating a revised version of TAM. With the attitude construct eliminated and the behavioral intention construct introduced, results achieved for the direct influence of PU on the actual technology use became explainable. Simultaneously, inexplicable direct influence noted from the system characteristics to the attitude variable was eliminated by removing said attitude variable (Marangunić & Granić, 2015). Further changes to the original TAM was the contemplation of additional factors, referred to as external variables (e.g. variables not included in the original TAM above), which may influence the beliefs of an individual toward a technology. Typical external variables include system characteristics, user training, user participation design, and the nature of the implementation process (Venkatesh & Davis, 1996). In 2003 Venkatesh et al., leveraging the constructs of eight prior models, formed the unified theory of acceptance and use of technology (UTAUT) which has four predictors of users' behavioral intention including 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions as well as four key moderators including 1) gender, 2) age, 3) voluntariness, and 4) experience (Venkatesh, Morris, Davis, & Davis, 2003). Subsequent validation of

UTAUT in a 2012 longitudinal study, UTAUT2, incorporated three new constructs into the original UTAUT model – 1) hedonic motivation, 2) price value, and 3) habit – which resulted in a considerable improvement in the variance explained in behavioral intention (from 56% to 74%) and actual technology use (from 40% to 52%) (Venkatesh, Thong, & Xu, 2012).

The literature landscape of TAM is vast and informed by the theory's broad applicability to not only various technologies but various fields of study. For conciseness and organizational purposes, I will leverage three literature streams – 1) application of TAM, 2) antecedents / determinants of TAM, and 3) moderators of TAM.

Application of TAM

A predominant thread of TAM literature focuses on application to information technology due to it continuous growth and almost exponential number of new users (Marangunić & Granić, 2015). Acceptance and usage studies of the internet itself have been conducted by Shih (2004) who extends TAM to internet consumption showing that the need for relevant information strongly determines PU, PEU, and user attitudes toward internet use for data discovery as well as heavily influences user performance during the information gathering stage (Shih, 2004). Lee and Kim's (2009) confirmatory study indicated that internet usage is influenced by various considerations, including technical support, online experience, task characteristics, and the extent to which one perceives the internet easy to use while Lee et al. (2012) extended TAM to explain the method by which attitude is influenced by social media marketing campaigns for Facebook event pages, finding that users' emotions exhibited on the social media pages indeed have a significant impact on the PU, PEU, and perceived enjoyment of such social media marketing (S. Lee & Kim, 2009; W. Lee, Xiong, & Hu, 2012). Wireless internet is explored by Yu et al. (2003) and Wu et al. (2011) with results indicating that TAM, either original or parsimonious, is successful in explaining user intention to use wireless technology in organizations (J. Lu, Yu, Liu, & Yao, 2003; C.-S. Wu, Cheng, Yen, & Huang, 2011).

Son et al. (2012) extended TAM to mobile internet use in the construction industry finding that user satisfaction was an important indicator of the intent to adopt mobile computing devices in that industry (Son, Park, Kim, & Chou, 2012). Park et al. (2016) studied factors affecting the adoption of long-term evolution mobile phone services in South Korea showing there were no distinctions between the effects of perceived usefulness, perceived ease of use, and perceived enjoyment on LTE service use intention (S.-T. Park, Im, & Noh, 2016). Citizen acceptance of mobile government (m-government) services was underpinned by TAM with Almarashdeh and Alsmadi (2017) finding that various independent variables, including not only PU and PEU but also social influence, cost of service, one's perception of trust in the government, influence citizen's behavioral intentions and actual use behaviors of mobile government services (Almarashdeh & Alsmadi, 2017). And, strategies to adopt cloud computing show that despite potential benefits, security and privacy risks are deterring many users from implementing (Eltayeb & Dawson, 2016; Stieninger, Nedbal, Wetzlinger, Wagner, & Erskine, 2018; Tripathi, 2017).

System-specific TAM applications have dominated the research landscape as well. Hong et al. (2002) applied TAM on a digital library system with results strongly endorsing leveraging TAM in predicting adoption intentions, and demonstrated key external variables effects on behavior intention through perceived ease of use and perceived usefulness (Hong, Thong, Wong, & Tam, 2002). These variables, which included a set of individual differences (computer self-efficacy and search engine knowledge) and system characteristics (relevance, terminology, and screen design), were studied in a college's online library finding that both variables significantly affect perceived ease of use of the platform. Additionally, relevance had the greatest influence on perceived usefulness of online libraries (Hong et al., 2002). Liaw and Huang (2003) examined user attitudes on search engines showing that use is affected by user experience, search engine quality, motivation, and technology acceptance perceptions (Liaw & Huang, 2003). Yi and Hwang (2003) employed TAM predictively to study online information systems and highlighted the critical roles of self-efficacy, enjoyment, and learning goal orientation in influencing actual system usage (Mun & Hwang, 2003). Serenko (2008) applied TAM to adoption of email alert notifications finding email users to be highly innovative operators who thoroughly enjoyed the usefulness and ease of use associated with the system functionality (Serenko, 2008). Lai (2017) proposed security as an extension to TAM by suggesting that security, along with perceived usefulness and perceived ease of use, significantly contribute to consumers' intention to utilize a single shared platform payment (Lai, 2017). According to Lai (2016), "…the security are the stimulus that represent the system and features capabilities while, the perceived ease of use and perceived usefulness are the organism that represents the motivation to use the system that leads to consumers' respond to use the system" (Lai, 2016, p. 113).

Application of TAM on internet banking systems is addressed by Chan and Lu (2004) who demonstrate that both subjective norm and computer self-efficacy indirectly plays significant parts in influencing adoption intentions toward online banking while Nasri and Charfeddine (2012) provided an integrated TAM and theory of planned behavior model, employing security and privacy, self-efficacy, and support (governmental and technological), with results confirming the applicability of TAM and the theory of planned behavior in predicting internet banking adoption (Chan, 2004; Nasri & Charfeddine, 2012).

Bridging systems and healthcare, Hu et al. (1999) posited that TAM is reasonably able to assess intention of physicians to utilize telemedicine technology with results suggesting perceived usefulness to be a significant determinant of attitude and intention while perceived ease of use was not (P. J. Hu, Chau, Sheng, & Tam, 1999). Similarly, Chau and Hu (2002) reaffirmed this finding based on responses from more than 400 physicians while focusing on internet-supported medical procedures, suggesting that TAM may be more appropriate than the theory of planned behavior for examining individual professionals' technology acceptance (Chau & Hu, 2002). Melas et al. (2011) predicted acceptance of clinical information systems showing that TAM predicts a substantial proportion of the intention to use clinical information systems (Melas, Zampetakis, Dimopoulou, & Moustakis, 2011). That same year, Pai and Huang (2011) applied TAM to healthcare information systems finding that perceived usefulness mediated information, service, and system quality with perceived ease of use found to influence intention to use a healthcare information system (Pai & Huang, 2011). Recently, Ebrahimi et al. (2018) researched technology acceptance determinants of physicians for mobile health services and found contemporary technology strategies could serve to improve the healthcare quality of service (Ebrahimi, Mehdipour, Karimi, Khammarnia, & Alipour, 2018).

An underserved field in incorporating new technologies is the domain of learning and teaching. Specifically, the educational system comprises a vast range of prospective technology users that could assist in the process of knowledge transfer and acquisition thereby emphasizing the criticality of technology acceptance or rejection (Marangunić & Granić, 2015). Park et al. (2007) and Farahat (2012) both utilized the original TAM, with the former suggesting perceived ease of use of an internet-based course management platform has a significant impact on perceived usefulness, and the latter revealing important determinants of students' intention to participate in online learning included perceived of ease of use and usefulness, attitudes, and the societal influence of referent groups (e.g. professors, teaching assistants, classmates) (Farahat, 2012; N. Park, Lee, & Cheong, 2007). Gong et al. (2004) focused on web-based learning with results showing that computer self-efficacy has a strong direct effect on intention to use and can significantly enhance users' perceived ease of use while Zhang et al. (2008) posited an intrinsic motivation perspective for online learning systems and finds a significant impact on learners' acceptance behavior towards using web-based learning systems (Gong, Xu, & Yu, 2004; S. Zhang, Zhao, & Tan, 2008). Cheung and Vogel (2013) predicted user acceptance of collaborative technologies finding major factors driving technology adoption are self-efficacy, sharing, and peer norms with peer norms moderating the relationship between attitude and behavioral intention (Cheung & Vogel, 2013). TAM application for mobile learning is the target of Huang et al. (2007) and showed positive consumer attitudes for mobile learning, recognizing it as an effective tool. In particular, the results implied user acceptance is greatly impacted by individual differences and that user intentions of mobile learning use can be predicted by perceived enjoyment and perceived mobility (J.-H. Huang, Lin, & Chuang, 2007). Lastly, Huang (2017) explored student acceptance of group messaging applications and discovered students with an appreciation / social presence of others are affected and spurred to utilize social media for collaboration and learning (Y. M. Huang, 2017).

Overall, research has provided significant support for the core technology acceptance model. Moreover, research has elaborated upon the core model, theorizing and finding support for key antecedents to perceived ease of use and perceived usefulness (e.g. individual-level differences across users, systems, and industries) and key moderators of the X-Y relationship (e.g. experience, voluntariness). While some key antecedents (covered in detail in the following section) organically overlap this section, the above focuses on the application of TAM literature stream whereby TAM is applied on different structures by introducing new factors with the goal of increasing predictive validity as well as better understanding determinants of technology acceptance.

Antecedents / Determinants of TAM

Davis and Venkatesh are prolific pioneers in the field of TAM and subsequently this stream of TAM antecedents / determinants. First Venkatesh and Davis (1996), in a practical attempt to aid in design of effective training interventions and user interfaces, researched the antecedents of perceived ease of use with a longitudinal, multisubject, multi-technology study with findings supporting the hypotheses – ease of use is continually anchored to an individual’s overall technology self-efficacy, and that perceived ease of use is impacted by objective usability only after direct experience with the technology (Venkatesh & Davis, 1996). Following, Davis and Venkatesh (1996) incorporated the external predictor of self-efficiency to address biases in TAM measurement, finding that grouping and intermixing of items had no significant (positive or negative) effect on the high levels of TAM scale reliability and validity (Davis & Venkatesh, 1996). After, Venkatesh (2000) introduced and examined an anchoring and adjustment-based theoretical model of technology-centric perceived ease of use determinants by examining a multi-organizational, multi-employee longitudinal study. Including anchors (general convictions about computers and computer utilization) and adjustments (views influenced by direct experience with the target system) as the antecedents to PEU, results concluded that individuals' computer-related beliefs determine PEU, even after direct interactions with the technology (Venkatesh, 2000). Specifically, "The model proposes control (internal and external – conceptualized as computer self-efficacy and facilitating conditions, respectively), intrinsic motivation (conceptualized as computer playfulness), and emotion (conceptualized as computer anxiety) as anchors that determine early perceptions about the ease of use of a new system" with adjustments including perceived enjoyment and objective usability (Venkatesh, 2000, p. 342).

With the aforementioned studies focusing on perceived ease of use and due to consistent findings that perceived usefulness is a key determining factor of intention to use (Davis, 1989; Davis et al., 1989), Venkatesh and Davis (2000) proposed an extended model named TAM 2 aiming to identify antecedents to perceived usefulness (Marangunić & Granić, 2015). These variables include subjective norm, image, job relevance, output quality, and result demonstrability (Venkatesh & Davis, 2000). First, subjective norm (defined earlier in this paper as individuals' perceptions of how others who are valuable to that person believe the individual should or should not carry out the behavior being considered), was adopted from the theory of reasoned action as a method for capturing societal influences on perceived usefulness since technology adoption happens within a communal environment and societal influences are often included in theoretical technology acceptance (or rejection) models (Anderson, Al-Gahtani, & Hubona, 2011; Srite & Karahanna, 2006). Of note, experience and voluntariness were incorporated as moderating factors on subjective norms. Image, a second mechanism of social influence and defined as "the degree to which use of an innovation is perceived to enhance one's…status in one's social system" (e.g. the desire of the user to maintain a favorable standing amongst others) is adopted from Moore and Benbasat (1991) (Moore & Benbasat, 1991, p. 195). Third, job relevance is defined as "as an individual's perception regarding the degree to which the target system is applicable to his or her job" (e.g. the degree to which the technology is applicable) (Venkatesh & Davis, 2000, p. 191). Fourth, output quality is defined as "perceptions of how well the technology performs tasks" (e.g. the extent to which the technology adequately performed the required tasks (Venkatesh & Davis, 2000, p. 191). And fifth, result demonstrability (also adopted from Moore and Benbasat, 1991) defined as "tangibility of the results of using the innovation" (Moore & Benbasat, 1991, p. 203). Conducting a longitudinal study of 156 subjects over two voluntary usage environments and two involuntary (mandatory) usage environments, Venkatesh and Davis (2000) discover that subjective norm, image, job relevance, and result demonstrability are significant determinants of perceived usefulness while subjective norm, perceived usefulness, and perceived ease of use are direct determinants of intention to use (Venkatesh & Davis, 2000). This followed Barki and Hartwick (1994) reintroducing the factor of subjective norm to the model through user participation, conflict, and conflict resolution in information system development discovering the dual role of influence in conflict emergence and conflict resolution (Barki & Hartwick, 1994).

TAM 2 is a response in part to one of the criticisms of the original TAM that there is trouble actioning the results of the model (Gefen & Keil, 1998) with a potential mitigation being the discovery of antecedents to perceived usefulness and perceived ease of use which could make TAM more pragmatically actionable (Anderson et al., 2011). As mentioned earlier, Davis (1989) had studied antecedents to TAM in his early exploration, but found that they were fully mediated by perceived usefulness and perceived ease of use (Davis, 1989).

Agarwal and Prasad (1997) introduced the additional belief factor of trialability, “the extent to which potential adopters perceive that they have an opportunity to experiment with the innovation prior to committing to its usage”, to TAM confirming that that innovation characteristics do explain acceptance behavior, that precise characteristics that are pertinent for each acceptance outcome vary, and that external pressure has an influence on adopters’ acceptance behavior (Agarwal & Prasad, 1997, p. 562). These innovation characteristics are as follows – 1) compatibility – belief that innovation aligns with innovator's work behavior, 2) visibility – perception of innovation being visible in organizational context, 3) trialability (defined above), and 4) voluntariness – perception of innovation use being voluntary (Agarwal & Prasad, 1997, p. 568). Trialability imparts users a commitment free test drive of the technology prior to agreeing to sustained usage; this experimental feeling allows adopters to freely explore a new technology and experience its complications first hand, the more likely they will be early stage adopters (Agarwal & Prasad, 1997). Plouffe et al. (2001) reaffirmed Agarwal and Prasad (1997) and incorporates technology characteristics in understanding merchant adoption of a smart card-based payment system discovering the perceived characteristics of innovation set of antecedents (relative advantage, compatibility, trialability, visibility, image, result demonstrability, and voluntariness) explains significantly more variance than TAM does, while correspondingly affording managers with more detailed data regarding the antecedents propelling innovative technology adoption (Plouffe, Hulland, & Vandenbosch, 2001). Plouffe et al. (2001) adds, “Perceived characteristics of innovation can have a direct impact on intentions even after controlling for the effects of usefulness (or relative-advantage) and ease-of-use” (Plouffe et al., 2001, p. 218). Interestingly, TAM 2 incorporated image and result demonstrability as antecedents to perceived usefulness but does not model their direct effects on intention (Venkatesh & Davis, 2000). Visibility (the degree to which the innovation is visible in the organization) is incorporated by Karahanna et al. (1999) with consideration adoption beliefs (pre and post) and attitudes of Windows technology usage, arguing that using a unitary set of beliefs to explain different stages of the innovation decision process may lead to important relationships being obfuscated (Karahanna, Straub, & Chervany, 1999). Further findings concluded that “users and potential adopters of technology differ on their determinants of behavioral intention, attitude, and subjective norm; potential adopter intention to adopt is solely determined by normative pressures, whereas user intention is solely determined by attitude; and potential adopters base their attitude on a richer set of innovation characteristics than users” (Karahanna et al., 1999, p. 183). Hardgrave et al.

(2003) investigated subjective norms via the intentions of software developers' to follow methodologies finding, contrary to popular belief, that an organizational mandate is not sufficient to guarantee use of the formalized methodology in a sustained manner (Hardgrave, Davis, & Riemenschneider, 2003).

Usage measures and perception for system operationalization is common across various studies and used to better understand determinants of technology acceptance. Szajna (1996) confirmed that TAM is a valuable tool for predicting intentions to use information technology via usage perception (Szajna, 1996). Horton et al. (2001) applied TAM in explaining intranet usage in two organizations with results indicating that its applicability may vary between groups and shows that the measures of self-reporting and usage are not exchangeable (Horton, Buck, Waterson, & Clegg, 2001). Moon and Kim (2001) extended TAM to encompass the world-wide-web and found PU and PEU to be important to user’s perceptions of world-wide-web systems. Additionally, perceived playfulness seems to influence an individual’s attitude toward using and therefore, perceived playfulness may also be an important factor in the design of future online platforms to ensure intensity, interest, and pleasure (Moon & Kim, 2001). Mathieson et al. (2001) extended TAM through exploring the influence of perceived user resources (e.g. time, money, expertise) and perceived behavioral control with results confirming that perceived user resources is a valuable addition to TAM and expanded the model’s range in scenarios with resource constraints (Mathieson, Peacock, & Chin, 2001).

Davis et al. (1989) incorporated attitude toward technology by comparing two theoretical models, the theory of reasoned action and TAM, finding 1) individual’s intentions were strongly effected by PU with the construct explaining more than half of the variance, 2) individual's intentions were significantly influenced (albeit minimally) by PEU but with the effect fading over time, 3) effects of these beliefs on intention experienced only partial mediation by attitudes, and 4) subjective norms had no effect on intentions (Davis et al., 1989). Davis also, along with Venkatesh (2004), investigated actual usage of technology through software project management, demonstrating that steady and prognostic assessments of a system's PEU should be centered on direct behavioral experience of individuals using the system. Yet, focused users with little to no direct / applied system experience can still provide steady and behaviorally prognostic measures of PU if they have been provided prior background information on a system's functionality (Davis & Venkatesh, 2004). This distinction is critical as, in comparison to ease of use, usefulness is normally considerably more strongly connected to future usage intentions and workplace behaviors.

Oh et al. (2003) and Burton-Jones and Hubona (2006) both incorporated prior usage and experience finding, respectively, that new technology adoption experiences and opportunities affect user attitudes via three extended TAM constructs (PU, PEU, and perceived resources) and that external variables can have direct effects on usage behavior in addition to their indirect effects (Burton-Jones & Hubona, 2006; Oh, Ahn, & Kim, 2003). The individual and combined effects of affect and technology anxiety on digital learning management platform usage perceptions are explored by Saade and Kira (2006) with results demonstrating the interplay that exists between affect and anxiety and their moderating roles on PU and PEU, and seemingly suggesting that affect and anxiety may exist concurrently (Saadé & Kira, 2006). Lee and Lehto (2013) introduced content richness through user acceptance of YouTube for technical education with results suggesting that behavioral intention was significantly influenced by both perceived usefulness and user satisfaction. Additionally, task-technology fit, content richness, vividness, and platform self-efficacy surfaced as significant predictors of perceived usefulness while perceived ease of use was not significantly predictive of either perceived usefulness or behavioral intention (D. Y. Lee & Lehto, 2013). For this study, perceived ease of use was evaluated with four items from Venkatesh et al. (2002), encompassing the perceived effortless nature of YouTube by users (Venkatesh, Speier, & Morris, 2002). Plausible explanations for the non-significant results could be that users did not keep perceived ease of use top of mind when considering acceptance decisions or, with the predominance of users in the current study having at least one year of YouTube experience, the influence of perceived ease of may not be able to explain a significant proportion of the distinct variances in perceived usefulness and behavioral intention (D. Y. Lee & Lehto, 2013). Perceived ease of use can then be looked at since it has a direct effect on perceived usefulness (Davis, 1985).

In summary, antecedents can include components from related models (e.g. subjective norm, perceived behavioral control, self-efficacy), supplementary belief influences (e.g. trialability, visibility, content richness) and external variables (e.g. system characteristics, user training, implementation process) – all included in this literature stream to explain the predictors of the core elements of TAM. Of major note and worth reinforcing, Venkatesh's (2000) study interested in identifying antecedents to perceived ease of use where two main groups of antecedents are identified – 1) anchors (e.g. general beliefs about technology and technology usage) and 2) adjustments (e.g. beliefs shaped by direct experience with a target technology) (Venkatesh, 2000). Contemplating these belief antecedents helped illuminate the role of trust within technology adoption. Specific to this dissertation, the critical importance (and current research gap) of trust of fintech solutions due to the novelty of the technologies and the highly confidential nature of data involved in the provision of the service.

Trust is a critical focus of research on the issue of adoption and is often used an additional basis to attract users besides perceived usefulness and perceived ease of use. Gefen incorporated trust and TAM via enterprise resource planning implementation with data showing that client trust in an enterprise resource planning customization vendor and the perceived usefulness of the enterprise resource planning system both help ascribe meaningful value to vendor relationships from a client perspective (Gefen, 2004) and in an electronic commerce (e-commerce) setting finding that returning customers trusted the e-commerce vendor more, perceived the platform to be more useful and easier to use, and were more predisposed to buy from it (Gefen, Karahanna, & Straub, 2003a). Wu et al. (2011) suggested through direct effect analysis that trust is an important variable that influences IT adoption (K. Wu, Zhao, Zhu, Tan, & Zheng, 2011). Trust is part decision (e.g. choosing to put your faith in a partner) and part expectation (e.g. the belief that partner will perform nobly and aligned with a mutually agreed upon standard) (Currall & Inkpen, 2002). Trust is an interdisciplinary concept that traverses the fields of sociology, management, and organizational behavior just to name a few (Ireland & Webb, 2007; M. K. Lee & Turban, 2001; Lewis & Weigert, 1985; McKnight & Chervany, 2001). In applying to fintech, the role of trust is important due to the sensitive, high-dimensional, and personal nature of the data involved in the transaction of the service (Z. Hu et al., 2019). There are several categorizations of trust (Barney & Hansen, 1994; Rousseau et al., 1998; Sako, 1992) as Ireland and Webb (2007) illustrate (Ireland & Webb, 2007). For purposes of this study, I use Sako's (1992) categorization which categorizes trust into three forms – 1) contractual, 2) competence, and 3) goodwill (Sako, 1992).

Risk is also a reoccurring theme. Featherman and Pavlou (2003) looked to predict electronic services (e-services) adoption and indicated that they are principally negatively affected by performance-based risk perceptions, yet these anxieties are reduced when perceived ease of use of the e-service is present (Featherman & Pavlou, 2003). Pavlou (2003) then furthered this research stream by integrating behavioral and environmental uncertainty variables (trust and perceived risk) with TAM constructs (PU and PEU) in a parsimonious model that together predicts e-commerce consumer acceptance (Pavlou, 2003).

Moderators of TAM

Igbaria et al. (1995) defined two aspects of motivation of computer usage in Finland – extrinsic (perceived usefulness) and intrinsic (perceived enjoyment), finding that an individual's behavior is significantly influenced by extrinsic motivation, that both perceived enjoyment and perceived usefulness are affected by perceived ease of use, in addition to usage, and that the relationship between perceived ease of use and computer usage was fully mediated (Igbaria, Iivari, & Maragahh, 1995). Similarly, Venkatesh considered and advocated for the role of intrinsic motivation, defined as "the pleasure and inherent satisfaction derived from a specific activity", as a means to create positive user perceptions during technology training (Venkatesh, 1999, p. 240). This research contained two studies comparing a conventional training method versus one that included an element of enhanced intrinsic motivation with results firmly favoring the latter training method's use of an intrinsic motivator (Venkatesh, 1999). Venkatesh et al. (2003) factored expectations – performance expectancy (the level to which an individual expects that using the technology will help improve job performance) and effort expectancy (the level of expected ease a technology provides when using) – while pushing towards a unified view of user IT acceptance and forming the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). And, Amoako-Gyampah (2007), like Gefen (2004) and Gumossy et al. (2007), leveraged ERP implementation to study perceived usefulness, user involvement, and behavioral intention with results suggesting that perceived usefulness, perceived ease of use, and the amount intrinsic involvement by the user all affect an individual's intention to use the technology. Further, managers may be able to contribute to their own implementation success efforts by promoting technology usefulness and personal relevance among users (Amoako-Gyampah, 2007).

Gefen and Straub (1997) studied gender differences in the use of e-mail as external variables to TAM by adding gender to an information technology diffusion model with findings that indicate women (who tend to focus on intimacy and solidarity) and men (who tend to focus discourse on hierarchy and independence) differ in their discernment but not utility of e-mail thus suggesting gender as a valuable construct, as well as other cultural effects, for information technology diffusion model research (Gefen & Straub, 1997). Venkatesh and Morris (2000) also introduced demographic characteristics of technology usage decisions by discovering that, comparatively, PU more strongly drives usage choices in men while PEU and subjective norm more strongly drives usage choices in women, although the effect of subjective norm diminished over time (Venkatesh & Morris, 2000). Subjective technical confidence as a moderating variable, along with age, gender, and technology expertise in the relationship between functional performance and acceptance is explored by Arning and Ziefle (2007) showing significant associations between performance (e.g. the relationship between the acceptance of technical devices and their successful utilization) and TAM factors (Arning & Ziefle, 2007). Interestingly, this relationship was much stronger for older respondents, particularly among performance and the ease of use, technology expertise and technical self-confidence played a minor role, and while gender effects on technical self-confidence and TAM factors were recognized they did not affect performance (Arning & Ziefle, 2007).

Gender and cultural diversity are requisite potential moderating contextual factors present in this path. Straub et al. (1997) tested TAM with email across a three country study with employees of three different airlines, suggesting that the model may not predict technology use across all cultures (Straub, Keil, & Brenner, 1997). Huang et al.'s (2003) study expanded cross-cultural TAM applicability by integrating social influence into its theoretical framework and finding PU is more strongly influenced by subjective norms among individuals with lower power distance (e.g. the willingness of members of an organization to accept an unequal distribution of power within that organization) than among those with higher power distance (L. Huang, Lu, & Wong, 2003). Perceived playfulness, gender differences, and TAM are blended in a learning situation by Padilla-Melendez et al. (2013) with results suggesting that gender disparities in attitude and intentions to use exist, attitude toward system use for females is influenced by playfulness, and playfulness influences attitude mediated by perceived usefulness in males (Padilla-MeléNdez, Del Aguila-Obra, & Garrido-Moreno, 2013).

Positing an all-inclusive agenda to examine numerous constructs proposed by literature that lead to the behavioral intention to use a technology, including situational (participation) and intrinsic (psychological) involvement, and argument for change (similar to the subjective norm component of the theory of reasoned action / how one feels others want him or her to behave), are studied in an organizational investment in information systems context by Jackson et al. (1997) found that the direct effect of situational involvement on behavioral intention, in addition to attitude, is significant (negatively), attitude appears to mediate, and intrinsic involvement significantly shapes perception (Jackson, Chow, & Leitch, 1997). Lucas and Spitler (1999) examined social norms, user performance, and two control variables (workload and prior performance) via a field study of broker workstations, concluding that fundamental perception variables in TAM do not predict use and that social norms and individual job requirements are of paramount importance in predicting usage as compared to workers' ease of use and usefulness perceptions (Lucas Jr & Spitler, 1999). Possibly, TAM simply does not align to a multifunctional workstation setting where there are captive and voluntary use elements (Adams, Nelson, & Todd, 1992). In these environments, there is a base level of use required to perform the job at hand, however, beyond this minimum threshold, it is likely that a complex system will be utilized in a myriad of ways with users having significant choice in employing different features and functionalities (Igbaria, Zinatelli, Cragg, & Cavaye, 1997; Jackson et al., 1997). As a result, workstations will demonstrate both voluntary and mandatory usage that will become inextricably linked and difficult to decouple when conducting usage research (Lucas Jr & Spitler, 1999). Gumussoy et al. (2007) examined subjective norms and educational level factors towards enterprise resource planning use with results indicating that subjective norms, perceived usefulness, and education level are determinants of behavioral intention to use the enterprise resource planning system. Additionally, attitude towards use affects perceived usefulness, and both perceived ease of use and compatibility affect perceived usefulness (Gumussoy, Calisir, & Bayram, 2007). Schepers and Wetzels (2007) compared moderating effects of respondent type, technology type, and culture with results indicating perceived usefulness and behavioral intention are significantly influenced by subjective norm (Schepers & Wetzels, 2007). Moderating effects were observed for all three factors with findings yielding managerial implications for both intra-company and market-based settings (Schepers & Wetzels, 2007).

Lin and Wu (2004) introduced internal and external organizational influences as casual factors of end user computing perception finding that perceived usefulness was directly affected by only management support and perceived ease of use while system usage was directly affected only by perceived usefulness – counter to findings in Igbaria et al. (1995) (Lin & Wu, 2004). In this study intraorganizational factors include internal computing support, internal computing training, and management support while extra-organizational factors consist of third party technology support and training by an external vendor (Lin & Wu, 2004). Chow et al. (2012) reexamined the topic of self-efficacy (Taylor and Todd, 1995), in the context of e-learning discovering perceived ease of use was the most influential construct to affect behavioral intention directly (Chow, Herold, Choo, & Chan, 2012). Taylor and Todd (1995) originally introduced the factor of self-efficacy to the model with results indicating that the decomposed theory of planned behavior offers a more robust understanding of behavioral intention by concentrating on the factors that are more likely to impact systems use through both design and implementation approaches (Taylor & Todd, 1995).

And while these various moderating variables (e.g. experience, voluntariness, demographic characteristics) have been introduced to provide new insights to TAMs two major belief constructs of perceived usefulness and perceived ease of use, the concept of trust and its impact specific to fintech adoption are sparse. Nonexistent to my knowledge from the lenses of contractual, competence, and goodwill trust with no study examining trust in the acceptance of artificial intelligence-driven virtual finance assistants utilizing TAM.

In summary, TAM has evolved to become a crucial model in understanding predictors of human behavior toward potential technology acceptance or rejection. Regarded as the most utilized framework in predicting information technology adoption (Legris et al., 2003) it has become so popular that it has been cited in the majority of research that studies user acceptance of technology (Y. Lee et al., 2003). TAM is a valid and robust model with the potential for broad applicability as evidenced by the variety of fields of application included in academic literature (King & He, 2006). Critically, it hypothesizes that perceived usefulness and perceived ease of use drive usage and extends other models of behavioral prediction (the theory of reasoned action and the theory of planned behavior).

2.2 Fintech

Fintech, a derived contraction short for financial technology, is defined as "a new financial industry that applies technology to improve financial activities" (Schueffel, 2016, p. 45). Although new to many in recent years, and sometimes encountered as

FinTech, Fin-Tech, or fin-tech, the term was already being used as early as 1972. While at Manufacturers Hanover Trust bank, Vice President Abraham Leon Bettinger was compiling detailed models of analyses and solutions on the days banking problems. He presented these findings in a scholarly article where he provided the following definition: “FINTECH is an acronym which stands for financial technology, combining bank expertise with modern management science techniques and the computer” (Bettinger, 1972, p. 62). Decades later fintech scholars Arner et al. (2015) in their research paper on the evolution of fintech suggested “The term's origin can be traced to the early 1990s and the Financial Services Technology Consortium, a project initiated by Citigroup to facilitate technological cooperation efforts” (D. W. Arner, J. N. Barberis, & R. P. Buckley, 2016, p. 1272). Yet, as Schueffel (2016) pointed out, it may well be the case that the initiators of the early 1990s Citibank fintech project were unaware of Bettinger’s research and unknowingly coined the identical term for their venture by pure chance adding, “It is already noteworthy at this point that neither academia nor practice can unambiguously be identified as the birthplace of the term Fintech as a practitioner published a scholarly journal article first applying the term” (Schueffel, 2016, p. 36). Fintech is generally the connection of innovative and, chiefly, online technologies (e.g. cloud computing, wireless internet) with traditional commercial pursuits of the financial services industry (e.g. loans, payments, and transaction banking) (Gomber et al., 2017). While similar foundational definitions of fintech, like the examples included herein, have gained general utility within the public and communications media lexicon, the same cannot be said for the topic’s path in scientific literature. With roughly 200 publications in the last forty years (since 1980), there is a lack of consensus around key research topics and trends (Milian et al., 2019). And while there has been substantial increased velocity in scholarly literature on fintech as of late, research tends to be sparsely linked with no clear research agenda (Kavuri & Milne, 2019).

It is necessary to first investigate fintech conceptually at a macro level and provide a brief background of its categorizations and overview of its typologies before delving into the micro level research agenda of consumer chatbot adoption in mobile banking that lies ahead in this paper. Milan (2019) modernizes Christensen's (2003) classic theory of disruptive innovation – "fintechs can be classified in two categories: 'Sustainable Fintechs' for traditional financial service providers that work to protect their market positions by using information technology through incremental innovations and 'Disruptive Fintechs' that are new companies and start-ups that challenge established providers by offering new products and services" (Christensen, 2003; Milian et al., 2019, p. 2). The latter grouping is investigated by such authors as McWaters (2015) who explained how disruptive innovations are reforming the manner in which financial services are structured, provisioned, and consumed; Chiu (2016) who described the role fintechs and disruptive business models play in financial products, intermediation, and markets-policy implications for financial regulators; and Lecasse et al. (2016) who compared fintech and crowdfunding (minimal capital contributions aggregated across a sizeable population to finance a new business venture) to a digital tsunami (Chiu, 2016; Lacasse, Lambert, Roy, Sylvain, & Nadeau, 2016; McWaters, Bruno, Lee, & Blake, 2015). These emerging solutions also have new business models that are offering consumers the promise of more flexibility, security, efficiency, and opportunities than founded financial services (P. Lee, 2015).

Alt and Puschmann (2012) designated that fintech refers to new technology solutions which exhibit an incremental or radical / disruptive innovation advance of applications, processes, products or business models in the financial services industry (Alt & Puschmann, 2012). Chuang (2015) divides these solutions into five distinct areas – "1) the banking or insurance sector are distinguished as potential business sectors with solutions for the insurance industry more often specifically named 'InsurTech'; 2) the solutions differ with regard to their supported business processes such as financial information, payments (e.g. mobile payment), investments, financing, advisory and cross-process support; 3) the targeted customer segment distinguishes between retail, private and corporate banking as well as life and non-life insurance; 4) the interaction form can either be business-to-business, business-to-consumer, or consumer-to-consumer; and 5) the solutions vary with regard to their market position" (Chuang et al., 2016, p. 3).

Arner et al. (2016) introduced an organizing landscape of the fintech industry that also encompasses five key areas – 1) finance and investment (alternative financing mechanisms, particularly crowd funding and person to person lending, robo-advisory services), 2) internal operations and risk management (finance theory and quantitative techniques of finance and their translation into financial institution operations and risk management), 3) payments and infrastructure (domestic and cross-border electronic payment systems, derivatives trading, 4) data security and monetization (cybersecurity and privacy), and 5) customer interface (online and mobile financial services) (Douglas W. Arner et al., 2016). With a legal lean and predominantly regulatory lens, this article attempted to provide a proactive agenda that encourages innovation in an adequately demanding context and that preserves confidence in the market while arguing that further experimentation and innovation in regulatory tactics is lacking both in developed markets and developing countries (D. W. Arner, J. Barberis, & R. P. Buckley, 2016).

Next, Gomber et al. (2017) approached classification from a subsector level of fintech activity by proposing the concept of the “Digital Finance Cube” which applies three central dimensions to structure the field – 1) digital finance business functions (e.g. digital financing, digital payments), 2) relevant technologies and technological concepts (e.g. blockchain technology, social networks), and 3) institutions providing digital finance solutions (e.g. fintech start-ups, traditional service providers) (Gomber et al., 2017). With the shifting focus of digitalization from improving the service delivery of conventional tasks to introducing essentially opportunistic new customers and business models for banks, this article defined digital finance as encompassing a myriad of new financial products, financial businesses, finance-related software, and innovative forms of communication and interaction with customers – delivered by fintech companies and pioneering financial service providers. With this foundation, finance and information systems research has begun to analyze these changes and the impact of digital progress on the financial sector with the “Digital Finance Cube” serving as the conceptual basis for reviewing this field (Gomber et al., 2017).

For purposes of this paper, I favor Milan et al. (2019) which offers a recent thorough and systematic yet concise review and contemporary profiling approach of fintech activity sectors that includes – “1) loan technology (peer-to-peer loan platforms, as well as platforms for loan underwriters using machine learning technologies and algorithms to assess the reliability of the borrowers); 2) payments / billing technology (payment and collection technologies including solutions to facilitate processing payments for the developers of payments by card (or bank slips) for software tools for billing by subscription); 3) personal finance / asset management (technologies that help individuals manage their accounts and / or personal credit, assets, and personal investments; 4) money transfer / remittance (technologies that transfer money including mainly peer-to-peer platforms to transfer funds between individuals in different countries); 5) blockchain / cryptocurrency (distributed ledger registers ranging from Bitcoin portfolios to suppliers of sidechain insurance); 6) institutional technology / capital markets (tools for financial institutions, such as banks, hedge funds, mutual funds or other institutional investors that range from alternative commercial systems to software modelling and financial analysis); 7) equity crowdfunding (platforms that allow a group of individuals to make financial contributions to projects or companies provisioned in an equity form); and 8) security technology (technology to protect confidential data and defend against cybersecurity incidents)" (Milian et al., 2019, p. 5). This study provided a multitude of benefits including a systematic literature review on fintechs from the 1980s to February 2018, listing of the most significant works, key references, and the major publications, identifies the fintech activity sectors and publications map, and recommends a categorization of the fintech literature.

Fintech Literature Review

Keeping in mind fintech research tends to be scantily connected with little to no coherent research agenda, the following are considered highly cited, seminal articles in the fintech literature landscape. Chandavarkar (1980) is regarded as the first true fintech article – a precursor work that examined money transmittals by immigrant workers to their home countries suggesting labor exporting countries need to supplement their macroeconomic policies to maximize migrant's remittances by policies to ensure their optimal use and growth in income and employment (Chandavarkar, 1980). Decades later, Neu et al. (2006) examined how the World Bank has attempted to influence Latin American education administration policies by leveraging an assembly of information creation and reporting practices underpinned by accounting / financial proficiency while Mulligan and Sala-i-Martin (2000) researched the exorbitant margins and demand for low interest rate capital, finding the cost of fintech adoption and pension plan participation to be negatively related (Mulligan & Sala-i-Martin, 2000; Neu, Gomez, Graham, & Heincke, 2006). Kane (2000) investigated the Asian financial crisis through the lens of agency-cost and contestable-markets theories emphasizing how misrepresentations created by flawed banking regulation affect capital allocation, asset prices, and bank solvency (Kane, 2000).

Bamford et al. (2000) examined the impact of preliminary founding decisions and circumstances on the success or failure of new bank start-ups finding a significant relationship between these initial founding activities and new venture growth potential (Bamford, Dean, & McDougall, 2000). Similarly, Davila et al. (2003) focused on venture capital financing and the growth of startup firms finding that employee totals increase in the months leading up to the venture capital funding round and continue to surge throughout the months after the event, thus, establishing venture capital funding events as vital indicators about the quality of the startup (Davila, Foster, & Gupta, 2003). Berger (2003) examined the economic effects of technology in the banking industry suggesting significant increased productivity with enhanced quality and variety of banking solutions (Berger, 2003). Banking services such as the economics of mobile payments and understanding stakeholder issues for an emerging financial technology application is studied by Au and Kaufmann (2008). In this article, “economic theory provides a unique point of view based on which it is possible to examine issues in relation to emerging technologies, where the standards and the adoption, the changes in the business processes and the results of implementation, information security, investments and commercial value and impact of the industry require care and consideration by senior managers, leadership and strategists in the financial industry” (Au & Kauffman, 2008; Milian et al., 2019, p. 11). Preda (2006) examined socio-technical agency in financial markets via the advent of the stock ticker, the first customized technology solution accepted by financial marketplaces, and illustrates the mental and sociological aspects of having real-time access to financial data (Preda, 2006). Grote et al. (2002) provided a value chain approach to financial centers resulting from the implementation of information and communication technologies in wholesale financial services (Grote, Lo, & Harrschar–Ehrnborg, 2002). And, Kim et al. (2015) studied service architecture for secure authentication systems with results suggesting that usefulness, ease of use, and credibility influenced intention to use, moderated by self-efficacy. Further, intention to use was impeded by information privacy concerns (Y. Kim et al., 2016).

This disparity of fintech subjects was confirmed by Milian (2019) as over half of the journals reviewed address topics that are not directly related to a given activity sector (e.g. research questions spanning different aspects related to fintech) thus despite the increasing interest in fintech, a definitional lack of consensus still exists among scholars and practitioners and on the theoretical underpinnings of the discipline (Milian et al., 2019).

Artificial Intelligence and Chatbots in Fintech

However, as Belanche et al. (2019) declared, “The concept of FinTech goes beyond e-banking and consumer digitalization and focuses on the development and successful introduction of innovative technology instruments to meet users’ financial needs and demands” (Belanche et al., 2019, p. 1). To that end, artificial intelligence signifies a clear-cut opening to further the digital transformation of the finance industry by delivering users greater value and increasing firms’ revenues (J. Park, Ryu, & Shin, 2016). As an example, in March 2019 it was announced that Erica, Bank of America’s artificial intelligence-driven virtual finance assistant surpassed more than six million users and completed more than thirty-five million client requests like answering basic banking questions, transferring money, and providing proactive insights (Crosman, 2019). Marinova et al. (2017) examined Nao, a small bank teller smart technology humanoid deployed at the Bank of Tokyo, that the authors propose, over time, can replace or supplement frontline employees’ efforts to deliver customized services, helping mitigate the age-old strain between service efficiency and effectiveness as they can both learn or enable learning from and across customers, employees, and interactions (Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017). Or, robo-advisers that, in contrast to traditional human advisers, reduce fees and provide round the clock financial access (Faubion, 2016; J. Park et al., 2016).

According to Acemoglu and Restrepo (2017), the occurrence of extraordinary cross-industry growth of artificial intelligence and robot-based systems is having a significant impact on the economic, social, and labor domains (Acemoglu & Restrepo, 2017). Huang and Rust (2018) labeled artificial intelligence as a key innovation source that will progressively supplant human-centered jobs in the future – expecting that automated technology will acquire mechanical intelligence first, with analytical capability (e.g. virtual finance assistants) to follow and, ultimately, innate and even empathetic intelligence; requiring a workforce proficient in duties that automation cannot yet perform (M.-H. Huang & Rust, 2018). An emerging thread of literature focuses on the challenges of introducing service innovations involving chatbots, droids, or artificial intelligence specifically when those customer-facing technologies interact directly with front of house operations (e.g. physically or online) (Han & Yang, 2018; Singh, Brady, Arnold, & Brown, 2017; Van Doorn et al., 2017). For example, Singh et al. (2017) affirmed that customer interactions with organizations, particularly along frontlines, are being intensely disrupted by intelligent interfaces (Singh et al., 2017). Grewal et al. (2017) predicted retail behaviors of consumers will be directly impacted by artificial intelligence systems (e.g. Siri, Alexa) while Van Doorn et al. (2017) suggested service-infused technology interactions will be predicated on the level of human and automated social presence (e.g. the social engagement capacity of customer-facing robots to correspond at the same level of a human customer) (Grewal, Roggeveen, & Nordfält, 2017; Van Doorn et al., 2017). Overall, there is a growing recognition of the necessity for firms to create artificial intelligence advances to improve their management practices and product offerings, and realize competitive advantage (Han & Yang, 2018).

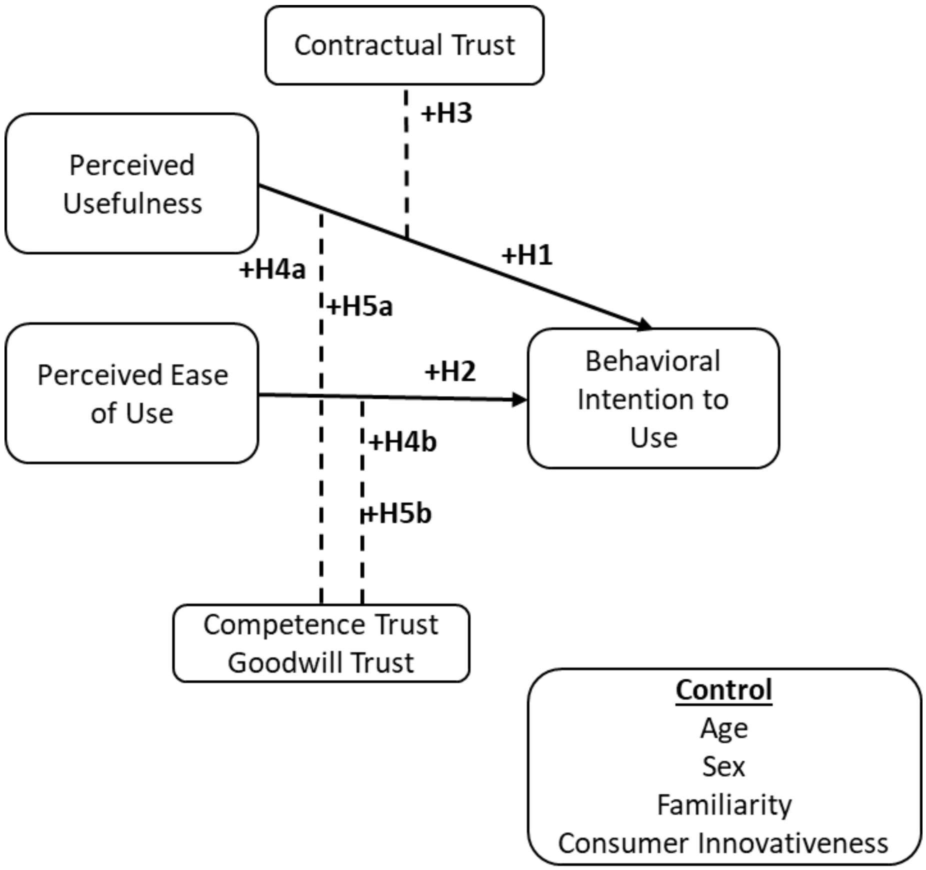
Under the umbrella of artificial intelligence, chatbots (also known as a talkbot or chatterbox) can be defined as “a computer program that mimics human conversations in its natural format including text or spoken language using artificial intelligence techniques such as natural language processing, image and video processing, and audio analysis" (Richad, Vivensius, Sfenrianto, & Kaburuan, p. 1271). Technically speaking, the foundation of a chatbot's ability to understand and enable conversation between human and machine is natural language processing. Natural language processing is a branch of artificial intelligence that investigates how computers can be programmed to analyze, explain, comprehend, and manipulate natural language text or speech in order to complete assigned tasks (Chowdhury, 2003). While chatbots originally were only capable of handling simple tasks, continuous natural language processing advancement and chatbot technology development now enables them to improve customer satisfaction by predicting customer personalities, favorite product proclivities, and fine-tune conversations based on those specifics (Nguyen & Sidorova, 2018). Across numerous industries (e.g. banking, insurance, e-commerce) and various platforms (e.g. Erica, Siri, Facebook) chatbots are having intelligent conversations with consumers all while collecting data that enables them to provide users better informed answers or future personal product and service recommendations. Horzyk et al. (2009) found that e-commerce chatbots are expected to positively impact online business when communicating with customers and assisting them during the sales process (Horzyk, Magierski, & Miklaszewski, 2009). Further, Semeraro et al. (2008) posited a direct relationship between user experience and satisfaction (both positively and negatively) with conversational agents on all the dimensions evaluated including impression, control, effectiveness, navigability, learnability, etc. (Semeraro, Andersen, Andersen, de Gemmis, & Lops, 2008).

2.3 Hypotheses Development

As Nguyen (2018) suggested, while human-computer interaction literature is a widespread topic within the information systems discipline, the interaction nature between humans and chatbots still needs to be better understood (Nguyen & Sidorova, 2018). And while Ransbotham (2017) offered that over 85% of executives think that artificial intelligence will drive a competitive advantage within their companies, consumer adoption of chatbot services has been deemed “slow so far” (Jung et al., 2018, p. 367; Ransbotham et al., 2017). Specific to chatbot technology acceptance, only Lucente (2002) in the context of e-commerce, Nguyen (2018) in the travel field, Belanche (2019) with robo-advisers, and Cardona (2019) in insurance have undertaken various levels of research (Belanche et al., 2019; Cardona et al., 2019; Lucente, 2000; Nguyen & Sidorova, 2018). Therefore, due to the novelty of artificial intelligence-driven virtual finance assistants, there is currently a lack of knowledge about key adoption determinants by consumers.

To fill this gap, this paper will examine consumer chatbot adoption, specifically artificial intelligence-driven virtual finance assistants (e.g. Bank of America’s Erica, Capital One’s Eno, USAA’s Clinc) utilizing the technology acceptance model (TAM). Moderators will include 1) contractual trust, 2) competence trust, and 3) goodwill trust.

Figure 2.4 Research Model



Technology Acceptance Model (TAM) Application

Because TAM does a thorough job illustrating consumer adoption disparities with information technology and can be enhanced and customized according to a study's problem, it has developed into one of the most commonly utilized models when researching information technology adoption (T. Zhang, Lu, & Kizildag, 2018). TAM is regarded as the most utilized framework in predicting information technology adoption (Legris et al., 2003) and has become so popular that it has been cited in the majority of research that studies user acceptance of technology (Y. Lee et al., 2003). For fintech services such as chatbots, TAM maintains a strong adaptability for this study as the spirit is to apply the newest cohort of technology solutions to financial innovation. Lee et al.

(2003) emphasized a need for incorporating more variables and exploring boundary conditions of TAM as part of their literature review (Y. Lee et al., 2003) while King and He (2006) showed TAM to be a valid and robust model, widely used, and implied its potential broader applicability (King & He, 2006). Hsiao and Yang (2011) identified three main trends in TAM application, one of which being e-commerce (fintech) systems (Hsiao & Yang, 2011).

Perceived Usefulness (PU) and Perceived Ease of Use (PEU)

The TAM model divides the factors affecting individual behavioral attitudes into PU and PEU, which have a significant impact on the adoption of new technology (Venkatesh & Bala, 2008). To promote a consumer's willingness to use a new technology, potential users must believe that they can benefit from using the new technology while simultaneously being easy to use (Chau & Hu, 2002; Davis, 1985; Davis et al., 1989).

Davis (1985) defined PU as the degree to which the person believes that using the particular system would enhance individual job performance (Davis, 1985). For purposes of this paper, Ryu's (2018) definition of PU, referring to a user's choice to adopt a service if they think the application of fintech can have a positive impact, is used to complement Davis' original description (Ryu, 2018). A sizable quantity of empirical studies on information technology adoption in the past ten years have demonstrated that PU can have a positive impact on users' intentions (Barakat & Hussainey, 2013; Featherman & Pavlou, 2003; Hong & Zhu, 2006; Ng & Kwok, 2017). Stated simply, users are motivated to adopt technology primarily because its functionality and often willing to endure some difficulty of use when critically required functionality is provided

– no amount of ease of use can offset for a technology that is functionally useless (Davis, 1989). I expect this finding to be consistent herein as consumers of artificial intelligence-driven virtual finance assistances are adopting for financial utility.

With that foundation, the following hypothesis is proposed:

Hypothesis 1 (H1): Perceived usefulness (PU) positively effects a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants.

Davis (1985) defined PEU as the extent to which individuals view using a technology as being relatively effort-free (Davis, 1985). For purposes of this paper, Hu et al.'s (2019) definition of PEU, incorporating consumer relaxation level and proactive willingness to learn to use fintech services, is used to compliment Davis' original description (Z. Hu et al., 2019). A key determinant of TAM is the assumption of behavioral intentions dependent upon a person's belief about their own ability to use a specific technology as well as their subjective assessment of the usefulness of that specific technology. This theme is present in a myriad of PEU literature (Bruner II & Kumar, 2005; Hernandez, Jimenez, & José Martín, 2009; Morgan-Thomas & Veloutsou, 2013; Palvia, 2009; Pavlou, Liang, & Xue, 2007). Specific to financial services research, numerous scholars have shown a significant correlation between PEU and emerging technology adoption attitudes (Akturan & Tezcan, 2012; Szopiński, 2016). Stated simply, all things equal, a technology viewed as easier to use than an alternative is more likely to be accepted by users – effort here is a finite resource allocated by a person based on activities for which they are responsible (Davis, 1989). I expect this finding to be consistent herein as consumers of artificial intelligence-driven virtual finance assistances are also adopting to save effort and make these financial activities easier to transact.

With that foundation, the following hypothesis is proposed:

Hypothesis 2 (H2): Perceived ease of use (PEU) positively effects a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants.

Regarding consumer-targeted fintech specifically, such technologies likely have important implications for how consumers manage their capital. Therefore, consumers are likely to have concerns about whether they are managing their capital in an appropriate and secure manner. As consumers adopt fintech, the onus of consumer transactions moves from a bank employee to the consumer and the consumer's ability to understand virtual finance assistant-based guidance in making effective and secure financial decisions. The increased responsibility associated with moving from human-to-human interaction to artificial intelligence-to-human interaction is likely to increase consumer wariness and likelihood of using artificial intelligence-driven virtual finance assistants.

However, I expect that contractual trust can have the potential to reduce consumer wariness and, in turn, increase consumer adoption of artificial intelligence-driven virtual finance assistants. Contractual trust is defined as mutual understanding between agents (e.g. a bank and consumer) to adhere to a specified agreement (e.g. end user / click-through agreement) (Sako, 1992). Due to bounded rationality, consumers cannot predict every potential risk associated with using artificial intelligence-driven virtual finance assistants. Further, drafting contracts to account for all potential unforeseen risks is both impossible and impractical for all parties (Williamson, 1981). And while contracts may address those unforeseen risks, they also vary in their quality to address risks

(Williamson, 1981). Contractual trust increases when contracts not only capture potential foreseeable risks but then also provide flexibility to address unforeseen risks and provide safeguards / assurances to consumers that the banks will help them ensure their financial security if potential risks manifest.

While artificial intelligence-driven virtual finance assistants may be perceived as useful and easy to use, not all banks may be perceived likely to adhere to their specified contractual agreement. When consumers perceive high contractual trust with their banks, they believe their banks will fulfill a minimum set of obligations, underpinned by honesty and promise keeping, that will limit potential risk(s) imposed on a consumer when utilizing their products and services. They are simultaneously guaranteed a minimum level of service (e.g. security, functionality, and operability) and recourse if or when things do not go as planned. This is regardless of bank and predicated on the absence of opportunistic behavior. In such cases, consumers might then feel adequately protected, freer, and more willing to try these innovative service offerings given increased perceived usefulness. Similarly, banks perceived as more contractually trustworthy are likely to be perceived, in turn, as understanding their customers and their needs in using technology efficiently and effectively. Therefore, the perceived ease of use is likely also to increase when consumers trust the mutually agreed to contractual agreement (and adherence thereto) with their banks, leading to increased consumer adoption.

In contrast, consumers can also have low levels of contractual trust with their banks. Here, consumers are more likely to view their banks as behaving opportunistically in the provision of advanced technologies while not strictly adhering to the reliable and repeatable course of actions and protections agreed to in the contract.

Potential product and service risk is left unlimited, and unclearly defined and allocated, with no clear recourse for damages. Given the lack of contractual trust in their banks, consumers will view the usefulness of artificial intelligence-driven virtual finance assistants less positively, due to uncertainty regarding contractual responsibilities, undermining perceived usefulness to where consumers will be less likely to adopt. Similarly, customers might also perceive the offerings as being more difficult to use (e.g. questioning whether the bank will honor the contract intended to adequately protect them), reducing intent to adopt.

With that foundation, the following hypothesis is proposed:

Hypothesis 3 (H3): The relationship between perceived usefulness (PU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's contractual trust. Specifically, when a high level of contractual trust is present a consumer's behavioral intention to use will increase.

Competence trust is defined as the belief that a given partner (e.g. a bank) has the structural and technical competences to suitably execute a given set of tasks (e.g. deliver a viable artificial intelligence-driven virtual finance assistant to consumers) (Sako, 1992). This dimension of trust is typically impersonal and relies on reputation. Barber (1983) and Gabarro (1978) stressed the importance of competence in trust (Barber, 1983; Gabarro, 1978). Other terms that have been used to denote competence include "ability" and "expertise" (Mayer, Davis, & Schoorman, 1995). When it comes to reducing perceived adoption risks, competence trust is a clear and relevant moderator of perceived usefulness and perceived ease of use. Competence is founded on various firm capabilities and resources including capital (financial and human), physical properties and geographic footprint, market share, technology, etc. – all of which provide the foundation for the competence that is needed in consumer relationships (Das & Teng, 2001).

Generally, consumers do not have as much critical information as the financial institution about areas such as the quality of a fintech product or service, or the financial institution's ability or willingness to perform. This is exacerbated in online scenarios as, in part, key elements of personal interactions are missing in the computer-mediated environment (Grabner-Kraeuter, 2002). A consumer's recognition of bank brand, reputation, and perception of service risk likely has a significant impact on the trust of that financial institution. It may influence the provision of reliable services and consumer perception of quality, value, and satisfaction (Z. Hu et al., 2019).

Consumers may prefer to adopt fintech services provided by familiar service providers with a good reputation. Or, when the quality and relevant functions of a product are unclear (as is the case with the novelty of most chatbot services) brand image can help consumers make a selection (Ratnasingam & Pavlou, 2003). Moreover, firms that have been successful in previous innovative technology offerings tend to build a reputation for competence, with that competence suggesting a high probability of the new technology being delivered successfully (Das & Teng, 2001). Fintech service providers can take advantage of their brand image and value (e.g. stability, long history) to overcome a consumer's trust concerns.

While artificial intelligence-driven virtual finance assistants might be perceived as useful and easy to use, not all banks might be perceived as competent in delivering the applications. When consumers perceive high competence trust with their banks, they believe their banks can effectively accomplish tasks, understand customer needs more accurately, and deliver quality services to their customers. In such cases, consumers might then expect the artificial intelligence-driven virtual finance assistants to include the necessary features that provide benefits beyond what might be offered by directly interacting with human bank tellers. Consumers would then be more willing to try these service offerings given increased perceived usefulness. Similarly, banks perceived as more competent are likely to be perceived, in turn, as understanding their customers and their needs in using technology efficiently and effectively. Therefore, the perceived ease of use is likely also to increase when consumers trust the competence of their banks, leading to increased consumer adoption.

In contrast, consumers can also have low levels of trust in the competence of their banks. Here, consumers are more likely to view their banks as lacking the capabilities to provide advanced technologies. Given the lack of perceived capabilities in their banks, consumers will view the usefulness of artificial intelligence-driven virtual finance assistants less positively, perhaps expecting glitches in the customer experience or the lack of necessary features to provide customer benefits, to where consumers will be more likely to adopt. Similarly, customers might also perceive the offerings as being more difficult to use (e.g. questioning whether the application can address complex questions or route the customer to the appropriate solution), reducing intent to adopt.

With that foundation, the following hypotheses are proposed:

Hypothesis 4a (H4a): The relationship between perceived usefulness (PU) and a consumer's behavioral intention to use artificial intelligence-driven virtual

finance assistants will be positively moderated by that individual's competence trust. Specifically, when a high level of competence trust is present a consumer's behavioral intention to use will increase.

Hypothesis 4b (H4b): The relationship between perceived ease of use (PEU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's competence trust. Specifically, when a high level of competence trust is present a consumer's behavioral intention to use will increase.

Goodwill trust is defined as when agents (e.g. a bank and a consumer) are willing to act in ways that exceed stipulated contractual agreements (Sako, 1992). Goodwill trust is about establishing good faith through good intentions and integrity – a firm's reputation for consumer fairness and attention / concern for consumer welfare (Das & Teng, 2001). With this reputation, a consumer feels secure that the firm will act in good faith rather than function opportunistically. Historically, scholars contend that goodwill trust leads to reduced transactions costs as the perceived probability of opportunistic behavior occurring is reduced (John, 1984; Nooteboom, 1996). Goodwill trust can be gained over time through preceding interactions (Gulati, 1995) and can be a source of competitive advantage (Barney & Hansen, 1994).

As it relates to financial services, goodwill trust only grows within long-term relationships through repeated interactions, much like the lifecycle of a banking customer (Sako, 1992). Most consumers probably initiated their banking relationships with a simple checking or savings account at an early age. Or perhaps, a debit or credit card. While all banking services and transactions are underpinned with certain contractual protections (e.g. user agreements, FDIC assurances), goodwill trust can develop and strengthen as the exchanges between consumer and bank continue over time and increase in scope – maturing from that simple checking account to a mortgage, retirement planning, or brokerage accounts (Ireland & Webb, 2007). Once established, goodwill trust may enable a more open and willing exchange of knowledge and resources between banks and consumers, such as use of innovative artificial intelligence-drive virtual finance assistants.

While artificial intelligence-driven virtual finance assistants may be perceived as useful and easy to use, not all banks may be perceived as engendering goodwill trust in delivering the applications. When consumers perceive high goodwill trust with their banks, they believe their banks will go above and beyond the formal governance structures of the stipulated contract to help remedy any issues that may arise when using the technology. In such cases, consumers might then expect the bank to work directly with them on training or technical assistance that may introduce, educate, and maximize the benefits of the product beyond what might be offered virtually (e.g. continuous improvement activities). Consumers would then be more willing to try these service offerings given increased perceived usefulness. It should be noted that absence of opportunistic behavior is not a sufficient condition for goodwill trust. Similarly, banks perceived as demonstrating goodwill are likely to be perceived, in turn, as understanding their customers and their needs in using technology efficiently and effectively. Therefore, the perceived ease of use is likely also to increase when goodwill trust exists between consumers and their banks, leading to increased consumer adoption.

In contrast, consumers can also have low levels of goodwill trust with their banks. Here, consumers are more likely to view their banks as unwilling to step outside the contractual agreement make things right in the provision of advanced technology services and offerings. Given the lack of goodwill trust with their banks, consumers will view the usefulness of artificial intelligence-driven virtual finance assistants less positively, perhaps expecting concerns or disputes raised to be solely the consumer's responsibility and receiving limited technical assistance via bank agents, to where the risks outweigh the benefits, usefulness decreases, and consumers will be less likely to adopt. Similarly, customers might also perceive the offerings as being more difficult to use (e.g. lack of technical understanding), reducing intent to adopt.

With that foundation, the following hypotheses are proposed:

Hypothesis 5a (H5a): The relationship between perceived usefulness (PU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's goodwill trust. Specifically, when a high level of goodwill trust is present a consumer's behavioral intention to use will increase.

Hypothesis 5b (H5b): The relationship between perceived ease of use (PEU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's goodwill trust. Specifically, when a high level of goodwill trust is present a consumer's behavioral intention to use will increase.

In summary, the hypotheses above present opportunities for extending and addressing gaps in the research of fintech adoption. Specifically, this research examines the relationships between PU and PEU and the role of trust on consumers' behavioral intention to adopt artificial intelligence-driven virtual finance assistants while also extending the applicability of TAM. Despite continuous advancement in demonstrating new factors with significant influence on TAM's core variables, several uncharted areas of potential model application still remain that could contribute to its predictive validity (Marangunić & Granić, 2015). Furthermore, most of the existing research studies adoption from the supply side of fintech services with little attention paid to the contrasting demand side – a lens of applied empirical extension within TAM. In the past, scholars rarely combined the consumer's point of view with intention models to analyze influences affecting behavioral intention to use a new technology (Legris et al., 2003; Szajna, 1996).

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

3.1 Data Collection

A web survey was administered by Qualtrics to collect the data for this study which enabled a diverse sample in terms of demographic characteristics such as gender, age, income, education, and employment status. Specific to design, a multi-stage, multi-respondent approach was utilized to separate the measurement of independent and dependent variables over time (in this case a one month period) and by different respondents. This design was intended to mitigate potential bias introduced by common method variance (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Podsakoff, MacKenzie, & Podsakoff, 2012; Podsakoff & Organ, 1986). Other design safeguards included respondents being systematically forced to respond to each question so partial responses were not accepted therefore eliminating the risk of any missing data, a "speeding check" threshold of four minutes whereby any respondent who completed the survey in under that time did not have their results retained, and automated and manual data reviews to remove those who responded in a pattern (e.g. straight-lined responses or high / low).

The survey randomly sampled U.S. adult age potential users of artificial intelligence-driven virtual finance assistants with a bank account. Leveraging the Qualtrics platform to develop, sample, and administer the web survey and collect the data helped ensure conciseness and guarantee anonymity of participants – both critical components of an increased response rate in web surveys (Illum, Ivanov, & Liang, 2010). Further, the sample size should exceed the minimum ratio of five samples for every variable and the desired level of between 15 to 20 observations for each variable (Hair, Black, Babin, & Anderson, 2010).

Based on these criteria, a sample size of 120 or greater was targeted, and achieved, for this study. The final sample size was 121. A total of 257 individuals completed the first respondent survey and 121 of those 257 (47%) returned to complete the second respondent survey. 136 (53%) did not respond to the recontact survey. Of the 121 individual respondents, 55 were female and 66 were male. Regarding age of the respondents, 77 respondents (64%) were between 65-74 years old. The next most frequent range included 25 respondents (21%) who were between 75-84 years old. 4 respondents (3%) were 85 or older. In terms of employment, 99 respondents (82%) were retired with the next closet range having 14 respondents (12%) employed full time.

First, all participants were offered a general description of artificial intelligence-driven virtual finance assistants. Next, participants answered the survey including a portion on their perceptions of artificial intelligence-driven virtual finance assistants (e.g. perceived usefulness, perceived ease of use), trustworthiness of artificial intelligence-driven virtual finance assistants and the financial institutions providing them (e.g. contractual trust, competence trust, and goodwill trust), and their behavioral intention to use artificial intelligence-driven virtual finance assistants (e.g. attitude). All scales were based on self-reported measures and use fully-anchored, seven-point Likert-type response formats from 1 (“strongly disagree”) to 7 (“strongly agree”). Initial items proposed to measure the following constructs come from an extensive review of relevant technology adoption, online banking, and e-commerce literature and were mined from previously validated measures in those fields of research and rephrased to relate specifically to this study's context.

The following section defines the variables and scales used to capture those constructs included in the survey. These are also provided, in their completeness, in Appendix 2 and 3.

3.2 Variables

Behavioral Intention to Use (Dependent Variable)

As introduced earlier via the theory of reasoned action (TRA), behavioral intention is the degree of the strength of an individual's intention to perform a stated behavior and is a construct influenced by two antecedents – attitude (e.g. positive or negative feelings about performing a behavior) and subjective norm (e.g. the perception of what those most important to an individual think of performing the behavior) (M. Fishbein & Ajzen, 1975). However, this study leveraged the TRA-influenced technology acceptance model (TAM) which suggests behavioral intention is determined by attitude (e.g. an individual's attitude toward using a technology) and attitude is jointly determined by perceived usefulness (e.g. an individual's belief that use of a particular technology will enhance job performance) and perceived ease of use (e.g. an individual's belief that use of a particular technology will be free of effort) (Davis et al., 1989). TAM does not include subjective norm as a determent of behavioral intention.

Behavioral intention to use measures were adapted from previous scales (Bhattacherjee, 2000; Mathieson et al., 2001). Behavioral intention to use consisted of three items (e.g. I intend to use artificial intelligence-driven virtual finance assistants to manage banking needs) and was assessed at time two (recontact survey).

Attitude measures were also adapted from previous scales (Bhattacherjee, 2000; Taylor & Todd, 1995). Attitude consisted of three items (e.g. Using artificial intelligence-driven virtual finance assistants seems like a good idea) and was assessed at time one (initial survey) and time two (recontact survey).

Perceived Usefulness and Perceived Ease of Use (Independent Variables)

Perceived usefulness refers to the extent to which individuals view the use of a given technology as potentially increasing their job performance, whereas perceived ease of use is defined as the degree to which the person believes that using the particular technology will be free of effort (Davis, 1985). Perceived usefulness and perceived ease of use measures are adapted from previous scales (Bhattacherjee, 2000; Davis et al., 1989).

Perceived usefulness consisted of four items (e.g. Using artificial intelligence-driven virtual finance assistants would improve my performance in managing banking needs). Perceived ease of use consisted of four items (e.g. Learning to use artificial intelligence-driven virtual finance assistants would be easy for me). Both measures were assessed at time one (initial survey).

Trust (Moderating Variables)

For purposes of this study, trust was categorized into three forms and thus three separate moderating variables. First, contractual trust involves a shared understanding by agents to abide by a quantified agreement; second, competence trust results from the belief that a partner or provider has the organizational and technical acumen to correctly perform a specified set of tasks or services; and third, goodwill trust which exists when agents are willing to act in ways over and above what is stipulated in contractual agreements (Sako, 1992). All measures were assessed at time one (initial survey).

Contractual trust measures are adapted from previous scales (Gefen, Karahanna, & Straub, 2003b; Parkhe, 1993; Zaheer, McEvily, & Perrone, 1998). Contractual trust consisted of four items (e.g. I feel safe using artificial intelligence-driven virtual finance assistants because the contract will protect me).

Competence trust measures are adapted from previous scales (Lui & Ngo, 2004). Competence trust consisted of four items (e.g. I believe the bank has the technical capabilities to properly provide artificial intelligence-driven virtual finance assistants).

Goodwill trust measures are adapted from previous scales (Zaheer et al., 1998). Goodwill trust consisted of four items (e.g. I believe the bank providing the artificial intelligence-driven virtual finance assistant is willing to act in ways exceeding stipulated contractual agreements).

Control Variables

Age

Literature suggests the influences of the predecessors of behavioral intentions could differ due to the heterogeneity across users depending upon sociodemographic characteristics such age or gender and may better help understand the dynamics of the adoption process (Sun & Zhang, 2006). Specifically, older people have more established beliefs and are less receptive to outside messaging in contrast to younger people (Hess, 1994). Age is operationalized in numeric years and assessed at time one (initial survey).

Sex

As first referenced above, Sun and Zhang’s (2006) literature also suggested gender among the sociodemographic characteristics that may help better understand the dynamics of the adoption process (Sun & Zhang, 2006). Women seem to be more inclined than men to consider outside opinions when deciding to use a new technology (Sun & Zhang, 2006; Venkatesh et al., 2003). Sex is a dichotomous variable operationalized as “1” for males and “2” for females and assessed at time one (initial survey).

Familiarity

Literature suggests that consumers with low familiarity with online banking need ancillary features (e.g. investment advice) compared to consumers with higher familiarity who often emphasize more utilitarian motives (Mäenpää, Kale, Kuusela, & Mesiranta, 2008). Applied to the fintech concept, consumers with a higher familiarity (e.g. previous interaction or training) with artificial intelligence and chatbots like Siri or Alexa may value the technology’s usefulness and have improved attitudes toward them due to the deeper knowledge of the practical value of these systems (Belanche et al., 2019). In opposition, consumers with lower familiarity may be more affected by subjective norms (e.g. outside opinions) due to their unclear and implicit knowledge about artificial intelligence (Venkatesh & Davis, 2000). Familiarity consisted of three items (e.g. I have worked with or studied artificial intelligence) and assessed at time one (initial survey).

Consumer Innovativeness

Literature suggests that when consumers are highly innovative (e.g. the degree of proclivity to try new products, technologies, or services), they can withstand a higher degree of ambiguity and are more positively intended to use the innovation. In short, consumers are less likely to realize risks and more open to innovations (Z. Hu et al., 2019). It is further suggested that innovation is a basic feature of the human condition, which indicates the degree of interest in a new field (Adeiza, Azizi Ismail, & Marissa Malek, 2017). Specific to mobile payment adoption, its offered as the majority of consumers have deficient expert knowledge of a broad array of mobile services, their individual innovation plays an essential positive role in their intention to use (C. Kim, Mirusmonov, & Lee, 2010). Consumer innovativeness consisted of two items (e.g. When I hear about a new product, I look for ways to try it) assessed at time one (initial survey).

Attitude (average)

Attitude (measured in both survey 1 and survey 2) was added as an additional control in averaged form due to high reliability when assessed across the initial survey and the recontact survey with an almost identical Cronbach's alpha (.969 v. .966). The three attitude items remained identical across the surveys.

3.3 Analytical Technique

The research in this dissertation attempted to understand and explain the relationships between PEU and PU and the moderating role of trust on consumers' behavioral intention to adopt artificial intelligence-driven virtual finance assistants while also extending the applicability of TAM. The analytical model consisted of one dependent variable, multiple independent variables, three moderators, and multiple control variables making hierarchical moderated linear regression the appropriate option for analysis (Baron & Kenny, 1986). All tests were performed using the latest version of IBM SPSS Statistics and AMOS software.

CHAPTER 4: RESULTS

The final sample size was 121. A total of 257 individuals completed the first respondent survey and 121 of those 257 (47%) returned to complete the second respondent survey. A total of 136 (53%) did not respond to the recontact survey. An independent samples t-test was performed to assess the statistical significance of the difference between the variables of age, sex, education, perceived usefulness, and perceived ease of use between the 121 who responded to the recontact survey and the 136 who did not. Results showed non-significant differences across all variables for these two response groups.

Table 4.1 provides the Cronbach's alpha for all multi-item scale constructs to assess internal consistency. Per George and Mallery (2003), results greater than 0.7 were deemed acceptable with these alphas suggesting the internal consistency of the items (George & Mallery, 2003).

Table 4.1 Scale Reliability Analysis

Construct	Items	α
Independent Variables		
Perceived Usefulness	4	0.970
Perceived Ease of Use	4	0.943
Dependent Variables		
Behavioral Intention to Use	3	0.966
Moderating Variables		
Contractual Trust	4	0.907
Competence Trust	4	0.903
Goodwill Trust	4	0.891
Trust (composite)	12	0.959

Table 4.2 provides the correlations and descriptive statistics for the variables in this study.

Table 4.2 Correlations and Descriptive Statistics

		Mean	Std. Deviation	1	2	3	4	5	6	7	8	9	10	11
1	Behavioral Intention to Use	2.355	1.542											
2	Perceived Usefulness	2.988	1.519	**0.584****										
3	Perceived Ease of Use	3.545	1.573	**0.429****	**0.666****									
4	Contractual Trust	3.477	1.399	**0.549****	**0.729****	**0.653****								
5	Competence Trust	3.928	1.386	**0.449****	**0.690****	**0.595****	**0.824****							
6	Goodwill Trust	3.793	1.306	**0.457****	**0.639****	**0.519****	**0.862****	**0.840****						
7	Age	6.091	0.866	0.061	-0.015	-0.081	0.067	0.009	0.072					
8	Sex	1.455	0.500	-0.020	0.046	-0.135	0.134	0.099	0.142	0.096				
9	Familiarity	2.945	1.525	**0.483****	**0.358****	**0.546****	**0.470****	**0.445****	**0.417****	0.016	-0.145			
10	Consumer Innovativeness	2.769	1.455	**0.504****	**0.475****	**0.450****	**0.476****	**0.392****	**0.374****	0.083	-0.072	**0.689****		
11	Attitude (average)	2.889	1.489	**0.765****	**0.787****	**0.585****	**0.767****	**0.693****	**0.668****	0.051	-0.019	**0.508****	**0.548****	

n=121 Listwise
** - Correlation is statistically significant at p<0.01
* - Correlation is statistically significant at p<0.05

After reviewing the correlations and descriptive statistics in Table 4.2, it was suspected that multicollinearity existed among some variables. When analyzing the control variables (age, sex, familiarity, consumer innovativeness, and attitude (average)), familiarity, consumer innovativeness, and attitude (average) significantly correlated with all other variables except age and sex. When analyzing the independent variables (perceived usefulness and perceived ease of use) and moderator variables (contractual, competence, and goodwill trust), each significantly correlated with each other. Of those, the three dimensions of trust – 1) contractual, 2) competence, and 3) goodwill as all had bivariate correlations above 0.8, indicating a potential problem with multicollinearity. Further, each dimension displayed a variance inflation factor (VIF) of above 3.1. Next, an exploratory factor analysis (EFA) was conducted to analyze interrelationships among the large number of trust variables and to explain these variables in terms of their common underlying dimensions (factors). Sampling adequacy was addressed by Kaiser-Meyer-Olkin (KMO) and registered .937 (Kaiser, 1970). A KMO correlation above 0.60 - 0.70 is considered adequate for analyzing the EFA output (Netemeyer, Bearden, & Sharma, 2003). Bartlett's test of sphericity (Bartlett, 1950) stipulates a chi-square output that must be statistically significant (p<.05) and tests that the correlation matrix is not an identity matrix (which indicates unrelated variables) thereby confirming suitability for factor analysis (Hair et al., 2010). Approximate chi-square was 1415.892. Results were statistically significant.

Next, a confirmatory factor analysis (CFA) was conducted to assess the extent to which a pre-defined structure fits the data. Each type of trust item was grouped (four respectively for each contractual, competence, and goodwill trust) and forced on their three respective trust constructs. Indices of fit were then compared between the CFAs including measures of Comparative Fit Index (CFI), Goodness of Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Results reported a CFI of .911 – above the .9 recommended threshold – thus indicating satisfactory good fit. A GFI of .810 was reported – below the .9 recommended threshold – not indicating satisfactory good fit. Results also reported a RMSEA of .143 – above the .1 recommended threshold – not indicating satisfactory fit. A SRMR of .059 was reported – below the .1 recommended threshold – indicating satisfactory good fit. Construct validity and reliability were also assessed. Per Hair et al. (2010), there are certain measures that are useful for establishing validity and reliability – composite reliability (CR), average variance extracted (AVE), maximum shared variance (MSV) (Hair et al., 2010). In this CFA, each dimension of trust met CR (> 0.7) and AVE (> 0.5) thresholds but demonstrated discriminant validity concerns as the square root of the AVE for contractual, competence, and goodwill trust was less than the absolute value of the correlations with another factor. Further, the AVE for these individual trust dimensions is less than their respective MSV.

Then, a CFA was conducted on all constructs contained within the proposed research model – perceived usefulness (PU), perceived ease of use (PEU), behavioral intention to use (BIU), contractual trust (CONT), competence trust, (COMP), and goodwill trust (GOOD). Results reported a CFI of .925 – above the .9 recommended threshold – thus indicating satisfactory good fit. A GFI of .770 was reported – below the .9 recommended threshold – not indicating satisfactory good fit. Results also reported a RMSEA of .098 – below the .1 recommended threshold – thus indicating satisfactory fit. A SRMR of .069 was reported – below the .1 recommended threshold – indicating satisfactory good fit. Construct validity and reliability was also assessed. Each construct met CR and AVE thresholds but demonstrated discriminant validity concerns as the square root of the AVE for contractual, competence, and goodwill trust was less than the absolute value of the correlations with another factor. Further, the AVE for these individual trust dimensions is less than their respective MSV. Based on these CFAs and previous scale reliability analysis it was decided that, overall, the proposed model indicated good fit with the data despite known issues in the trust scales (further addressed as a limitation later in this study). Detailed results are reported in Appendix 1.

The following models were tested with hierarchical moderated linear regression (Baron & Kenny, 1986). In all models, the study controlled for age, sex, familiarity, consumer innovativeness, and attitude (average). All variables were also centered up front before model testing. Regression results are included in Table 4.3.

4.1 Proposed Hypotheses Regression Results

Model 1

As seen in Table 4.3, Model 1 included the control variables of age, sex, familiarity, consumer innovativeness, and attitude (average), leading to the dependent variable of behavioral intention to use. The output illustrated that attitude (average) was statistically significant and positively related to behavioral intention to use (β=.682, $p<.01$). The model was statistically significant ($p<.00$) with an adjusted R^2 of 0.584 and suggests that as the average of attitude increases, the higher the behavioral intention to use.

Model 2

Model 2 included the control variables of age, sex, familiarity, consumer innovativeness, and attitude (average), plus the two independent variables of perceived usefulness and perceived ease of use, leading to the dependent variable of behavioral intention to use. The output illustrated that both perceived usefulness (β=.004, p=.971) and perceived ease of use (β=-.088, p=.335) were not statistically significant. The model was statistically significant ($p<.001$) with an adjusted R^2 of 0.581. The delta R squared from model 1 to model 2 was 0.605.

Hypothesis 1 (H1) suggested perceived usefulness (PU) positively effects a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants. This was not supported based on the results of model 2.

Hypothesis 2 (H2) suggested perceived ease of use (PEU) positively effects a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants. This was not supported based on the results of model 2.

Model 3

Model 3 included the control variables of age, sex, familiarity, consumer innovativeness, and attitude (average), the two independent variables of perceived usefulness and perceived ease of use, plus the direct effect of contractual, competence, and goodwill trust, leading to the dependent variable of behavioral intention to use. The output illustrated that contractual (β=.007, p=.965), competence (β=-.190, p=.123), and goodwill (β=-.002, p=.988) trust were all not statistically significant. The model was statistically significant ($p<.01$) with an adjusted R^2 of 0.586. The delta R squared from model 2 to model 3 was 0.620.

Model 4

Model 4 included the control variables of age, sex, familiarity, consumer innovativeness, and attitude (average), the two independent variables of perceived usefulness and perceived ease of use, the direct effect of contractual, competence, and goodwill trust, plus the proposed moderating effects of each type of trust, leading to the dependent variable of behavioral intention to use.

The first output (model 4A on the regression table) illustrated that the moderating effects of contractual trust on perceived usefulness (β=-.075, p=.498) and contractual trust on perceived ease of use (β=.051, p=.651) were not statistically significant. The model was statistically significant ($p<.01$) with an adjusted R^2 of 0.580. The delta R squared from model 3 to model 4A was 0.002. Further, even though not proposed, contractual trust's moderation effect on perceived ease of use was calculated as a robustness check with all findings not statistically significant.

Hypothesis 3 (H3) suggested the relationship between perceived usefulness (PU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's contractual trust. Specifically, when a high level of contractual trust is present a consumer's behavioral intention to use will increase. This was not supported based on the results of model 4.

The second output (model 4B on the regression table) illustrated that the moderating effects of competence trust on perceived usefulness (β=-.105, p=.216) and competence trust on perceived ease of use (β=.054, p=.506) were not statistically significant. The model was statistically significant ($p<.01$) with an adjusted R^2 of 0.584. The delta R squared from model 4A to model 4B was 0.005.

Hypothesis 4a (H4a) suggested the relationship between perceived usefulness (PU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's competence trust. Specifically, when a high level of competence trust is present a consumer's behavioral intention to use will increase. This was not supported based on the results of model 4.

Hypothesis 4b (H4b) suggested the relationship between perceived ease of use (PEU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's competence trust. Specifically, when a high level of competence trust is present a consumer's behavioral intention to use will increase. This was not supported based on the results of model 4.

The third output (model 4C on the regression table) illustrated that the moderating effects of goodwill trust on perceived usefulness (β=-.116, p=.189) and goodwill trust on perceived ease of use (β=.029, p=.748) were not statistically significant. The model was statistically significant ($p<.01$) with an adjusted R^2 of 0.587. The delta R squared from model 4B to model 4C was 0.008.

Hypothesis 5a (H5a) suggested the relationship between perceived usefulness (PU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's goodwill trust.

Specifically, when a high level of goodwill trust is present a consumer's behavioral intention to use will increase. This was not supported based on the results of model 4.

Hypothesis 5b (H5b) suggested the relationship between perceived ease of use (PEU) and a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants will be positively moderated by that individual's goodwill trust. Specifically, when a high level of goodwill trust is present a consumer's behavioral intention to use will increase. This was not supported based on the results of model 4.

Lastly, the fourth output (model 4D on the regression table) tests all proposed moderating effects of each type of trust together in one model. The model was statistically significant (p<.01) with an adjusted R^2 of 0.581. The delta R squared from model 4C to model 4D was 0.637.

Table 4.3 Regression Results

Variables	Model 1	Model 2	Model 3	Model 4A	Model 4B	Model 4C	Model 4D
	β	β	β	β	β	β	β
Controls							
Age	0.018	0.009	0.010	0.110	0.001	0.000	-0.006
Sex	0.009	0.003	0.027	0.032	0.032	0.330	0.030
Familiarity	0.092	0.121	0.154	0.155	0.151	0.144	0.145
Consumer Innovativeness	0.066	0.066	0.041	0.041	0.041	0.051	0.050
Attitude (average)	0.682**	0.717**	0.779**	0.788**	0.806**	0.804**	0.790**
Main Effects							
Perceived Usefulness		0.004	0.060	0.640	0.062	0.059	0.048
Perceived Ease of Use		-0.088	-0.055	0.044	-0.043	-0.037	-0.027
Contractual Trust			0.007	-0.007	0.032	0.002	0.062
Competence Trust			-0.190	-0.167	-0.25	-0.168	-0.247
Goodwill Trust			-0.002	-0.029	0.002	-0.060	-0.042
Moderators							
Contractual Trust							
Perceived Usefulness				-0.075			0.197
Perceived Ease of Use				0.051			-0.034
Competence Trust							
Perceived Usefulness					-0.105		-0.056
Perceived Ease of Use					0.054		0.078
Goodwill Trust							
Perceived Usefulness						-0.116	-0.230
Perceived Ease of Use						0.029	-0.024
R	0.775	0.778	0.787	0.789	0.791	0.793	0.798
R^2	0.601	0.605	0.620	0.622	0.626	0.628	0.637
Adjusted R^2	0.584	0.581	0.586	0.580	0.584	0.587	0.581
ΔR^2	0.601	0.605	0.620	0.002	0.005	0.008	0.637
F	34.677**	24.736**	17.954**	14.797**	15.034**	15.212**	11.400**

Standardized regression coefficients shown
** - Correlation is statistically significant at p<0.01
* - Correlation is statistically significant at p<0.05

4.2 Post Hoc Analyses

As reported, the findings of this dissertation did not statistically support any of the proposed hypotheses. To further evaluate these non-findings, post hoc analyses was conducted whereby the individual direct effects of contractual, competence, and goodwill trust were replaced with a trust composite variable (all twelve individual trust items added together and divided by twelve) to assess any differences and perhaps combat the multicollinearity that existed between the individual trust types (contractual, competence, and goodwill). Attitude (average) was also removed.

Additionally, a third CFA was conducted where all twelve trust items (four respectively for each contractual, competence, and goodwill trust) were forced on a single trust construct. This post hoc CFA reported a CFI of .870 and GFI of .722 – both fall below the .9 recommended threshold – not indicating satisfactory good fit. Results also reported a RMSEA of .168 – above the .1 recommended threshold – not indicating satisfactory good fit. Lastly, results reported a SRMR of .544 – above the .1 recommended threshold – not indicating satisfactory good fit. Although this post hoc CFA did not provide any better results than the first two models, it was still valuable and worth running as another method to attempt to address the multicollinearity concerns herein. And while perhaps going against established theory, this post-hoc CFA was used as a tool to further analyze, diagnose, and understand the significant multicollinearity across different constructs as respondents clearly did not seem to be able to disentangle the provided dimensions of trust. It could be that there is a different focus on trust based on the various types of relationships (e.g. interorganizational v. consumer). For example, partners in a supply chain or a venture capitalist may distinctly see and require multiple dimensions of trust to underpin their relationships / transactions due to intricacies such as supporting a supplier ecosystem or protecting a large investment of personal capital. Conversely, consumers who are merely using a service may feel they have less invested and less to lose so they may not care about delineated measures of trust in their transactional relationship. This is included in Appendix 1.

Model 5

Model 5 included the control variables of age, sex, familiarity, consumer innovativeness, the two independent variables of perceived usefulness and perceived ease of use, and the direct effect of trust (composite), leading to the dependent variable of behavioral intention to use. The output illustrated that trust (composite) (β=.088, p=.437) was not statistically significant. However, the direct effect of perceived usefulness was statistically significant and positively related to behavioral intention to use (β=.456, $p<.01$). The direct effect of familiarity was also statistically significant and positively related to behavioral intention to use (β=.259, $p<.05$). The model was statistically significant ($p<.01$) with an adjusted R^2 of 0.413 and suggests that as perceived usefulness and familiarity increases, the higher the behavioral intention to use.

Model 6

Model 6 included the control variables of age, sex, familiarity, consumer innovativeness, the two independent variables of perceived usefulness and perceived ease of use, the direct effect of trust (composite), plus the moderating effect of trust (composite), leading to the dependent variable of behavioral intention to use.

The output illustrated that the moderation effect of trust (composite) on perceived usefulness (β=-.046, p=.680) and trust (composite) on perceived ease of use (β=.113, p=.326) were not statistically significant. However, the direct effect of perceived usefulness was statistically significant and positively related to behavioral intention to use (β=.442, $p<.01$). The direct effect of familiarity was also statistically significant and positively related to behavioral intention to use (β=.275, $p<.05$). The model was statistically significant ($p<.01$) with an adjusted R^2 of 0.409 and suggests that as perceived usefulness and familiarity increases, the higher the behavioral intention to use. The delta R squared from model 5 to model 6 was 0.453.

Table 4.4 Post Hoc Regression Results

Variables		Model 5	Model 6
		β	β
Controls			
Age		0.041	0.057
Sex		-0.028	-0.014
Familiarity		0.259*	0.275*
Consumer Innovativeness		0.122	0.098
Attitude (average)			
Main Effects			
Perceived Usefulness		0.456**	0.442**
Perceived Ease of Use		-0.127	-0.103
Contractual Trust			
Competence Trust			
Goodwill Trust			
Trust (composite)		0.088	0.086
Moderators			
Contractual Trust			
Perceived Usefulness			
Perceived Ease of Use			
Competence Trust			
Perceived Usefulness			
Perceived Ease of Use			
Goodwill Trust			
Perceived Usefulness			
Perceived Ease of Use			
Interaction Effects			
Trust (composite)*Perceived Usefulness			-0.046
Trust (composite)*Perceived Ease of Use			0.113
	R	0.669	0.673
	R^2	0.447	0.453
	Adjusted R^2	0.413	0.409
	ΔR^2	0.447	0.453
	F	13.044**	10.211**

Standardized regression coefficients shown
** - Correlation is statistically significant at $p<0.01$
* - Correlation is statistically significant at $p<0.05$

CHAPTER 5: DISCUSSION AND CONCLUSION

The objective of this study was to examine what drives a consumer's decision to use a financial technology and what potentially moderates a fintech's perceived usefulness in relation to a consumer's behavioral intention to use as these are important questions with the ever-growing development of technology and its increasing integration into users' personal financial lives yet ones that remain largely unanswered regarding specific decisions to accept or reject a financial technology (Marangunić & Granić, 2015). Further, would consumers, who (1) have traditionally interacted face to face with bank employees, often transacting based on a level of trust, and (2) are potentially placing their financial wealth at risk by interfacing with technology (or at least have significant concerns of this risk, whether real or not), be willing to adopt fintech remains an important question for banks and other financial services seeking significant gains in efficiencies offered by reducing employee numbers and brick-and-mortar locations and increased market share by improving the quality and variety of banking services. More specifically, from a consumer perspective, would users adapt to emerging service offerings that play the social role customarily assigned to a human worker (Belanche et al., 2019).

Grounded in Davis' seminal technology acceptance literature that splits the influences affecting individual behavioral attitudes into perceived usefulness (PU) – the extent to which individuals view the use of a given technology as potentially increasing their job performance, and perceived ease of use (PEU) – the extent to which individuals view using a technology as being relatively effort-free, which have a significant impact on the adoption of new technology (Davis, 1985, 1989) and incorporating extant research on consumer adoption and the role of trust, this dissertation integrates TAM with trust research to provide a more holistic understanding of how trust influences consumers' intentions to use / adopt chatbot services, whether all forms of trust are relevant, and how organizations can engender the different forms of trust to encourage consumer adoption of technologies. More specifically, it aimed to examine the extent to which each form of selected trust – competence, contractual, and goodwill – potentially moderates the relationships between perceived usefulness and perceived ease of use with consumer adoption of artificial intelligence-driven chatbots.

The intended contributions of this study were to investigate and explain opportunities for extending and addressing gaps in the research of technology acceptance as applied to fintech. Specifically, leveraging TAM to examine trust in consumer adoption of artificial intelligence-driven virtual finance assistants. Simultaneously, bridging the mature and well-established technology acceptance research stream with the disparate and incoherent fintech research stream. As far as I am aware, no study has examined trust, as a construct and in these dimensions, in the acceptance of artificial intelligence-driven virtual finance assistants utilizing TAM. This dissertation attempted to address what drives a consumer’s decision to use a financial technology (“fintech”) and what potentially moderates a fintech’s perceived usefulness in relation to a consumer’s behavioral intention to use. And although the results did not lend support for the intended contributions, this study hopefully adds to the literature on technology acceptance through the lens of the latest technological revolution.

Before discussing the central findings of the proposed model, control variable results should be briefly reviewed. The analysis output illustrated that only one control variable, attitude (average), was significantly positively correlated with, and the strongest predictor of, behavioral intention to use. It is worth reporting the mean of attitude (average) was quite low at 2.889. A logical anecdotal argument could be made that this could be expected as simply having a favorable attitudinal inclination towards using artificial intelligence-driven virtual finance assistants is far from actual adoption / use. It is purely speculative with no tangible action or risk associated therewith. It may also align with Fishbein and Ajzen (1975) who suggest customers are not only driven by their positive or negative assessment of the use of fintech services but also consider the expectations of others when making usage decisions (M. Fishbein & Ajzen, 1975). Or perhaps, in a new situation where there is no obvious course of action (e.g. when first using an artificial intelligence-driven virtual finance assistant) consumers may require some fundamental social confirmation and potentially seek information from surrounding sources to better understand and navigate (Wei & Zhang, 2008). This supports prior literature that posits that attitude is a central tenet in emerging technology-based service adoption (Hernandez et al., 2009). Many of the demographic attributes, such as age, education, employment, familiarity, and consumer innovativeness are discussed in the below limitations section.

Regarding the suggested model's core findings, Hypothesis 1 proposed perceived usefulness (PU) positively effects a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants while Hypothesis 2 proposed perceived ease of use (PEU) positively effects a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants. Neither of these hypotheses were supported by this dissertation's data. These non-significant results are somewhat surprising as both perceived usefulness and perceived ease of use are the core constructs of the technology acceptance model and have been repeatedly shown to affect individual behavioral attitudes, which have a significant impact on the adoption of new technology (Venkatesh & Bala, 2008). Individually, a plethora of empirical studies on technology adoption from the past ten years demonstrate that perceived usefulness can have a positive impact on users' intentions (Barakat & Hussainey, 2013; Featherman & Pavlou, 2003; Hong & Zhu, 2006; Ng & Kwok, 2017) while, specific to research in the area of banking, several scholars have exhibited a significant correlation between perceived ease of use and emerging technology adoption attitudes (Akturan & Tezcan, 2012; Szopiński, 2016). Akturan and Tezcan (2012) was a consumer study focused on student adoption at a local university while Szopiński (2016) investigated online banking in Poland. On the macro level, TAM as a model has seen numerous iterations (e.g. TAM2, TAM3, UTAUT, UTAUT2) that incorporate a myriad of determinants and continues to increase in robustness and exploratory power. Some studies have suggested the effect of perceived usefulness on behavioral intention to use is more consistent in post-acceptance stages (e.g. after several months of using a product) (Bhattacherjee, 2001; Casaló, Flavián, & Guinalíu, 2010). To pull that thread further, it is also worth noting that this survey had respondents that did not have prior experience (89%) and familiarity with artificial intelligence-driven virtual finance assistants. With that in mind, respondents in this study may not have enough experience (or any experience at all) with artificial intelligence-driven virtual finance assistants to be able to respond to perceived usefulness and its effect on behavioral intention to use.

The remaining hypotheses all posited the moderating effect of different trust dimensions on the study's suggested model. Hypothesis 3 proposed contractual trust positively moderates perceived usefulness (PU) of a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants. Hypothesis 4 (a and b) proposed competence trust positively moderates perceived usefulness (PU) and perceived ease of use (PEU) of a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants. Hypothesis 5 (a and b) proposed goodwill trust positively moderates perceived usefulness (PU) and perceived ease of use (PEU) of a consumer's behavioral intention to use artificial intelligence-driven virtual finance assistants. None of these moderating hypotheses were supported by this dissertation's data. These results were unexpected as, in general, trust is the main catalyst for most business transactions (Illia, Ngniatedema, & Huang, 2015). Further, trust was demonstrated to be an antecedent of engaging in online banking (Shen, Huang, Chu, & Hsu, 2010). Perhaps the findings were non-significant in part as high levels of trust are not necessary in all relationships (Ireland & Webb, 2007). More likely I would suggest the multicollinearity that exists among the three dimensions of trust coupled with the survey administration / platform and demographics may have contributed to these results. Respondents, 88% of whom were 65 or older and 82% retired, likely were on the Qualtrics panel list as a source of supplemental income in their retirement phase of life – dedicated survey-takers who spend their days quickly clicking through as many surveys as possible to maximize their financial returns. These constraints led to the creation of the composite trust item (all twelve individual trust items added together and divided by twelve).

In post hoc analysis, the moderating effects of each type of trust (contractual, competence, and goodwill) were combined as a composite, producing significant and positive results for perceived usefulness. These results were aligned with expectations and affirmed users are driven to adopt a technology chiefly because of its functionality and often prepared to deal with some difficulty of use when the functionality provided is critically required – no ease of use amount can offset a useless functioning technology (Davis, 1989). As mentioned, while this practice may go against standard theory it was mainly used as another diagnostic method to understand the limitations of the data. At that point, the data was not changing nor were its shortcomings, so it was decided to utilize every lens feasible to understand the sample and provide some salient limitation points for later in this study. Regarding trust as a moderator, each individual type of trust (contractual, competence, and goodwill) was hypothesized to have a positive effect on perceived usefulness in this dissertation's model. Although that was not the case individually, the combination of these dimensions of trust as moderators at least provided a few significant findings in respect to perceived usefulness. It seems reasonable to believe that contractual trust can have the potential to reduce consumer wariness and, in turn, increase consumer adoption of artificial intelligence-driven virtual finance assistants. Or, that consumers may prefer to adopt fintech services provided by familiar banks with a good reputation. Or, when the quality and relevant functions of a product are unclear (as is the case with the novelty of most chatbot services) brand image can help consumers make a selection (Ratnasingam & Pavlou, 2003). And while all banking services and transactions are underpinned with certain contractual protections (e.g. user agreements, FDIC assurances), goodwill trust can develop and strengthen as the exchanges between consumer and bank continue over time and increase in scope (Ireland & Webb, 2007) and, once established, goodwill trust may enable a more open and willing exchange of knowledge and resources between banks and consumers, such as use of innovative artificial intelligence-drive virtual finance assistants.

Overall, although the are several non-findings in this dissertation, this study hopefully supplements or advances (even minimally) research on the role of consumer trust dimensions in the acceptance of artificial intelligence-driven virtual finance assistants utilizing TAM.

5.1 Implications

Non-findings withstanding, this study may provide limited implications for practitioners and scholars – even if minimal in fashion. Practitioners could realize that artificial intelligence and the technological revolution as a whole is pressuring established economic and employment principles, with penetration of automated technology increasing at a rate of 20% annually (Belanche et al., 2019). Further, Ransbotham et al. (2017) offered that more than 85% of executives think that artificial intelligence will realize sustained competitive advantages for their companies (Ransbotham et al., 2017), yet consumer adoption of chatbot services has been deemed “slow so far” (Jung et al., 2018, p. 367). Due to the novelty of artificial intelligence-driven virtual finance assistants, there is presently a paucity of knowledge about their key adoption determinants by consumers. The role of trust within fintech is also of critical importance due to this novelty and the highly confidential nature of data involved in the provision of the service. With recent literature positioning this technological advance as a disruptive innovation, financial institutions should carefully understand their position and strategic integration options in order to accomplish a successful digital transformation (Singh et al., 2017; Van Doorn et al., 2017). This dissertation aimed (and hoped) to identify the key determinants of consumer adoption of artificial intelligence-driven virtual finance assistants while incorporating the potential moderating dimensions of trust.

For scholars, from a general fintech perspective, research tends to be disparate with no intelligible research plan highlighting substantial research gaps with critical questions remaining (Kavuri & Milne, 2019). Additionally, bridging the technology acceptance and fintech research streams, only Lucente (2002) in the context of e-commerce, Nguyen (2018) in the travel field, Belanche (2019) with robo-advisers, and Cardona (2019) in insurance have undertaken various levels of research (Belanche et al., 2019; Cardona et al., 2019; Lucente, 2000; Nguyen & Sidorova, 2018). This is also a new domain to apply Sako's (1992) categorization of trust. Again, due to the novelty of artificial intelligence-driven virtual finance assistants, there is currently a lack of knowledge about key adoption determinants by consumers and, to the best of my knowledge, no study has examined trust in the acceptance of artificial intelligence-driven virtual finance assistants utilizing TAM. It may also serve as a cautionary tale to scholars to ensure their research design has well thought-out respondent requirements if they are considering the use of survey companies like Qualtrics to avoid the highly skewed age distribution encountered in this study.

5.2 Limitations

The present research has several limitations. First and foremost, I acknowledge the presence of multicollinearity amongst the proposed trust dimensions (contractual, competence, and goodwill). I tried to proactively avoid this shortcoming by taking survey items only from previously established and validated measures from relevant technology adoption, online banking, and e-commerce literature, with minimal rewording, to align specifically to the current framework of this study. Multicollinearity may have also been exacerbated by the survey collection approach of leveraging Qualtrics to panel and administer both surveys. Purchasing data is always a precarious proposal due to the personal lack of control on respondents. Although preemptive design safeguards included respondents being systematically forced to respond to each question so partial responses were not accepted therefore eliminating the risk of any missing data, a "speeding check" threshold of four minutes whereby any respondent who completed the survey in under that time did not have their results retained, and automated and manual data reviews to remove those who responded in a pattern (e.g. straight-lined responses or high / low), more could have been done in hindsight. For instance, adding a marker question to the effect of "For this question, select 'Strongly Disagree'" or "I like to drive fast cars." And, as discussed prior, more likely I would suggest the multicollinearity that exists amongst the three dimensions of trust coupled with the survey administration / platform and demographics may have contributed to these overarching results. After performing the EFA and CFA, creating a composite trust item (all twelve individual trust items added together and divided by twelve) to also include in models 3 and 4, to compare with the individual trust dimensions in those same models was the best option available.

As introduced above regarding age, respondents, 88% of whom were 65 or older and 82% retired, likely were on the Qualtrics panel list as a source of discretionary / secondary income in their retirement phase of life – dedicated survey-takers who spend their days quickly clicking through as many surveys as possible to maximize their financial returns. It is simply the logical distribution nature of who would be available to take surveys on-demand requiring quick turn-around and motivated by financial incentive. It begs the question if, in general, this age distribution is tech savvy enough to grasp the concept of an artificial intelligence-driven virtual finance assistant (or furthermore have a probability of using one). In a recent study on smartphone adoption, findings showed age to be a significant moderator – principally, age moderated the relationship between behavioral intention and five independent factors including 1) culture-specific beliefs and values, 2) perceived relative advantage, 3) price value, 4) effort expectancy, and 5) enjoyment. Moreover, age moderated the effect of habit on actual use of smartphones (Ameen & Willis, 2018). Looking back, perhaps smaller more defined age ranges may have produced a more desirable sample. Prior literature has posited that older individuals have more established beliefs and are less vulnerable to messaging from others compared to that of younger people (Hess, 1994). However, that is offset by more recent studies that suggest new technology adoption may be unaffected by age when it is aimed to a broad enough population (Belanche-Gracia, Casaló-Ariño, & Pérez-Rueda, 2015). A pilot study could also have been beneficial to preliminarily evaluate the quality of the survey items and sample respondent base, allowing review and modifications by content experts before a general release (Fan & Yan, 2010).

From a model design perspective, this study leveraged Fred Davis' original technology acceptance model from 1985 rather that more recent iterations (e.g. TAM2, TAM3, UTAUT) that incorporate a myriad of determinants and continue to increase in robustness and exploratory power. This was an intentional design choice to streamline this study and avoid the potentially cumbersome inner workings of those more advanced models. This could be seen as a limitation however and worthwhile potential prospect for future research.

Next, several categorizations of trust with different foundations could have been used as a potential moderator in this study (Barney & Hansen, 1994; McAllister, 1995; Rousseau et al., 1998). Sako (1992) was selected as his dimensions of contractual, competence, and goodwill trust aligned nicely with the premise of this study and emphasized the partner / organization distinction of trust versus trust in a situation (Ireland & Webb, 2007). One could examine how might Barney and Hansen's (1994) weak form trust, semi-strong form trust, and strong form trust shape acceptance of an emerging technology and provide a source of competitive advantage to financial institutions or technology designers and providers. Or could cognition-based trust, focusing on peer reliability and dependability, and affect-based trust, focusing on care and concern as described by McAllister (1994) be extended from simply peer networks to service provider networks (McAllister, 1995).

Lastly, both surveys included in this study are quite basic and minimalistic. They only include the specific constructs needed to test my dissertation but nothing more. This is a valid limitation as I could have added additional controls, constructs, or scales to better position myself for multiple studies and possible publication in the future. That said, knowing what I know now with the quality of survey data I received back, it seemingly would have been an increased cost with little to no benefit.

5.3 Prospects for Future Research

This dissertation's research may inform future research in a few ways. First, this study focuses on behavioral intention to use as its dependent variable. Venkatesh and Davis (2000) have established that intention to use and actual use are often highly correlated in the case of volitional behaviors (Venkatesh & Davis, 2000). And although the study of behavioral intention to use helps explain initial stages of the adoption process, as time progresses intentions are continuously honed and adapted leading to long-term continuance or discontinuance (Bhattacherjee, 2001). Thus, a longitudinal study may be in order to measure actual use of artificial intelligence-driven virtual finance assistants thereby further validating or extending this dissertation (Bagozzi, 2007).

Next, this dissertation's suggested TAM-based model could be modified or wholly-replaced with other technology acceptance versions including TAM2, TAM3, UTAUT, UTAUT2, etc. Additional risk moderators could also be included in the model(s) such as regulatory, cybersecurity, or privacy to investigate their effect on a consumer's intention to use – all prevailing considerations with emerging technology such as fintech. The same could be applied to Sako's chosen categorization of trust for this study by leveraging an alternative from the myriad of established trust types and observing if results change. Attitude could also potentially be examined in a consumer behavioral, quality, happiness, satisfaction lens to understand the ways these, and other servicing components, drive or deter usage. This study also captured survey items on product attractiveness (e.g. Artificial intelligence-drive virtual finance assistants would be fun to use) and overall anxiety towards technology usage (e.g. It scares me to think I could lose a lot of information using artificial intelligence-driven virtual finance assistants by hitting the wrong button) that were not leveraged as part of this dissertation. Perhaps product attractiveness could be a component of brand and service trust, an alternative dimension of trust, that investigates how usage is affected from a marketing and image standpoint. From a business perspective, further understanding anxiety may help drive critical mass – a complimentary theory to TAM which in essence suggests that as the number of users of a specific technology increases it becomes self-sustaining and may put more pressure on others in society (e.g. friends, coworkers, family) to adopt. This could also be investigated from a design perspective to implore application architects to design more intuitive, appealing, and seamless feel when using a product.

Users may also perceive artificial intelligence-driven virtual finance assistants differently based on their delivery method / platform – for example, application based v. website delivered. This could be an additional control variable since these specific fintech services are still gaining acceptance and potential users may need to search the internet or a website for their desired services. As literature demonstrates, when quality and relevant functionality are unclear, brand can help consumers make a selection (Veloutsou, 2007). Perhaps this lens (brand) can be extrapolated to competence or goodwill trust.

And finally, as this dissertation focuses on financial services (primarily financial institutions), it could be of merit to apply and investigate the parameters of this study to other segments being disrupted by the technology revolution other than just banks. These include robo-advisers / personal finance (e.g. Vanguard), regtechs (e.g. Corlytics), payments / remittances (e.g. PayPal), blockchain / distributed ledger technology / bitcoin (e.g. Coinbase), insurtechs (e.g. Cuvva), and alternative finance (e.g. SoFi). Agriculture, manufacturing, and service industries also come to mind.

5.4 Conclusion

This study had two objectives – (1) to examine what drives a consumer's decision to use a fintech and what potentially moderates a fintech's perceived usefulness and perceived ease of use in relation to a consumer's behavioral intention to use and (2) to examine what role does trust play in consumer adoption of artificial intelligence-driven virtual finance assistants. A substantial amount of research has established the positive direct effect between a technology's perceived usefulness, the extent to which individuals view the use of a given technology as potentially increasing their job performance, and perceived ease of use, the extent to which individuals view using a technology as being relatively effort-free, with the significant impact both have on the adoption of new technology. The research here has extended this relationship to include the moderating effects of contractual, competence, and goodwill trust on a consumer's behavioral intention to use. Although the study found few significant results across the proposed model, I hope this research encourages other scholars to 1) continue to examine and expand the boundaries on technology acceptance specific to current fintech applications as this is a vastly underserved area of study and 2) continue to ride the wave of the ever-expanding technology revolution and drive the intersect between academia and practitioner.

REFERENCES

Acemoglu, D., & Restrepo, P. (2017). Robots and jobs: Evidence from US labor markets.

Adams, D. A., Nelson, R. R., & Todd, P. A. (1992). Perceived usefulness, ease of use, and usage of information technology: A replication. *MIS Quarterly*, 227-247.

Adeiza, A., Azizi Ismail, N., & Marissa Malek, M. (2017). An Empirical Examination of the Major Relationship Factors Affecting Franchisees' Overall Satisfaction and Intention to Stay. *Iranian Journal of Management Studies, 10*(1), 31-62.

Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences, 28*(3), 557-582.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In *Action Control* (pp. 11-39): Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behaviour.

Ajzen, I., & Madden, T. J. (1986). Prediction of goal-directed behavior: Attitudes, intentions, and perceived behavioral control. *Journal of Experimental Social Psychology, 22*(5), 453-474.

Akturan, U., & Tezcan, N. (2012). Mobile banking adoption of the youth market: Perceptions and intentions. *Marketing Intelligence & Planning, 30*(4), 444-459.

Almarashdeh, I., & Alsmadi, M. K. (2017). How to make them use it? Citizens acceptance of M-government. *Applied Computing and Informatics*, *13*(2), 194-199.

Alt, R., & Puschmann, T. (2012). The rise of customer-oriented banking-electronic markets are paving the way for change in the financial industry. *Electronic Markets*, *22*(4), 203-215.

Ameen, N., & Willis, R. (2018). *An Analysis of the Moderating Effect of Age on Smartphone Adoption and Use in the United Arab Emirates.* Paper presented at the Proceedings for the UK Academy of Information Systems (UKAIS) Conference.

Amoako-Gyampah, K. (2007). Perceived usefulness, user involvement and behavioral intention: an empirical study of ERP implementation. *Computers in Human Behavior, 23*(3), 1232-1248.

Anderson, C. S., Al-Gahtani, S., & Hubona, G. (2011). The value of TAM antecedents in global IS development and research. *Journal of Organizational and End User Computing (JOEUC), 23*(1), 18-37.

Arner, D. W., Barberis, J., & Buckley, R. P. (2016). 150 YEARS OF FINTECH: An evolutionary analysis. *JASSA*(3), 22-29.

Arner, D. W., Barberis, J. N., & Buckley, R. P. (2016). The Evolution of Fintech: A New Post-Crisis Paradigm? *University of Hong Kong Faculty of Law Research Paper No. 2016/047*.

Arning, K., & Ziefle, M. (2007). Understanding age differences in PDA acceptance and performance. *Computers in Human Behavior, 23*(6), 2904-2927.

Au, Y. A., & Kauffman, R. J. (2008). The economics of mobile payments: Understanding stakeholder issues for an emerging financial technology application. *Electronic Commerce Research and Applications, 7*(2), 141-164.

Bagozzi, R. P. (1982). A field investigation of causal relations among cognitions, affect, intentions, and behavior. *Journal of Marketing Research, 19*(4), 562-584.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(4), 3.

Bamberg, S., Ajzen, I., & Schmidt, P. (2003). Choice of travel mode in the theory of planned behavior: The roles of past behavior, habit, and reasoned action. *Basic and Applied Social Psychology, 25*(3), 175-187.

Bamford, C. E., Dean, T. J., & McDougall, P. P. (2000). An examination of the impact of initial founding conditions and decisions upon the performance of new bank start-ups. *Journal of Business Venturing, 15*(3), 253-277.

Barakat, A., & Hussainey, K. (2013). Bank governance, regulation, supervision, and risk reporting: Evidence from operational risk disclosures in European banks. *International Review of Financial Analysis, 30*, 254-273.

Barber, B. (1983). *The Logic and Limits of Trust* (Vol. 96): Rutgers University Press New Brunswick, NJ.

Barki, H., & Hartwick, J. (1994). User participation, conflict, and conflict resolution: the mediating roles of influence. *Information Systems Research, 5*(4), 422-438.

Barney, J. B., & Hansen, M. H. (1994). Trustworthiness as a source of competitive advantage. *Strategic Management Journal, 15*(S1), 175-190.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173.

Bartlett, M. S. (1950). Tests of significance in factor analysis. *British Journal of Statistical Psychology, 3*(2), 77-85.

Belanche-Gracia, D., Casaló-Ariño, L. V., & Pérez-Rueda, A. (2015). Determinants of multi-service smartcard success for smart cities development: A study based on citizens' privacy and security perceptions. *Government Information Quarterly, 32*(2), 154-163.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*.

Berger, A. (2003). The economic effects of technological progress: evidence from the banking industry. *Journal of Money, Credit and Banking, 35*, 141–176.

Bettinger, A. (1972). FINTECH: A Series of 40 Time Shared Models Used at Manufacturers Hanover Trust Company. *Interfaces, 2*(4), 62-63.

Bhattacherjee, A. (2000). Acceptance of e-commerce services: the case of electronic brokerages. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and humans, 30*(4), 411-420.

Bhattacherjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model. *MIS Quarterly*, 351-370.

Bruner II, G. C., & Kumar, A. (2005). Explaining consumer acceptance of handheld Internet devices. *Journal of Business Research, 58*(5), 553-558.

Burton-Jones, A., & Hubona, G. S. (2006). The mediation of external variables in the technology acceptance model. *Information & Management, 43*(6), 706-717.

Cardona, D. R., Werth, O., Schönborn, S., & Breitner, M. H. (2019). A Mixed Methods Analysis of the Adoption and Diffusion of Chatbot Technology in the German Insurance Sector.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2010). Antecedents and consequences of consumer participation in on-line communities: The case of the travel sector. *International Journal of Electronic Commerce, 15*(2), 137-167.

Chan, S.-c. (2004). Understanding internet banking adoption and use behavior: A Hong Kong perspective. *Journal of Global Information Management (JGIM), 12*(3), 21-43.

Chandavarkar, A. G. (1980). Use of migrants' remittances in labor-exporting countries. *Finance and Development, 17*(2), 36.

Chang, M. K. (1998). Predicting unethical behavior: a comparison of the theory of reasoned action and the theory of planned behavior. *Journal of Business Ethics, 17*(16), 1825-1834.

Chaouali, W., Yahia, I. B., & Souiden, N. (2016). The interplay of counter-conformity motivation, social influence, and trust in customers' intention to adopt Internet banking services: The case of an emerging country. *Journal of Retailing and Consumer Services, 28*, 209-218.

Chau, P. Y., & Hu, P. J.-H. (2002). Investigating healthcare professionals' decisions to accept telemedicine technology: an empirical test of competing theories. *Information & Management*, *39*(4), 297-311.

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education, 63*, 160-175.

Chiu, I. H. (2016). Fintech and disruptive business models in financial products, intermediation and markets-policy implications for financial regulators. *J. Tech. L. & Pol'y, 21*, 55.

Chow, M., Herold, D. K., Choo, T.-M., & Chan, K. (2012). Extending the technology acceptance model to explore the intention to use Second Life for enhancing healthcare education. *Computers & Education*, *59*(4), 1136-1144.

Chowdhury, G. G. (2003). Natural language processing. *Annual review of information science and technology, 37*(1), 51-89.

Christensen, C. M. (2003). *The innovator's dilemma: The revolutionary book that will change the way you do business*: HarperBusiness Essentials New York, NY.

Chuang, L.-M., Liu, C.-C., & Kao, H.-K. (2016). The adoption of fintech service: TAM perspective. *International Journal of Management and Administrative Sciences, 3*(7), 1-15.

Conner, M., Martin, E., Silverdale, N., & Grogan, S. (1996). Dieting in adolescence: An application of the theory of planned behaviour. *British Journal of Health Psychology, 1*(4), 315-325.

Crosman, P. (2019). How 6 million Bank of America customers are using Erica. *American Banker*.

Currall, S. C., & Inkpen, A. C. (2002). A multilevel approach to trust in joint ventures. *Journal of International Business Studies, 33*(3), 479-495.

Das, T. K., & Teng, B.-S. (2001). Trust, control, and risk in strategic alliances: An integrated framework. *Organization Studies, 22*(2), 251-283.

Davidson, A. R., & Morrison, D. M. (1983). Predicting contraceptive behavior from attitudes: a comparison of within-versus across-subjects procedures. *Journal of Personality and Social Psychology, 45*(5), 997.

Davila, A., Foster, G., & Gupta, M. (2003). Venture capital financing and the growth of startup firms. *Journal of Business Venturing*, *18*(6), 689-708.

Davis, F. D. (1985). *A Technology Acceptance Model for Empirically Testing New End-user Information Systems: Theory and Results.* Massachusetts Institute of Technology,

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

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies, 38*(3), 475-487.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management Science, 35*(8), 982-1003.

Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: three experiments. *International Journal of Human-Computer Studies, 45*(1), 19-45.

Davis, F. D., & Venkatesh, V. (2004). Toward preprototype user acceptance testing of new information systems: implications for software project management. *IEEE Transactions on Engineering Management, 51*(1), 31-46.

Ebrahimi, S., Mehdipour, Y., Karimi, A., Khammarnia, M., & Alipour, J. (2018). Determinants of Physicians' Technology Acceptance for Mobile Health Services in Healthcare Settings. *Journal of Health Management and Informatics, 5*(1), 9-15.

Eltayeb, M., & Dawson, M. (2016). Understanding user’s acceptance of personal cloud computing: Using the Technology Acceptance Model. In *Information Technology: New generations* (pp. 3-12): Springer.

Fan, W., & Yan, Z. (2010). Factors affecting response rates of the web survey: A systematic review. *Computers in Human Behavior*, *26*(2), 132-139.

Farahat, T. (2012). Applying the technology acceptance model to online learning in the Egyptian universities. *Procedia-Social and Behavioral Sciences, 64,* 95-104.

Faubion, B. (2016). Effect of automated advising platforms on the financial advising market.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451-474.

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, and behavior: An introduction to theory and research. *Reading, Mass.: Addison Wessley*.

Fishbein, M., Ajzen, I., Albarracin, D., & Hornik, R. (2007). A reasoned action approach: Some issues, questions, and clarifications. *Prediction and change of health behavior: Applying the reasoned action approach*, 281-295.

Fishbein, M. E. (1967). Readings in attitude theory and measurement.

Fredricks, A. J., & Dossett, D. L. (1983). Attitude–behavior relations: A comparison of the Fishbein-Ajzen and the Bentler-Speckart models. *Journal of Personality and Social Psychology, 45*(3), 501.

Gabarro, J. J. (1978). The development of trust, influence and expectations. *Interpersonal behavior: Communication and understanding in relationships*, 290-303.

Gangwar, H., & Date, H. (2016). Critical factors of cloud computing adoption in organizations: An empirical study. *Global Business Review, 17*(4), 886-904.

Gefen, D. (2004). What makes an ERP implementation relationship worthwhile: Linking trust mechanisms and ERP usefulness. *Journal of Management Information Systems*, *21*(1), 263-288.

Gefen, D., Karahanna, E., & Straub, D. W. (2003a). Inexperience and experience with online stores: The importance of TAM and trust. *IEEE Transactions on Engineering Management, 50*(3), 307-321.

Gefen, D., Karahanna, E., & Straub, D. W. (2003b). Trust and TAM in online shopping: an integrated model. *MIS Quarterly, 27*(1), 51-90.

Gefen, D., & Keil, M. (1998). The impact of developer responsiveness on perceptions of usefulness and ease of use: an extension of the technology acceptance model. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 29*(2), 35-49.

Gefen, D., & Straub, D. W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS Quarterly*, 389-400.

George, D., & Mallery, M. (2003). Using SPSS for Windows step by step: a simple guide and reference.

Glaser, F., Iliewa, Z., Jung, D., & Weber, M. (2019). Towards designing robo-advisors for unexperienced investors with experience sampling of time-series data. In *Information Systems and Neuroscience* (pp. 133-138): Springer.

Gomber, P., Koch, J. A., & Siering, M. (2017). Digital Finance and FinTech: current research and future research directions. *Business Economics*(87), 537-580. doi:10.1007/s11573-017-0852-x

Gong, M., Xu, Y., & Yu, Y. (2004). An enhanced technology acceptance model for web-based learning. *Journal of Information Systems Education, 15*(4).

Gorsuch, R. L., & Ortberg, J. (1983). Moral obligation and attitudes: Their relation to behavioral intentions. *Journal of personality and Social Psychology, 44*(5), 1025.

Goslar, M. D. (1986). Capability criteria for marketing decision support systems. *Journal of Management Information Systems, 3*(1), 81-95.

Grabner-Kraeuter, S. (2002). The role of consumers' trust in online-shopping. *Journal of Business Ethics, 39*(1-2), 43-50.

Grant, A. M., & Pollock, T. G. (2011). Publishing in AMJ—Part 3: Setting the hook. In: Academy of Management Briarcliff Manor, NY.

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. *Journal of Retailing, 93*(1), 1-6.

Grote, M. H., Lo, V., & Harrschar–Ehrnborg, S. (2002). A value chain approach to financial centres–the case of Frankfurt. *Tijdschrift voor economische en sociale geografie, 93*(4), 412-423.

Gulati, R. (1995). Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. *Academy of Management Journal, 38*(1), 85-112.

Gumussoy, C., Calisir, F., & Bayram, A. (2007). *Understanding the behavioral intention to use ERP systems: An extended technology acceptance model.* Paper presented at the 2007 IEEE International Conference on Industrial Engineering and Engineering Management.

Hagger, M. S., Chatzisarantis, N. L., & Biddle, S. J. (2002). A meta-analytic review of the theories of reasoned action and planned behavior in physical activity: Predictive validity and the contribution of additional variables. *Journal of Sport and Exercise Psychology, 24*(1), 3-32.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis Edisi Ketujuh. In: New Jersey: Pearson Education Inc.

Han, S., & Yang, H. (2018). Understanding adoption of intelligent personal assistants: A parasocial relationship perspective. *Industrial Management & Data Systems, 118*(3), 618-636.

Hardgrave, B. C., Davis, F. D., & Riemenschneider, C. K. (2003). Investigating determinants of software developers' intentions to follow methodologies. *Journal of Management Information Systems, 20*(1), 123-151.

Hernandez, B., Jimenez, J., & José Martín, M. (2009). Adoption vs acceptance of e-commerce: two different decisions. *European Journal of Marketing, 43*(9/10), 1232-1245.

Hess, T. M. (1994). Social cognition in adulthood: Aging-related changes in knowledge and processing mechanisms. *Developmental Review, 14*(4), 373-412.

Hong, W., Thong, J. Y., Wong, W.-M., & Tam, K.-Y. (2002). Determinants of user acceptance of digital libraries: an empirical examination of individual differences and system characteristics. *Journal of Management Information Systems*, *18*(3), 97-124.

Hong, W., & Zhu, K. (2006). Migrating to internet-based e-commerce: Factors affecting e-commerce adoption and migration at the firm level. *Information & Management, 43*(2), 204-221.

Horst, M., Kuttschreuter, M., & Gutteling, J. M. (2007). Perceived usefulness, personal experiences, risk perception and trust as determinants of adoption of e-government services in The Netherlands. *Computers in Human Behavior, 23*(4), 1838-1852.

Horton, R. P., Buck, T., Waterson, P. E., & Clegg, C. W. (2001). Explaining intranet use with the technology acceptance model. *Journal of Information Technology, 16*(4), 237-249.

Horzyk, A., Magierski, S., & Miklaszewski, G. (2009). An Intelligent Internet Shop-Assistant Recognizing a Customer Personality for Improving Man-Machine Interactions. *Recent Advances in Intelligent Information Systems*, 13-26.

Hrubes, D., Ajzen, I., & Daigle, J. (2001). Predicting hunting intentions and behavior: An application of the theory of planned behavior. *Leisure Sciences, 23*(3), 165-178.

Hsiao, C. H., & Yang, C. (2011). The intellectual development of the technology acceptance model: A co-citation analysis. *International Journal of Information Management, 31*(2), 128-136.

Hu, P. J., Chau, P. Y., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the technology acceptance model using physician acceptance of telemedicine technology. *Journal of Management Information Systems, 16*(2), 91-112.

Hu, Z., Ding, S., Li, S., Chen, L., & Yang, S. (2019). Adoption Intention of Fintech Services for Bank Users: An Empirical Examination with an Extended Technology Acceptance Model. *Symmetry, 11*(3), 340.

Huang, J.-H., Lin, Y.-R., & Chuang, S.-T. (2007). Elucidating user behavior of mobile learning: A perspective of the extended technology acceptance model. *The Electronic Library, 25*(5), 585-598.

Huang, L., Lu, M.-T., & Wong, B. K. (2003). The impact of power distance on email acceptance: Evidence from the PRC. *Journal of Computer Information Systems, 44*(1), 93-101.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155-172.

Huang, Y.-C. (2009). *Examining the antecedents of behavioral intentions in a tourismcontext*: Texas A&M University.

Huang, Y. M. (2017). Exploring students' acceptance of team messaging services: The roles of social presence and motivation. *British Journal of Educational Technology, 48*(4), 1047-1061.

Igbaria, M., Iivari, J., & Maragahh, H. (1995). Why do individuals use computer technology? A Finnish case study. *Information & Management, 29*(5), 227-238.

Igbaria, M., Zinatelli, N., Cragg, P., & Cavaye, A. L. (1997). Personal computing acceptance factors in small firms: A structural equation model. *MIS Quarterly, 21*(3).

Illia, A., Ngniatedema, T., & Huang, Z. (2015). A conceptual model for mobile banking adoption. *Journal of Management Information and Decision Sciences*, *18*(1), 111-122.

Illum, S. F., Ivanov, S. H., & Liang, Y. (2010). Using virtual communities in tourism research. *Tourism Management, 31*(3), 335-340.

Ireland, R. D., & Webb, J. W. (2007). A multi-theoretic perspective on trust and power in strategic supply chains. *Journal of Operations Management*, *25*(2), 482-497.

Jackson, C. M., Chow, S., & Leitch, R. A. (1997). Toward an understanding of the behavioral intention to use an information system. *Decision Sciences, 28*(2), 357-389.

Ji, M. (2017). Are Robots Good Fiduciaries: Regulating Robo-Advisors under the Investment Advisers Act of 1940. *Colum. L. Rev., 117*, 1543.

John, G. (1984). An empirical investigation of some antecedents of opportunism in a marketing channel. *Journal of Marketing Research, 21*(3), 278-289.

Jung, D., Dorner, V., Weinhardt, C., & Pusmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, *28*(3), 367-380.

Kaiser, H. F. (1970). A second generation little jiffy.

Kane, E. J. (2000). Capital movements, banking insolvency, and silent runs in the Asian financial crisis. *Pacific-Basin Finance Journal, 8*(2), 153-175.

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly,* 183-213.

Kavuri, A. S., & Milne, A. (2019). *FinTech and the future of financial services: What are the research gaps?* Centre for Applied Macroeconomic Analysis (CAMA) Working Paper.

Kesharwani, A., & Singh Bisht, S. (2012). The impact of trust and perceived risk on internet banking adoption in India: An extension of technology acceptance model. *International Journal of Bank Marketing, 30*(4), 303-322.

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior, 26*(3), 310-322.

Kim, Y., Park, Y., & Choi, J. (2016). The Adoption of Mobile Payment Services for "Fintech". *International Journal of Applied Engineering Research, 11*(2), 1058-1061.

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740-755.

Kiriakidis, S. (2015). Theory of planned behaviour: The intention-behaviour relationship and the perceived behavioural control (PBC) relationship with intention and behaviour. *International Journal of Strategic Innovative Marketing, 3*(2), 40-51.

Klein, G., & Beck, P. O. (1987). A decision aid for selecting among information system alternatives. *MIS Quarterly*, 177-185.

Lacasse, R., Lambert, B., Roy, N., Sylvain, J., & Nadeau, F. (2016). *A digital tsunami: FinTech and Crowdfunding.* Paper presented at the International Scientific Conference on Digital Intelligence.

Lai, P. (2016). Design and Security impact on consumers' intention to use single platform E-payment. *Interdisciplinary Information Sciences, 22*(1), 111-122.

Lai, P. (2017). Security as an Extension to TAM Model: Consumers' Intention to Use a Single Platform E-Payment. *Asia-Pacific Journal of Management Research and Innovation, 13*(3-4), 110-119.

Lee, D. Y., & Lehto, M. R. (2013). User acceptance of YouTube for procedural learning: An extension of the Technology Acceptance Model. *Computers & Education, 61*, 193-208.

Lee, M. K., & Turban, E. (2001). A trust model for consumer internet shopping. *International Journal of Electronic Commerce, 6*(1), 75-91.

Lee, P. (2015). The fintech entrepreneurs aiming to reinvent finance. *Euromoney (UK), 46*(552), 42-48.

Lee, S., & Kim, B. G. (2009). Factors affecting the usage of intranet: A confirmatory study. *Computers in Human Behavior, 25*(1), 191-201.

Lee, W., Xiong, L., & Hu, C. (2012). The effect of Facebook users' arousal and valence on intention to go to the festival: Applying an extension of the technology acceptance model. *International Journal of Hospitality Management, 31*(3), 819-827.

Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems, 12*(1), 50.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191-204.

Lewis, J. D., & Weigert, A. (1985). Trust as a social reality. *Social Forces, 63*(4), 967-985.

Liaw, S.-S., & Huang, H.-M. (2003). An investigation of user attitudes toward search engines as an information retrieval tool. *Computers in Human Behavior, 19*(6), 751-765.

Lin, F.-H., & Wu, J.-H. (2004). An empirical study of end-user computing acceptance factors in small and medium enterprises in Taiwan: Analyzed by structural equation modeling. *Journal of Computer Information Systems, 44*(3), 98-108.

Lu, J., Yu, C.-S., Liu, C., & Yao, J. E. (2003). Technology acceptance model for wireless Internet. *Internet Research, 13*(3), 206-222.

Lu, Y., Yang, S., Chau, P. Y., & Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management, 48*(8), 393-403.

Lucas Jr, H. C., & Spitler, V. (1999). Technology use and performance: A field study of broker workstations. *Decision Sciences, 30*(2), 291-311.

Lucente, M. (2000). Conversational interfaces for e-commerce applications. *Communications of the ACM, 43*(9), 59-61.

Lui, S. S., & Ngo, H.-y. (2004). The role of trust and contractual safeguards on cooperation in non-equity alliances. *Journal of Management, 30*(4), 471-485.

Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A comparison of the theory of planned behavior and the theory of reasoned action. *Personality and social psychology Bulletin, 18*(1), 3-9.

Mäenpää, K., Kale, S. H., Kuusela, H., & Mesiranta, N. (2008). Consumer perceptions of Internet banking in Finland: The moderating role of familiarity. *Journal of Retailing and Consumer Services, 15*(4), 266-276.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society, 14*(1), 81-95.

Marcoux, B. C., & Shope, J. T. (1997). Application of the theory of planned behavior to adolescent use and misuse of alcohol. *Health Education Research, 12*(3), 323-331.

Mareev, S. N. (2016). Understand Global Capitalism (Reflections on the Book" Global Capital", by AV Buzgalin and AI Kolganov). *Voprosy Filosofii*(5), 60-67.

Marinova, D., de Ruyter, K., Huang, M.-H., Meuter, M. L., & Challagalla, G. (2017). Getting smart: Learning from technology-empowered frontline interactions. *Journal of Service Research, 20*(1), 29-42.

Mathieson, K. (1991). Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior. *Information Systems Research, 2*(3), 173-191.

Mathieson, K., Peacock, E., & Chin, W. W. (2001). Extending the technology acceptance model: the influence of perceived user resources. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 32*(3), 86-112.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review, 20*(3), 709-734.

McAllister, D. J. (1995). Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of Management Journal, 38*(1), 24-59.

McKnight, D. H., & Chervany, N. L. (2001). What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International Journal of Electronic Commerce, 6*(2), 35-59.

McWaters, J., Bruno, G., Lee, A., & Blake, M. (2015). *The Future of Financial Services-How disruptive innovations are reshaping the way financial services are structured, provisioned and consumed.* Paper presented at the World Economic Forum.

Melas, C. D., Zampetakis, L. A., Dimopoulou, A., & Moustakis, V. (2011). Modeling the acceptance of clinical information systems among hospital medical staff: an extended TAM model. *Journal of Biomedical Informatics, 44*(4), 553-564.

Milian, E. Z., Spinola, M. d. M., & Carvalho, M. M. d. (2019). Fintechs: A literature review and research agenda. *Electronic Commerce Research and Applications, 34*.

Moon, J.-W., & Kim, Y.-G. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*, *38*(4), 217-230.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192-222.

Morgan-Thomas, A., & Veloutsou, C. (2013). Beyond technology acceptance: Brand relationships and online brand experience. *Journal of Business Research*, *66*(1), 21-27.

Mulligan, C. B., & Sala-i-Martin, X. (2000). Extensive margins and the demand for money at low interest rates. *Journal of Political Economy, 108*(5), 961-991.

Mun, Y. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies, 59*(4), 431-449.

Nasri, W., & Charfeddine, L. (2012). Factors affecting the adoption of Internet banking in Tunisia: An integration theory of acceptance model and theory of planned behavior. *The Journal of High Technology Management Research, 23*(1), 1-14.

Netemeyer, R. G., Bearden, W. O., & Sharma, S. (2003). *Scaling procedures: Issues and applications*: Sage Publications.

Neu, D., Gomez, E. O., Graham, C., & Heincke, M. (2006). "Informing" technologies and the World Bank. *Accounting, Organizations and Society, 31*(7), 635-662.

Ng, A. W., & Kwok, B. K. (2017). Emergence of Fintech and cybersecurity in a global financial centre: Strategic approach by a regulator. *Journal of Financial Regulation and Compliance*, *25*(4), 422-434.

Nguyen, Q. N., & Sidorova, A. (2018). Understanding user interactions with a chatbot: a self-determination theory approach.

Nooteboom, B. (1996). Trust, opportunism and governance: A process and control model. *Organization Studies, 17*(6), 985-1010.

Oh, S., Ahn, J., & Kim, B. (2003). Adoption of broadband Internet in Korea: the role of experience in building attitudes. *Journal of Information Technology, 18*(4), 267-280.

Padilla-MeléNdez, A., Del Aguila-Obra, A. R., & Garrido-Moreno, A. (2013). Perceived playfulness, gender differences and technology acceptance model in a blended learning scenario. *Computers & Education, 63*, 306-317.

Pai, F.-Y., & Huang, K.-I. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting and Social Change, 78*(4), 650-660.

Palvia, P. (2009). The role of trust in e-commerce relational exchange: A unified model. *Information & Management, 46*(4), 213-220.

Park, J., Ryu, J., & Shin, H. (2016). Robo Advisors for Portfolio Management. *Advanced Science and Technology Letters, 141*, 104-108.

Park, N., Lee, K. M., & Cheong, P. H. (2007). University instructors' acceptance of electronic courseware: An application of the technology acceptance model. *Journal of Computer-Mediated Communication, 13*(1), 163-186.

Park, S.-T., Im, H., & Noh, K.-S. (2016). A study on factors affecting the adoption of LTE mobile communication service: The case of South Korea. *Wireless Personal Communications, 86*(1), 217-237.

Parkhe, A. (1993). Strategic alliance structuring: A game theoretic and transaction cost examination of interfirm cooperation. *Academy of Management Journal, 36*(4), 794-829.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101-134.

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS Quarterly*, 105-136.

Plouffe, C. R., Hulland, J. S., & Vandenbosch, M. (2001). Richness versus parsimony in modeling technology adoption decisions—understanding merchant adoption of a smart card-based payment system. *Information Systems Research, 12*(2), 208-222.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*, 539-569.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management, 12*(4), 531-544.

Preda, A. (2006). Socio-technical agency in financial markets: The case of the stock ticker. *Social Studies of Science, 36*(5), 753-782.

Prestholdt, P. H., Lane, I. M., & Mathews, R. C. (1987). Nurse turnover as reasoned action: Development of a process model. *Journal of Applied Psychology, 72*(2), 221.

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. *MIT Sloan Management Review, 59*(1).

Ratnasingam, P., & Pavlou, P. A. (2003). Technology trust in internet-based interorganizational electronic commerce. *Journal of Electronic Commerce in Organizations (JECO), 1*(1), 17-41.

Reimann, B. C., & Waren, A. D. (1985). User-oriented criteria for the selection of DSS software. *Communications of the ACM, 28*(2), 166-179.

Richad, R., Vivensius, V., Sfenrianto, S., & Kaburuan, E. R. ANALYSIS OF FACTORS INFLUENCING MILLENNIAL'S TECHNOLOGY ACCEPTANCE OF CHATBOT IN THE BANKING INDUSTRY IN INDONESIA.

Richardson, B. K., Wang, Z., & Hall, C. A. (2012). Blowing the whistle against Greek hazing: The theory of reasoned action as a framework for reporting intentions. *Communication Studies, 63*(2), 172-193.

Rosenberg, M. J. (1960). Cognitive, affective, and behavioral components of attitudes. *Attitude organization and change*.

Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review, 23*(3), 393-404.

Ryu, H.-S. (2018). What makes users willing or hesitant to use Fintech?: the moderating effect of user type. *Industrial Management & Data Systems, 118*(3), 541-569.

Saadé, R. G., & Kira, D. (2006). The emotional state of technology acceptance. *Issues in Informing Science & Information Technology, 3*.

Sako, M. (1992). *Price, quality and trust: Inter-firm relations in Britain and Japan*: Cambridge University Press.

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management, 44*(1), 90-103.

Schueffel, P. (2016). Taming the Beast: A Scientific Definition of Fintech. *Journal of Innovation Management, 4*(4), 32–54.

Semeraro, G., Andersen, V., Andersen, H. H., de Gemmis, M., & Lops, P. (2008). User profiling and virtual agents: a case study on e-commerce services. *Universal Access in the Information Society, 7*(3), 179-194.

Semuel, H., & Lianto, A. S. (2014). Analisis ewom, brand image, brand trust dan minat beli produk smartphone di Surabaya. *Jurnal Manajemen Pemasaran, 8*(2), 7-54.

Serenko, A. (2008). A model of user adoption of interface agents for email notification. *Interacting with Computers, 20*(4-5), 461-472.

Shen, Y.-C., Huang, C.-Y., Chu, C.-H., & Hsu, C.-T. (2010). A benefit–cost perspective of the consumer adoption of the mobile banking system. *Behaviour & Information Technology, 29*(5), 497-511.

Shih, H.-P. (2004). Extended technology acceptance model of Internet utilization behavior. *Information & Management, 41*(6), 719-729.

Shim, Y., & Shin, D. (2016). Analyzing China's Fintech Industry from the Perspective of Actor–Network Theory. *Telecommunications Policy, 40*(2-3), 168-181.

Singh, J., Brady, M., Arnold, T., & Brown, T. (2017). The emergent field of organizational frontlines. *Journal of Service Research, 20*(1), 3-11.

Son, H., Park, Y., Kim, C., & Chou, J.-S. (2012). Toward an understanding of construction professionals' acceptance of mobile computing devices in South Korea: An extension of the technology acceptance model. *Automation in construction, 28*, 82-90.

Sparrowe, R. T., & Mayer, K. J. (2011). Publishing in AMJ—part 4: grounding hypotheses. In: Academy of Management Briarcliff Manor, NY.

Srite, M., & Karahanna, E. (2006). The role of espoused national cultural values in technology acceptance. *MIS Quarterly*, 679-704.

Stieninger, M., Nedbal, D., Wetzlinger, W., Wagner, G., & Erskine, M. (2018). Factors influencing the organizational adoption of cloud computing: A survey among cloud workers. *International Journal of Information Systems and Project Management, 6*(1), 5-23.

Straub, D., Keil, M., & Brenner, W. (1997). Testing the technology acceptance model across cultures: A three country study. *Information & Management, 33*(1), 1-11.

Sun, H., & Zhang, P. (2006). The role of moderating factors in user technology acceptance. *International Journal of Human-Computer Studies, 64*(2), 53-78.

Szajna, B. (1996). Empirical evaluation of the revised technology acceptance model. *Management Science, 42*(1), 85-92.

Szopiński, T. S. (2016). Factors affecting the adoption of online banking in Poland. *Journal of Business Research, 69*(11), 4763-4768.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144-176.

Timko, C. (1987). Seeking medical care for a breast cancer symptom: Determinants of intentions to engage in prompt or delay behavior. *Health Psychology, 6*(4), 305.

Tripathi, S. (2017). Understanding the determinants affecting the continuance intention to use cloud computing. *Journal of International Technology and Information Management, 26*(3), 124-152.

van der Weerd, W., Timmermans, D. R., Beaujean, D. J., Oudhoff, J., & van Steenbergen, J. E. (2011). Monitoring the level of government trust, risk perception and intention of the general public to adopt protective measures during the influenza A (H1N1) pandemic in the Netherlands. *BMC public health, 11*(1), 575.

Van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research, 20*(1), 43-58.

Veloutsou, C. (2007). Identifying the dimensions of the product-brand and consumer relationship. *Journal of Marketing Management*, *23*(1-2), 7-26.

Venkatesh, V. (1999). Creation of favorable user perceptions: exploring the role of intrinsic motivation. *MIS Quarterly*, 239-260.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342-365.

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

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*(3), 451-481.

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

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly,* 115-139.

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

Venkatesh, V., Speier, C., & Morris, M. G. (2002). User acceptance enablers in individual decision making about technology: Toward an integrated model. *Decision Sciences, 33*(2), 297-316.

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

Wei, L., & Zhang, M. (2008). The impact of Internet knowledge on college students' intention to continue to use the Internet. *Information Research: An International Electronic Journal, 13*(3).

Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American Journal of Sociology, 87*(3), 548-577.

Wu, C.-S., Cheng, F.-F., Yen, D. C., & Huang, Y.-W. (2011). User acceptance of wireless technology in organizations: A comparison of alternative models. *Computer Standards & Interfaces, 33*(1), 50-58.

Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management, 31*(6), 572-581.

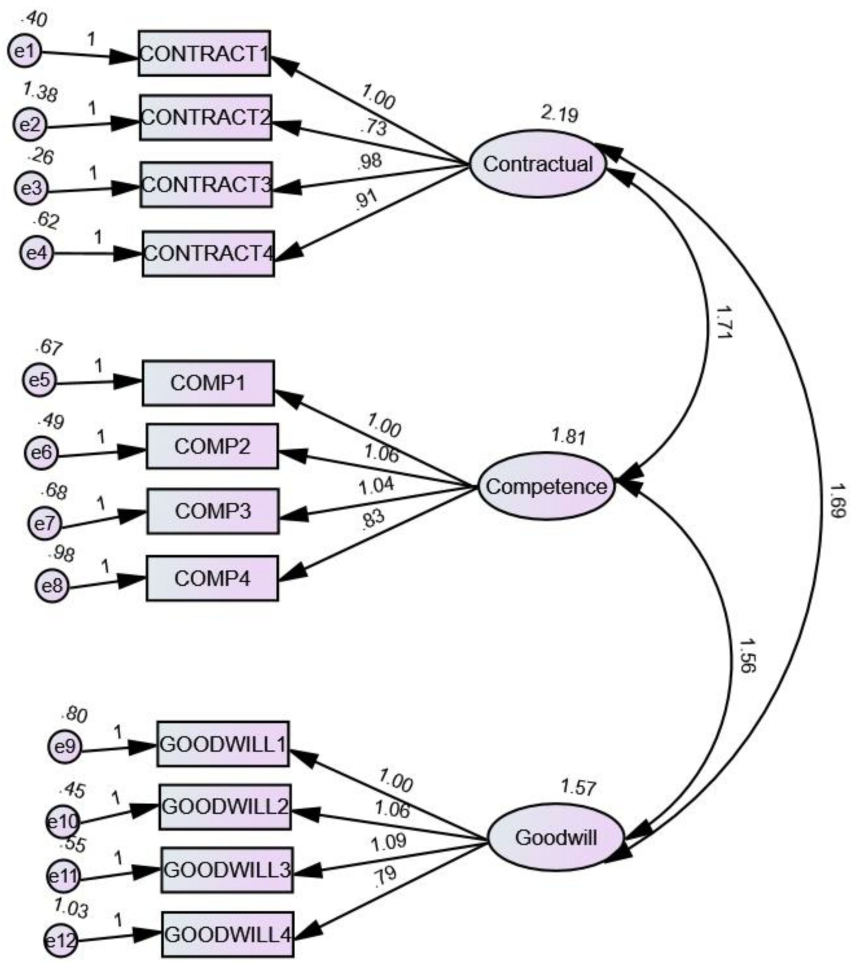
Zaheer, A., McEvily, B., & Perrone, V. (1998). Does trust matter? Exploring the effects of interorganizational and interpersonal trust on performance. *Organization Science, 9*(2), 141-159.

Zhang, S., Zhao, J., & Tan, W. (2008). Extending TAM for online learning systems: An intrinsic motivation perspective. *Tsinghua Science and Technology, 13*(3), 312-317.

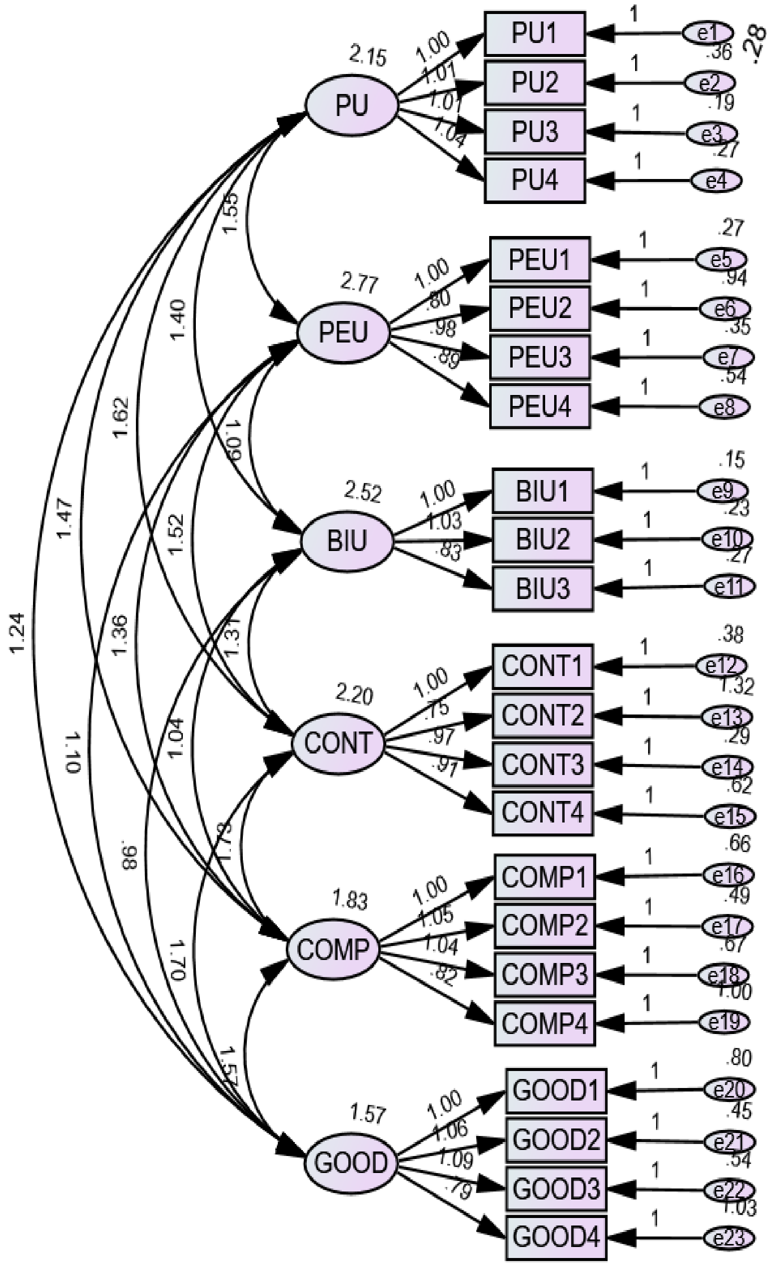
Zhang, T., Lu, C., & Kizildag, M. (2018). Banking “on-the-go”: examining consumers’ adoption of mobile banking services. *International Journal of Quality and Service Sciences, 10*(3), 279-295.

Zuckerman, M., & Reis, H. T. (1978). Comparison of three models for predicting altruistic behavior. *Journal of Personality and Social Psychology, 36*(5), 498.

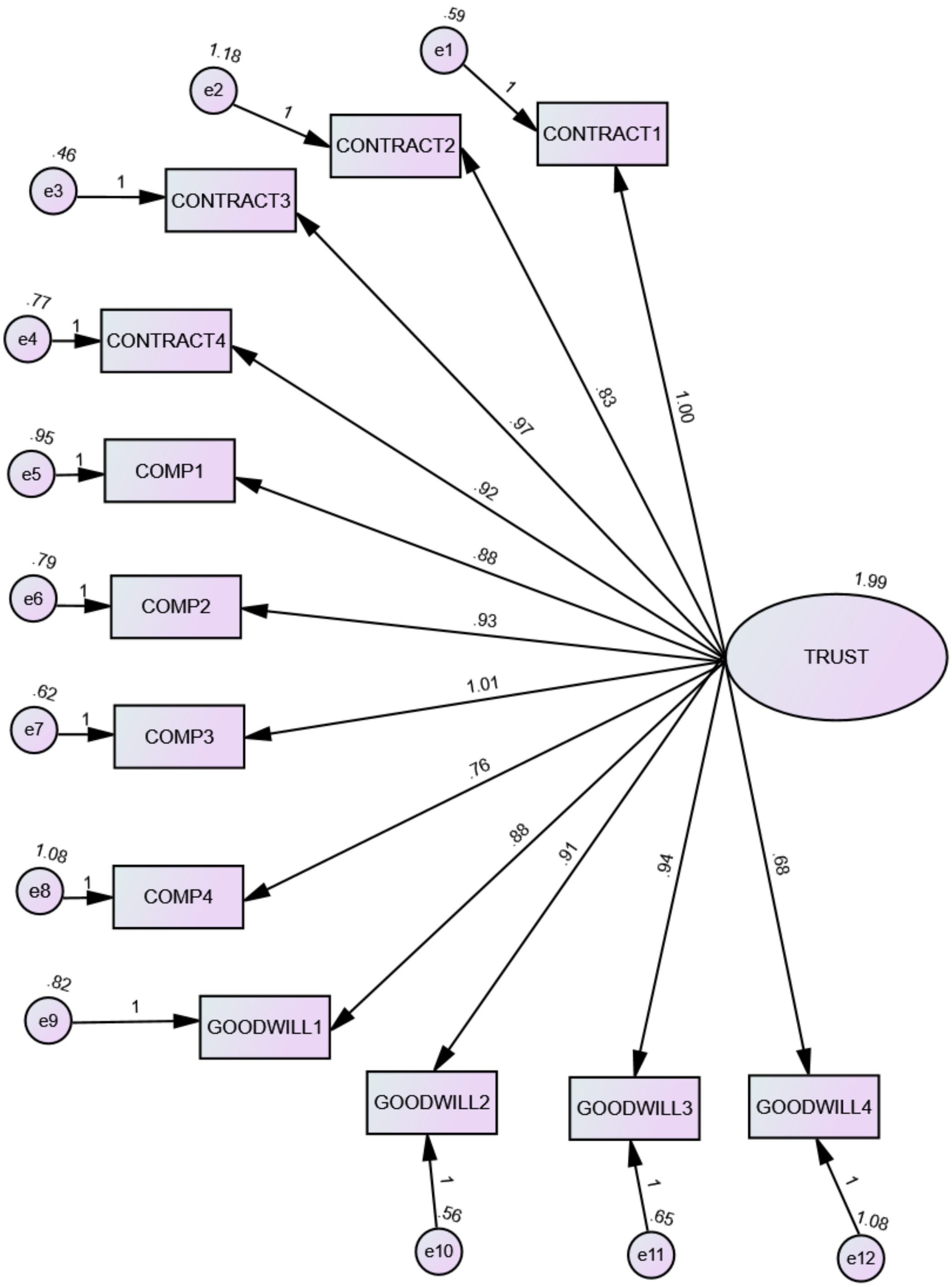
APPENDIX 1: Confirmatory Factor Analyses



Primary CFA



Secondary CFA


.59
e1
1
CONTRACT1
1.18
e2
1
CONTRACT2
.46
e3
1
CONTRACT3
.77
e4
1
CONTRACT4
.95
e5
1
COMP1
.79
e6
1
COMP2
.62
e7
1
COMP3
1.08
e8
1
COMP4
.82
e9
1
GOODWILL1
GOODWILL2
GOODWILL3
GOODWILL4
1
.56
e10
1
.65
e11
1
1.08
e12
1.00
.83
.97
.92
.88
.93
1.01
.76
.88
.91
.94
.89
1.99
TRUST

Post Hoc CFA

APPENDIX 2: Survey 1

Trust in Consumer Adoption of Financial Technology (Fintech) vT1

Start of Block: Default Question Block

Q1 During this study you will be asked about artificial intelligence-driven virtual finance assistants.
Artificial intelligence-driven virtual finance assistants help financial institutions with a set of tasks previously only made possible by humans. This technology is driven by artificial intelligence (technology that can perform tasks that normally require human intelligence) and combines predictive analytics and natural language processing to listen to and observe consumer behaviors, thereby allowing the technology to predict and recommend actions for consumers. This technology can have intelligent conversations with the user and can communicate with humans in their natural language and answer questions, perform required tasks, or provide information.
This technology is automatically available via mobile banking apps and can help users access balance information, transfer money between accounts, send money, and schedule meetings at financial centers. Users can also search for transactions, view balance information and bills, get credit scores, and access account numbers.
There are no additional downloads necessary or opt-in requirements as this technology is already embedded in your mobile banking app and subject to the same contractual provisions of the mobile banking app’s end user licensing agreement you originally accepted via click-through. This technology only becomes active once you sign into your mobile banking app and tap the artificial intelligence-driven virtual finance assistant icon. You will need to be authenticated through the app to be able to use this technology and your interactions are protected by the same privacy and security features as the mobile app and online banking.
You can chat with artificial intelligence-driven virtual finance assistants by voice using your phone's microphone for voice commands or on screen only, by texting or tapping, with no microphone interaction. Whether you talk or type is totally up to you. The more users interact with artificial intelligence-driven virtual finance assistants, the more the assistant learns, and the better it becomes at providing help.

End of Block: Default Question Block

Start of Block: Block 8

Q38 What is the name of your primary financial institution (e.g. where you conduct typical banking business, have standard accounts, etc.)?

____

End of Block: Block 8

Start of Block: Block 2

Q18 Please consider the following questions in relation to your primary financial institution, regardless of whether they currently offer an artificial intelligence-driven virtual finance assistant or not. The following questions are relevant to any respondent whether they have used an artificial intelligence-driven virtual finance assistant or have not. The questions are concerned with what your expectations would be in using an artificial intelligence-driven virtual finance assistant through your primary financial institution.
The following questions ask about your perceived usefulness and perceived ease of use regarding artificial intelligence-driven virtual finance assistants.

End of Block: Block 2

Start of Block: Block 1

Q4
Learning to use artificial intelligence-driven virtual finance assistants would be easy for me

- ◯ Strongly disagree (1)
- ◯ Disagree (2)
- ◯ Somewhat disagree (3)
- ◯ Neither agree nor disagree (4)
- ◯ Somewhat agree (5)
- ◯ Agree (6)
- ◯ Strongly agree (7)

Q6 I would find it easy to manage banking needs using artificial intelligence-driven virtual finance assistants

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q8 It would be easy for me to become skilled at using artificial intelligence-driven virtual finance assistants

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q9 I would find artificial intelligence-driven virtual finance assistants easy to use

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q11 Using artificial intelligence-driven virtual finance assistants would improve my performance in managing banking needs

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q13 Using artificial intelligence-driven virtual finance assistants would improve my productivity in managing banking needs

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q15 Using artificial intelligence-driven virtual finance assistants would enhance my effectiveness in managing banking needs

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q17 I would find artificial intelligence-driven virtual finance assistants useful in managing banking needs

- ○ Strongly disagree (1)
- ○ Disagree (2)
- ○ Somewhat disagree (3)
- ○ Neither agree nor disagree (4)
- ○ Somewhat agree (5)
- ○ Agree (6)
- ○ Strongly agree (7)

End of Block: Block 1

Start of Block: Block 3

Q12 Again, please consider the following questions in relation to your primary financial institution, regardless of whether they currently offer an artificial intelligence-driven virtual finance assistant or not. The following questions are relevant to any respondent whether they have used an artificial intelligence-driven virtual finance assistant or have not. The questions are concerned with what your expectations would be in using an artificial intelligence-driven virtual finance assistant through your primary financial institution.

The following questions ask about your trust-related concerns (or lack thereof) regarding artificial intelligence-driven virtual finance assistants.

End of Block: Block 3

Start of Block: Block 4

Q14 I feel safe using artificial intelligence-driven virtual finance assistants because the contract will protect me

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q16 I feel I have adequate time to understand the contract before using artificial intelligence-driven virtual finance assistants

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q18 I feel safe using artificial intelligence-driven virtual finance assistants because of the contract's statement of guarantees

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q20 I feel safe using artificial intelligence-driven virtual finance assistants because of the contract's designation of certain information as confidential

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q22 I believe the bank has the technical capabilities to properly provide artificial intelligence-driven virtual finance assistants

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q24 I believe the bank has the managerial capabilities to properly provide artificial intelligence-driven virtual finance assistants

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q26 I feel safe using artificial intelligence-driven virtual finance assistants because of the bank's prior success in financial technology provisioning

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q28 The bank providing the artificial intelligence-driven virtual finance assistant has a good reputation

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q30 I believe the bank providing the artificial intelligence-driven virtual finance assistant is willing to act in ways exceeding stipulated contractual agreements

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q32 Based on my experience with the bank providing the artificial intelligence-driven virtual finance assistant in the past, I know it is honest

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q34 Based on my experience with the bank providing the artificial intelligence-driven virtual finance assistant in the past, I know it cares about customers

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q36 Based on my experience with the bank providing the artificial intelligence-driven virtual finance assistant in the past, I know it is not opportunistic

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

End of Block: Block 4

Start of Block: Block 5

Q24 Again, please consider the following questions in relation to your primary financial institution, regardless of whether they currently offer an artificial intelligence-driven virtual finance assistant or not. The following questions are relevant to any respondent whether they have used an artificial intelligence-driven virtual finance assistant or have not. The questions are concerned with what your expectations would be in using an artificial intelligence-driven virtual finance assistant through your primary financial institution.

The following questions ask about your attitude, familiarity, and general innovativeness regarding artificial intelligence-driven virtual finance assistants.

End of Block: Block 5

Start of Block: Block 6

Q26 Using artificial intelligence-driven virtual finance assistants seems like a good idea

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q28 I like the idea of using artificial intelligence-driven virtual finance assistants to manage banking needs

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q30 Using artificial intelligence-driven virtual finance assistants to manage banking needs seems like a wise idea

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q32 I have worked with or studied artificial intelligence

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q34 Throughout my life I have had experience interacting with artificial intelligence

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q36 I am familiar with artificial intelligence products (Siri, Alexa, etc.)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q38 When I hear about a new product, I look for ways to try it

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q40 Among my peers, I am usually the first one to try a new product

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

End of Block: Block 6

Start of Block: Block 9

Q39 Have you ever used an artificial intelligence-driven virtual finance assistant?

- Yes (1)
- No (2)

Q40 If you answered yes to the above, what was the quality of the experience?

- Terrible (1)
- Poor (2)
- Average (3)
- Good (4)
- Delightful (5)

End of Block: Block 9

Start of Block: Block 7

Q34 What is your gender?

- Male (1)
- Female (2)

Q36 How old are you? (in years)

- 18 - 24 (1)
- 25 - 34 (2)
- 35 - 44 (3)
- 45 - 54 (4)
- 55 - 64 (5)
- 65 - 74 (6)
- 75 - 84 (7)
- 85 or older (8)

Q38 What is your annual income?

- ○ Less than $10,000 (1)
- ○ $10,000 - $19,999 (2)
- ○ $20,000 - $29,999 (3)
- ○ $30,000 - $39,999 (4)
- ○ $40,000 - $49,999 (5)
- ○ $50,000 - $59,999 (6)
- ○ $60,000 - $69,999 (7)
- ○ $70,000 - $79,999 (8)
- ○ $80,000 - $89,999 (9)
- ○ $90,000 - $99,999 (10)
- ○ $100,000 - $149,999 (11)
- ○ More than $150,000 (12)

Q40 What is your employment status?

- Employed full time (1)
- Employed part time (2)
- Unemployed looking for work (3)
- Unemployed not looking for work (4)
- Retired (5)
- Student (6)
- Disabled (7)

Q42 What is the highest level of education you have completed?

- Less than high school (1)
- High school graduate (2)
- Some college (3)
- 2 year degree (4)
- 4 year degree (5)
- Professional degree (6)
- Doctorate (7)

End of Block: Block 7

APPENDIX 3: Survey 2

Trust in Consumer Adoption of Financial Technology (Fintech) vT2

Start of Block: Default Question Block

Q5 During this study you will be asked about artificial intelligence-driven virtual finance assistants. This is a follow-up to the survey you previously responded to about artificial intelligence-driven virtual finance assistants approximately four weeks ago.
Artificial intelligence-driven virtual finance assistants help financial institutions with a set of tasks previously only made possible by humans. This technology is driven by artificial intelligence (technology that can perform tasks that normally require human intelligence) and combines predictive analytics and natural language processing to listen to and observe consumer behaviors, thereby allowing the technology to predict and recommend actions for consumers. This technology can have intelligent conversations with the user and can communicate with humans in their natural language and answer questions, perform required tasks, or provide information.
This technology is automatically available via mobile banking apps and can help users access balance information, transfer money between accounts, send money, and schedule meetings at financial centers. Users can also search for transactions, view balance information and bills, get credit scores, and access account numbers.
There are no additional downloads necessary or opt-in requirements as this technology is already embedded in your mobile banking app and subject to the same contractual provisions of the mobile banking app's end user licensing agreement you originally accepted via click-through. This technology only becomes active once you sign into your mobile banking app and tap the artificial intelligence-driven virtual finance assistant icon. You will need to be authenticated through the app to be able to use this technology and your interactions are protected by the same privacy and security features as the mobile app and online banking.
You can chat with artificial intelligence-driven virtual finance assistants by voice using your phone's microphone for voice commands or on screen only, by texting or tapping, with no microphone interaction. Whether you talk or type is totally up to you. The more users interact with artificial intelligence-driven virtual finance assistants, the more the assistant learns, and the better it becomes at providing help.

End of Block: Default Question Block

Start of Block: Block 1

Q7 Please consider the following questions in relation to your primary financial institution, regardless of whether they currently offer an artificial intelligence-driven virtual finance assistant or not. The following questions are relevant to any respondent whether they have used an artificial intelligence-driven virtual finance assistant or have not. The questions are concerned with what your expectations would be in using an artificial intelligence-driven virtual finance assistant through your primary financial institution.

The following questions ask about your behavioral intention to use artificial intelligence-driven virtual finance assistants.

End of Block: Block 1

Start of Block: Block 2

Q9 I intend to use artificial intelligence-driven virtual finance assistants to manage banking needs

○ Strongly disagree (1)

○ Disagree (2)

○ Somewhat disagree (3)

○ Neither agree nor disagree (4)

○ Somewhat agree (5)

○ Agree (6)

○ Strongly agree (7)

Q11 Using artificial intelligence-driven virtual finance assistants to manage banking needs is something I would do

- ○ Strongly disagree (1)
- ○ Disagree (2)
- ○ Somewhat disagree (3)
- ○ Neither agree nor disagree (4)
- ○ Somewhat agree (5)
- ○ Agree (6)
- ○ Strongly agree (7)

Q13 My intention is to use artificial intelligence-driven virtual finance assistants rather than any human financial services provider

- ○ Strongly disagree (1)
- ○ Disagree (2)
- ○ Somewhat disagree (3)
- ○ Neither agree nor disagree (4)
- ○ Somewhat agree (5)
- ○ Agree (6)
- ○ Strongly agree (7)

End of Block: Block 2

Start of Block: Block 6

Q14 Again, please consider the following questions in relation to your primary financial institution, regardless of whether they currently offer an artificial intelligence-driven virtual finance assistant or not. The following questions are relevant to any respondent whether they have used an artificial intelligence-driven virtual finance assistant or have not. The questions are concerned with what your expectations would be in using an artificial intelligence-driven virtual finance assistant through your primary financial institution.

The following questions ask about your product attractiveness regarding artificial intelligence-driven virtual finance assistants.

End of Block: Block 6

Start of Block: Block 3

Q15 Artificial intelligence-driven virtual finance assistants are a great idea

- ○ Strongly disagree (1)
- ○ Disagree (2)
- ○ Somewhat disagree (3)
- ○ Neither agree nor disagree (4)
- ○ Somewhat agree (5)
- ○ Agree (6)
- ○ Strongly agree (7)

Q16 Artificial intelligence-driven virtual finance assistants would be fun to use

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q17 Many people will use artificial intelligence-driven virtual finance assistants

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q19 Artificial intelligence-driven virtual finance assistants are here to stay

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q20 Artificial intelligence-driven virtual finance assistants fill a real need for me

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q21 Artificial intelligence-driven virtual finance assistants can give me real value

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q22 Artificial intelligence-driven virtual finance assistants are just another gimmick

- Strongly agree (1)
- Agree (2)
- Somewhat agree (3)
- Neither agree nor disagree (4)
- Somewhat disagree (5)
- Disagree (6)
- Strongly disagree (7)

End of Block: Block 3

Start of Block: Block 7

Q14 Again, please consider the following questions in relation to your primary financial institution, regardless of whether they currently offer an artificial intelligence-driven virtual finance assistant or not. The following questions are relevant to any respondent whether they have used an artificial intelligence-driven virtual finance assistant or have not. The questions are concerned with what your expectations would be in using an artificial intelligence-driven virtual finance assistant through your primary financial institution.

The following questions ask about your anxiety regarding artificial intelligence-driven virtual finance assistants.

End of Block: Block 7

Start of Block: Block 8

Q15 I feel apprehensive about using artificial intelligence-driven virtual finance assistants

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q16 It scares me to think I could lose a lot of information using artificial intelligence-driven virtual finance assistants by hitting the wrong button

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q17 I hesitate to use artificial intelligence-driven virtual finance assistants for fear of making mistakes I cannot correct

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q18 Artificial intelligence-driven virtual finance assistants are somewhat intimidating to me

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

End of Block: Block 8

Start of Block: Block 4

Q19 Again, please consider the following questions in relation to your primary financial institution, regardless of whether they currently offer an artificial intelligence-driven virtual finance assistant or not. The following questions are relevant to any respondent whether they have used an artificial intelligence-driven virtual finance assistant or have not. The questions are concerned with what your expectations would be in using an artificial intelligence-driven virtual finance assistant through your primary financial institution.

The following questions ask about your attitude regarding artificial intelligence-driven virtual finance assistants.

End of Block: Block 4

Start of Block: Block 5

Q21 Using artificial intelligence-driven virtual finance assistants seems like a good idea

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q23 I like the idea of using artificial intelligence-driven virtual finance assistants to manage banking needs

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

Q25 Using artificial intelligence-driven virtual finance assistants to manage banking needs seems like a wise idea

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

End of Block: Block 5