Personal financial management technology: extending UTAUT2 to understand the determinants of the acceptance and use

by

Brian Walsh

B.S., Valparaiso University, 2008
M.S., The American College, 2017

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Personal Financial Planning
College of Health and Human Sciences

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Abstract

As researchers explore interventions to improve financial decisions beyond financial education and access to financial advisors, experts believe that technology will reshape the financial services industry by democratizing access to insights in real time (Lee & Shin, 2018). Personal financial management (PFM) technology is a type of financial technology with the opportunity to influence responsible financial behavior at scale, as it enhances consumer awareness and provides targeted recommendations (Li & Forlizzi, 2010). PFM technology includes common features such as net worth tracking, budgeting, credit score monitoring, investment tracking, and goal planning. PFM technology collects, consolidates, and presents financial data in a concise user interface on a website or through a mobile application (Dorfleitner et al., 2016). Consumers access PFM technology through standalone tools such as Mint.com or as an integrated feature provided by their financial institution (Tajimi, 2021).

PFM technology can only drive change if individuals accept and use this innovative technology. So, understanding the factors that influence this technology's adoption is critical to future innovation development. This study leveraged the extended unified theory of acceptance and use of technology (UTAUT2) and a systematic literature review of studies that used unified theory of acceptance and use of technology (UTAUT) or UTAUT2 to identify key variables that influenced consumer financial technology adoption that are both part of UTAUT2 and extensions. The combination of the broader information systems review and concentrated focus on consumer financial technology served as the foundation for the conceptual framework, hypotheses, and analysis.

To test the hypotheses, this study leveraged primary data collection using a survey specifically designed to collect the preceding measures. After collecting responses, a strict

quality control procedure was implemented to ensure high-quality responses were used in the PLS-SEM analysis. The analysis followed the steps outlined by Hair et al. (2019), including an evaluation of the measurement model, an evaluation of the structural model, and assessment of predictor relationships.

Seven relationships were statistically significant in the model. Performance expectancy, hedonic motivation, habit, gender, and number of financial accounts have a positive effect on PFM technology use. Age has a negative effect on PFM technology use and number of financial accounts has a positive moderating effect on the relationship between habit and PFM technology use. An importance performance map analysis found that hedonic motivation and habit are important predictors of PFM technology use but with room for improvement.

Three practical implications from this study could have a positive effect on financial institutions and consumers. First, PFM technology providers should use gamification to improve hedonic motivation and make using PFM technology a habit. Second, PFM technology providers should communicate both the financial and intrinsic benefits of using PFM technology when acquiring consumers. Third, financial institutions should invest in PFM technology, as it attracts consumers with more financial accounts that are more likely to be a fit for a variety of financial products.

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Approved by:

Major Professor
Stuart Heckman

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Dedication

Before every practice or game, I remind my kids to do three things: (1) listen, (2) work hard, and (3) have fun. Over the years, I've explained that regardless of the outcome or their performance, those are the three things that matter. After every practice or game, I ask them about the three things. Initially my kids thought I was crazy, maybe still do, but there are reasons I focus on the three things.

1. They can control whether they do the three things regardless of any external factors.
2. If they listen, they will learn something new every time they practice or play. That learning will allow them to make incremental improvements that lead to substantial changes over the long-term.
3. If they work hard, they will minimize regrets and avoid wasting the gifts God has given them.
4. If they have fun, they will enjoy the process rather than solely finding joy in the outcome.

Continuous improvement, work ethic, and enjoying the experience will allow them to accomplish anything in life, so this simple request goes well beyond sports. A perfect example is these principles empowered me to complete my dissertation on my way to earning my PhD. This dissertation is dedicated to Michael and Grace as an example of why the three things are important and a reminder that I will try to lead by example as a father.

Chapter 1 - Introduction

A startling number of households struggle to cover essential expenses, spend less than they earn, and use debt responsibly (Lin et al., 2022). Many believe that financial education and professional financial advice are the best anecdote to US household financial mismanagement, but research suggests results are mixed. Financial education is efficient and accessible, but the lack of personalization and ongoing follow-through limits its long-term effectiveness (Fernandes et al., 2014). Professional financial advice is effective and personalized, but the monetary and time commitments involved limit the efficiency and ability to serve households at scale (Hung & Yoong, 2010).

Recent technological improvements present a unique opportunity to adjust the interventions used to influence responsible financial decisions by increasing technology adoption among households and enabling advanced algorithms to provide personalized insights in real time through an individual's phone (Wesner & Miller, 2008). PFM technology is a type of financial technology (FinTech) designed to enhance consumer awareness and provide targeted recommendations that influences responsible financial behavior at scale (Li & Forlizzi, 2010). PFM technology increases awareness by collecting, consolidating, and presenting financial data in a concise user interface on a website or through a mobile application before making targeted recommendations that are personalized to the user (Dorfleitner et al., 2016).

FinTech is a broad term for financial services business models driven by innovative technology that improve the process and delivery of financial services and products (Mention, 2019). FinTech includes financial innovations such as cryptocurrencies, digital advisory services, peer-to-peer lending, mobile payment systems, and PFM technology (Philippon, 2016). As

FinTech companies mature, and new entrants enter the space, investment in FinTech continues to grow.

FinTech is changing the interaction between consumers and financial institutions. Yet, limited research is dedicated to this delivery channel and its long-term effectiveness for consumers' financial behavior. PFM technology can only be effective if individuals accept and use this innovative technology. Therefore, understanding the factors that influence this technology's adoption is critical to future innovation.

The US households' fragile financial state, despite increased access to traditional interventions such as financial education and financial advisors, drives this research's importance (Fernandes et al., 2014; Hung & Yoong, 2010; Lin et al., 2022). An emerging sector of the financial services industry seeks to leverage technology to improve users' financial behavior (Philippon, 2016). Peer-reviewed research indicates the promise of PMF technology's scalable and low-cost intervention (Kersten-van Dijk et al., 2017; Walsh & Lim, 2020). But insights from related disciplines must be considered to understand and test the factors associated with PFM technology adoption and its impact on subsequent financial behavior (Roll & Moulton, 2019; Stango & Zinman, 2014).

Financial Challenges of US Households

An extensive body of research explores US households' financial challenges. For example, data from the 2021 National Financial Capability Study (NFCS), funded by the Financial Industry Regulatory Authority (FINRA) and commissioned by the FINRA Investor Education Foundation, provides insight into these financial challenges. Over 25,000 survey responses provide an in-depth look into US households' financial capability, demographics, financial behavior, and attitudes.

The NFCS results indicate concerning trends related to US households' spending and borrowing behavior (Lin et al., 2022). Half of all households experience difficulty covering essential expenses, and the level of difficulty is associated with income and educational attainment, which results in less affluent households disproportionately experiencing financial hardships. Less than half of households live within their means, and less than half of households are confident they could cover an unexpected expense of $2,000. From a financial perspective, the pressure of managing cash flow has led to one-third of employed households taking on additional work to help meet essential expenses. From a psychological perspective, this pressure is associated with increased levels of anxiety and stress (Lin et al., 2022).

US households are in an equally precarious position from their borrowing behavior. Over three-fourths of households have at least one credit card, but only half pay their credit card balance in full every month. One-quarter of households have student loan debt, and half of those households have made a late payment. And more than one-third of households relied on alternative financial services lenders such as pawnshops, payday loans, rent-to-own arrangements, auto title loans, or tax refund advances in the last five years (Lin et al., 2022).

Limitations of Traditional Interventions into Financial Decisions

A common intervention to improve individuals' financial behavior is financial education. Financial education is thought to increase individuals' financial literacy, which is associated with more responsible financial behavior (Collins & O'Rourke, 2010; Lusardi & Mitchell, 2014; Lusardi & Tufano, 2015). Over the last twenty years, policymakers, educators, and industry professionals have spent billions of dollars in direct and indirect costs on financial education initiatives (Fernandes et al., 2014). However, research suggests that the outcomes of these initiatives are mixed (Collins & O'Rourke, 2010).

When controlling for behavioral characteristics and socioeconomic factors and introducing appropriate control groups, financial education programs' long-term impact is negligible (Fernandes et al., 2014; Collins & O'Rourke, 2010). Financial education has been shown to increase knowledge and responsible decision making in the short term, but even the benefits of rigorous programs decrease over time (Fernandes et al., 2014). Some researchers have questioned whether financial education programs accommodate different cultural and socioeconomic perspectives that would make them useful to the groups that could most benefit from their content (Guérin, 2012).

Introducing financial education earlier into an individual's life such as during high school also has mixed outcomes. Financial education at the high school level might not increase long-term financial knowledge (Mandell & Klein, 2009), but it has been shown to reinforce key behavioral traits that might influence responsible financial behavior (Willis, 2011). Financial education's mixed results mean that when considering the program's enormous cost, researchers have suggested exploring alternative means of improving outcomes such as regulations, access to experts, and behavioral nudges (Burke et al., 2020; Hastings et al., 2013; Willis, 2009).

Another common intervention to improve individuals' financial behavior is working with a financial advisor. Factors such as income, educational attainment, and financial literacy are associated with the likelihood of working with a financial advisor (Collins, 2012; Hackethal et al., 2012); therefore, individuals who are most in need of financial advice might not know how to seek their help or have access to their services (Bhattacharya et al., 2012; Calcagno & Monticone, 2015; Hanna, 2011). Research has shown that financial advisors might introduce additional bias into financial decisions based on their conflicts of interest (Mullainathan et al., 2012). Individuals might benefit from working with a financial advisor, but an individual must have the means, knowledge, and desire to work with a professional and follow their advice (Hung & Yoong, 2010).

The Evolving Role of FinTech

As researchers explore interventions to improve financial decisions beyond financial education and access to financial advisors, experts believe that technology will reshape the financial services industry by democratizing access to expert insights in real time (Lee & Shin, 2018). Technology is a part of peoples' daily lives and affects everything from how we engage with peers to how we consume news (Wesner & Miller, 2008). YouTube has more than a billion views every month, and more millennials view content on YouTube than any individual cable network. This trend is not unique to YouTube, as 59% of millennials cite the internet as their primary source of news and current events (Ciccotello & Yakoboski, 2014). As technology continues to develop and preferences adapt, the demand for online content continues to expand and alter the way consumers access information, engage with peers, and behave (Wesner & Miller, 2008).

Traditional banks were early adopters of technological enhancements and now provide customers with access to digital banking features such as online banking, mobile banking, mobile payments, and peer-to-peer payments. Digital banking features may also benefit financial institutions by reducing costs since digital banking can be more cost effective once it is implemented and achieves economies of scale. As more financial institutions offer digital banking features and general technology preferences among consumers evolve, a larger portion of transactions occur via web and mobile platforms (Pikkarainen et al., 2004).

Alternative business models affecting how individuals earn their money and innovative technology affecting how individuals spend and save their money lowered the barriers to technology adoption among consumers (Mention, 2019). Although traditional banks enjoy the cost efficiencies of digital banking, the savings do not reduce consumers' costs, as in other industries. Lower barriers to entry and the opportunity to provide valuable services at lower price points by passing along savings opened the door for FinTech companies to dis-intermediate the financial services market (Philippon, 2016).

FinTech is the marriage of personal finance products or services and information technology (Arner et al., 2015). As individuals become more tech savvy and expect more transparency and personalized real-time insights, FinTech companies are rapidly launching innovative experiences due in part to lower regulatory hurdles and better information systems architecture compared to traditional financial institutions (Eickoff et al., 2017; Gomber et al., 2018). FinTech is a broad term that describes various experiences, including cryptocurrency, payment processing, lending, robo-advice, and PFM (Eickoff et al., 2017). More FinTech offerings suggest that the factors that could limit future expansion include access to venture capital funding, operating in geographies with sufficient internet service, and access to mobile devices (Gai et al., 2018; Haddad & Hornuf, 2019).

The Emerging Role of PFM Technology

While FinTech presents a broad suite of experiences that might advance households' personal finances, the focus of this study is to explore the implications of PFM technology. PFM technology collects, consolidates, and presents financial data in a concise user interface on a website or through a mobile application (Dorfleitner et al., 2016). Consumers access PFM technology through standalone tools such as Mint.com or as an integrated feature provided by their financial institution (Tajimi, 2021).

PFM technology includes common features such as net worth tracking, budgeting, credit score monitoring, investment tracking, and goal planning. Net worth tracking sites such as Mint.com aggregate linked and manually entered financial accounts to provide real-time insights into the user's assets, liabilities, and net worth. Budgeting technology such as Mint.com or You Need a Budget (YNAB) analyze the transactions of all linked accounts to help the user understand their spending, identify opportunities to reduce their expenses, and track how they compare to user defined targets. Credit score monitoring sites such as Credit Karma access data from the credit bureaus to provide the user with their credit score, to provide key factors affecting their score, and to identify ways to improve their credit score. Investment tracking tools such as Personal Capital aggregates linked and manually entered investment accounts to provide the user with their overall asset allocation and suggest changes to better align with model portfolios based on their risk appetite and time horizon. Goal planning technology such as Mint.com or Wealthfront collects basic information about the user's objectives such as retirement or debt paydown and assesses their progress while providing suggestions to improve their probability of success. Some PFM providers offer only one feature, whereas others provide all features to present a holistic view of the user's finances.

From an information systems perspective, PFM technology can be classified as personal informatics, which enables users to collect, review, and act on relevant information. The basic premise of personal informatics is that self-tracking drives insights, and those insights change behavior (Kersten-van Dijk et al., 2017). Personal informatics have been implemented in a variety of fields, most notably in the health industry. Personal informatics such as fitness or nutrition trackers have been shown to help users accomplish goals by tracking toward a specific target and documenting their current state by providing simple insights (Rooksby et al., 2014).

Further, Li et al. (2010) posit that PFM technology follows the five stages of personal informatics: preparation, collection, integration, reflection, and action. PFM technology provides a specific value proposition that motivates users and guides them through the preparation stage by helping them link accounts or enroll in the program. The underlying technology handles data collection and integration by aggregating the applicable data from linked institutions or credit bureaus before condensing it into one cohesive ecosystem. Reflection is encouraged through visual representation in a simple user interface that allows the user to comprehend key components of their personal finances. Finally, PFM helps drive action by providing specific recommendations from the user's unique circumstances based on underlying algorithms (Li et al., 2010).

The application of personal informatics in the personal finance industry is new, but ample research supports the impact of technological nudges and insights on subsequent financial behavior. Stango and Zinman (2014) found that simple surveys related to overdrafts created greater awareness of balances, which was associated with paying lower overdraft fees. Roll and Moulton (2019) found that automated payment reminders to high-risk borrowers led to more responsible credit behavior. Multiple communication channels demonstrated promise, as text reminders reduced penalties for late payments and targeted video education was more effective than the same messages delivered in written form (Karlan et al., 2016; Lusardi et al., 2017). Several researchers found methods to increase the users' engagement through gamified rewards and creating a social component (Phillips et al., 2013; Neokleous & Madan, 2019).

Researchers have also investigated PFM technology's specific impact on subsequent financial behavior. Walsh and Lim (2020) found that heavy adopters of PFM technology were more likely to exhibit responsible financial behavior characteristics such as owning an emergency fund, paying off credit cards every month, owning a retirement account, owning an investment account, saving for retirement, and owning a will.

From an institutional perspective, PFM technology is associated with client preferences when selecting a financial institution, so the technology is becoming a larger part of the value proposition presented to consumers (Green & Craven, 2017). An extensive study of banking clients who adopt PFM technology found that targeted messages related to overspending were associated with a temporary reduction in spending on that category and a long-term reduction in spending (S. K. Lee, 2019). A study of general PFM users found that adoption frequency increased users' responsible financial behavior by experiencing fewer fees and penalties (Carlin et al., 2017). Interestingly, when the researchers removed targeted insights and only considered the impact of users understanding their current financial picture, it resulted in more responsible borrowing behavior because of increased transparency (Carlin et al., 2019). These promising findings suggest that PFM technology use might affect users through both reflection and targeted insights similar to how fitness trackers impact users through goal tracking and basic documentation.

Technology is only as effective as the number of people who adopt it and the degree to which those users engage with the experience. Unfortunately, little direct research focuses on the factors associated with PFM adoption. From a demographic perspective, younger individuals are more likely than older individuals and men are more likely than women to adopt PFM technology (Carlin et al., 2017). Individuals are more likely to use PFM technology when income is deposited into their account, as their attention is drawn to their finances, and those in precarious financial positions might be less likely to adopt the technology to avoid facing their financial circumstances (Phillips et al., 2013). In sum, substantial previous information on technology acceptance research can serve as the foundation for the experimental design of this study.

Purpose and Importance of the Study

This study uses primary data collected from adults in the United States to leverage a thorough review of information systems research to develop an understanding of the factors that explain and predict PFM technology adoption. Understanding and predicting the acceptance and use of PFM technology is an innovative and important contribution to personal finance research. Despite significant investments in FinTech (Mention, 2019) and evidence suggesting that PFM can improve consumers' financial behavior (Carlin et al., 2017; Carlin et al., 2019; S. K. Lee, 2019; Stango & Zinman, 2014; Walsh & Lim, 2020), only one-third of US households currently use PFM technology (Lin et al., 2022).

Innovative technology is only effective if it is accepted and used by consumers, yet only two studies have investigated this topic and they were limited to basic demographics (Carlin et al., 2017) and simple models using proxy variables (Walsh & Lim, 2020). Through theoretical grounded primary data collection and predictive modeling, to the author's best knowledge, this study will be the most in-depth assessment of PFM technology adoption to date. This study's insights will (a) explain key determinants that can influence future research and (b) explore predictive relationships that can affect client acquisition by PFM technology providers through simple marketing or machine learning models.

Chapter 2 - Literature Review

Understanding the factors that influence PFM adoption starts with a thorough review of prior information systems research, with a focus on the factors found to be associated with consumer FinTech adoption. This study leverages the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), which enhanced the Unified Theory of Acceptance and Use of Technology (UTAUT) for consumer technology. Since PFM technology is a consumer financial technology, this study also conducted a systematic literature review of studies that used UTAUT or UTAUT2 to identify key variables that influenced consumer FinTech adoption that are both part of UTAUT2 and extensions. The combination of the broader information systems review and concentrated focus on consumer FinTech is the foundation for the conceptual framework, hypotheses, and analysis that follows in subsequent chapters.

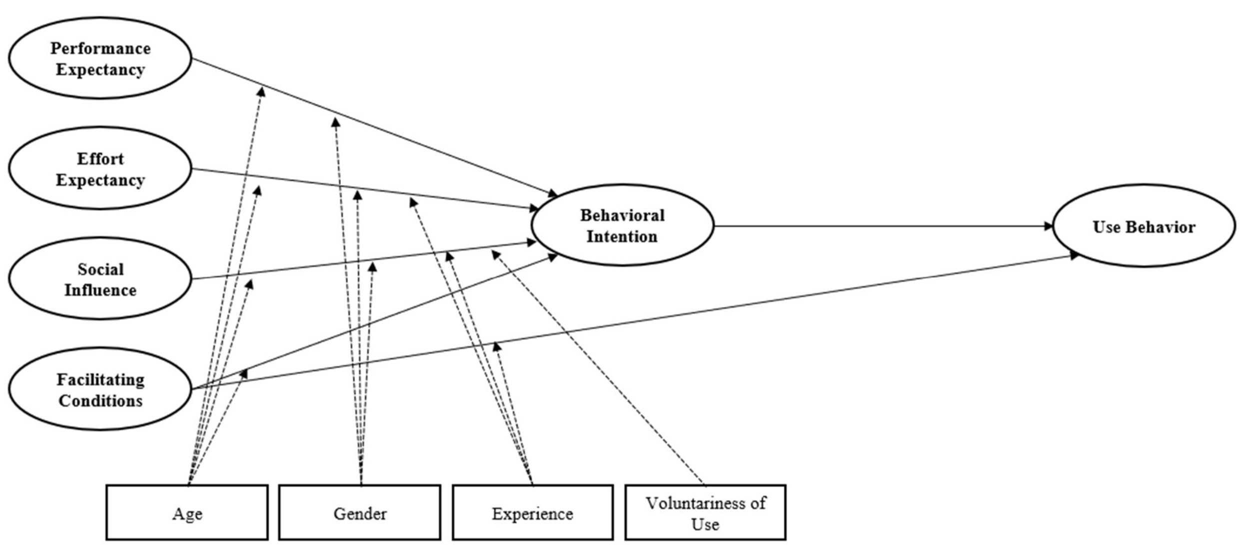
Unified Theory of Acceptance and Use of Technology

Venkatesh et al. (2003) developed UTAUT after an in-depth analysis of leading information systems theories. The authors then determined the constructs and relationships based on the following leading information systems theories—theory of reasoned action (TRA), technology acceptance model (TAM), motivational model (MM), theory of planned behavior (TPB), decomposed theory of planned behavior (DTPB), a combined theory of planned behavior/technology acceptance model (C-TPB-TAM), model of PC utilization (MPCU), innovation diffusion theory (IDT), and social cognitive theory (SCT)—to gain insights on consumers' acceptance and technology use (Dwivedi et al., 2011). Since its inception in 2003, UTAUT has been applied to software adoption in a variety of fields, specifically focusing on worker adoption of enterprise technology (Venkatesh et al., 2016). The UTAUT posits that intentions and behaviors can be predicted by an individual's performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003).

Venkatesh et al. (2003) described how performance expectancy is a construct derived from TAM, MM, MPCU, IDT, and SCT that represents the degree to which an individual believes that using a specific technology application will improve their performance. Effort expectancy is a construct derived from TAM, MPCU, and IDT that represents ease associated with the use of a specific technology. Social influence is a construct derived from TAM, TRA, TPB, DTPB, MPCU, and IDT that represents the degree to which an individual believes others think they should adopt a specific technology. Facilitating conditions is a construct derived from MPCU, TPB, DTPB, and IDT that represents the degree to which an individual believes that adoption of specific technology is supported by technical and organizational resources (Venkatesh et al., 2003). Please see Figure 1 for a visual depiction of the original UTAUT theoretical model.

Figure 2.1

Unified Theory of Acceptance and Use of Technology (UTAUT)

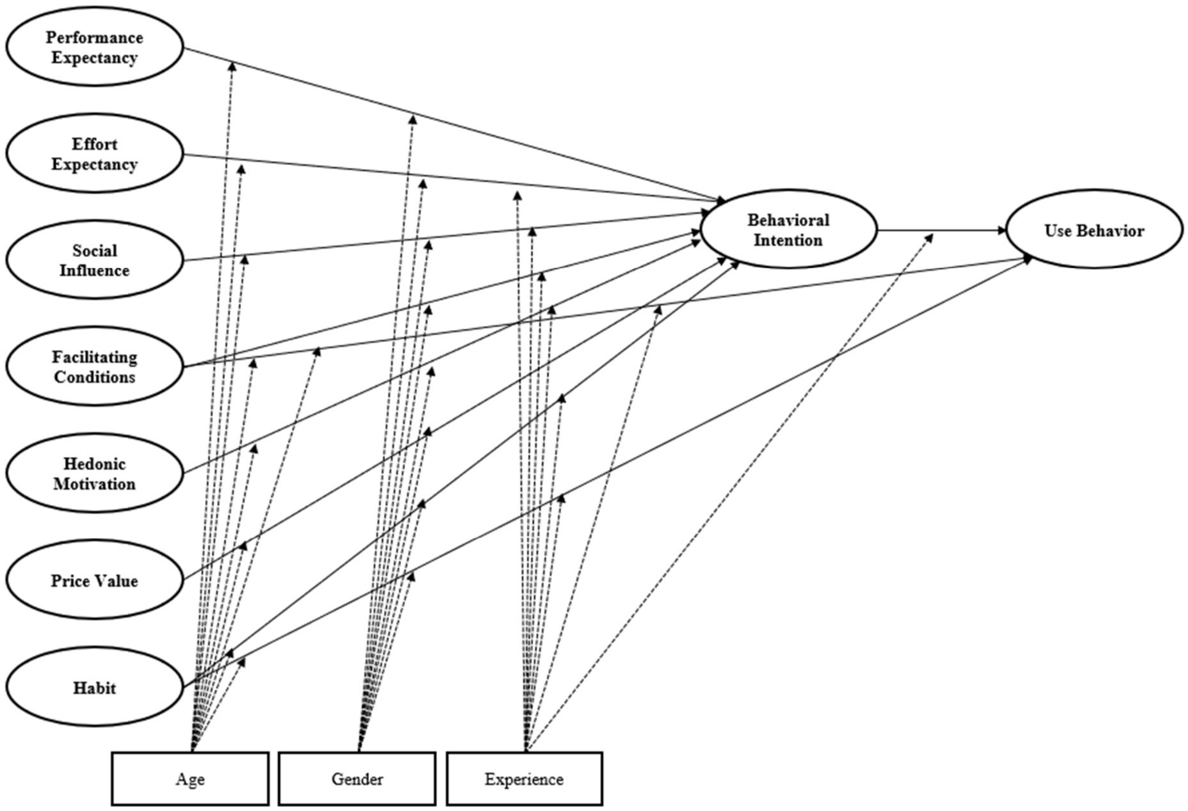


The leading information systems theories described above explained between 17% and 53% of the intention to adopt enterprise technology, whereas UTAUT explained 70% of intention (Dwivedi et al., 2019). Despite widespread use and high explanatory power, Dwivedi et al.'s (2019) systemic literature review and Dwivedi et al.'s (2011) meta-analysis found that most studies that leveraged UTAUT extended the theory with additional variables related to the applicable technology, especially in consumer technology.

Venkatesh et al. (2012) created UTAUT2 by enhancing UTAUT for consumer technology acceptance and use by incorporating the three additional constructs of hedonic motivation, price value, and habit. Hedonic motivation represents the fun or pleasure derived from using a specific technology, which measures the intrinsic motivation of technology use that complements the extrinsic motivation measured by performance expectancy in UTAUT. Price value represents the consumer's perceived tradeoff between the benefits derived from technology and the monetary costs of that technology. Price value is important in the consumer context because consumers bear the costs of technology, whereas in the enterprise context, employees do not pay for technology. Habit represents the extent to which a consumer automatically performs an action because of learning it, which has been a critical factor in consumer adoption in previous information systems research (Venkatesh et al., 2012). Please see Figure 2 for the UTAUT2 theoretical model.

Figure 2.2

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



In a study of consumer adoption of mobile internet technology, Venkatesh et al. (2012) found that UTAUT2 substantially improved the explanatory power of behavioral intention from 56% to 74% and use behavior from 40% to 52%. In the consumer context, Venkatesh et al. (2012) posited that the three additional constructs combined with removing voluntariness of use as a moderating variable accounted for the differences between employee adoption in an enterprise setting and consumer adoption in a free market. Beyond the structural enhancements to the model, the authors also suggested that acceptance and use in a consumer context should focus on specific features rather than a broader measure of the overall technology. For example, rather than only measuring the acceptance and use of mobile internet technology, the study analyzed specific features such as messaging, e-mail, and booking flights (Venkatesh et al., 2012).

Tamilmani, Rana, Wamba, et al. (2021) conducted a systematic literature review of 650 studies that leveraged UTAUT2 to evaluate the theory's robustness and quality based on a multilevel framework. They concluded that the theory is robust and high-quality for both consumer technology's acceptance and use. The authors also found that the theory is widely adopted, with over six thousand citations in less than one decade, and many researchers extended the model with specific variables applicable to the specific technology. For example, several FinTech applications extended UTAUT2 to include measures of trust and security (Tamilmani, Rana, Wamba, et al., 2021).

Tamilmani, Rana, and Dwivedi (2021), using quantitative methods, conducted a meta-analysis of 60 studies that used UTAUT2, with over 122,000 observations. They found the constructs were highly reliable, with Cronbach's alpha ranging from .837 to .899. They also found the model has substantial predictive power, and that the newly introduced habit construct had the second strongest path to behavioral intention (Tamilmani, Rana, Wamba, et al., 2021).

Supporting Literature

To focus the application of UTAUT2 on PFM technology, a systematic literature review was conducted to examine research that used either UTAUT or UTAUT2 and focused on consumer FinTech adoption. The titles, abstracts, and listings of studies on Google Scholar and Web of Science were analyzed using the keywords "unified theory of acceptance and use of technology" or "UTAUT" and "fintech" or "banking" or "payments" or "investing." This resulted in 246 unique studies but 138 were excluded for the following reasons: did not actually use UTAUT (77), were not primary research (21), were not consumer FinTech (20), could not access (18), and were not in English (2). The remaining 108 studies were analyzed to understand their study design and findings. Please see Table 1 for an overview of independent variables that were found to be statistically significant in the greatest number of studies.

Table 2.1

Systematic Literature Review: Statistically Significant Independent Variables

Variable	# of studies with significant relationship	# of studies that considered relationship	% of studies with significance when considered
	UTAUT2 Variables		
Performance Expectancy	100	107	93.46%
Effort Expectancy	60	102	58.82%
Social Influence	66	100	66.00%
Facilitating Conditions	64	90	71.11%
Hedonic Motivation	25	39	64.10%
Price Value	24	33	72.73%
Habit	23	29	79.31%
	Extension Variables		
Trust	43	45	95.56%
Security	23	28	82.14%
Risk	20	22	90.91%
Attitude	20	21	95.24%
Task Technology Fit	17	19	89.47%
Innovativeness	10	12	83.33%
Convenience	9	10	90.00%

Among the 108 studies, the split between those using UTAUT (56%) and UTAUT2 (44%) as the theoretical framework was fairly even. Consistent with Tamilmani, Rana, Wamba, et al. (2021), using UTAUT or UTAUT2 as a theoretical framework does not always mean the conceptual framework of the study will be consistent with the models outlined by Venkatesh et al. (2003; 2012). Among the 47 studies that used UTAUT2 as their theoretical framework, only 22 of them considered all the variables outlined in Figure 2. Regardless of the application of

UTAUT or UTAUT2, a common theme in the studies was extending the model with additional variables with 80% of studies being extended with statistically significant exogenous variables.

On an absolute basis, performance expectancy (100), social influence (66), facilitating conditions (64), and effort expectancy (60) were most often associated with consumer FinTech adoption. Among studies with exogenous extensions, trust (45) and security (28) were included in the analysis most often. On a relative basis, trust (96%), attitude (95%), performance expectancy (93%), and convenience (90%) were found to be statistically significant most often when included in the analysis.

Based on this review, the factors examined in this study can be classified into nine categories: (1) performance expectancy, (2) effort expectancy, (3) social influence, (4) facilitating conditions, (5) hedonic motivation, (6) price value, (7) habit, (8) trust, and (9) security. Performance expectancy, effort expectancy, social influence, and facilitating conditions are based on UTAUT research (Venkatesh, 2003), while hedonic motivation, price value, and habit are based on the consumer focus of UTAUT2 (Venkatesh, 2012). Trust (Gefen et al., 2003) and security (Cheng et al., 2006; Salisbury et al., 2001) expand on UTAUT2 based on the literature review that follows.

Performance Expectancy and Technology Adoption

Performance expectancy relates to the degree to which an individual believes that using a specific technology application will improve their performance (Venkatesh et al., 2003). Based on an extensive review of information technology research, Venkatesh et al. (2003) found that performance expectations are represented by six different components included in leading information systems theories: performance expectancy (UTAUT), perceived usefulness (TAM), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT), and outcome expectations (SCT).

In UTAUT2, performance expectancy is an aggregate measure of five components from previous research to provide a holistic measure of performance expectations. The five components are perceived usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectancies (Venkatesh et al., 2012). Perceived usefulness is the degree to which an individual believes that adopting a particular technology would improve their performance (Venkatesh et al., 2003). Extrinsic motivation is an individual's perception that adopting particular technology helps to achieve valuable outcomes unique to the technology itself. Job-fit is the degree to which an individual believes that specific technology is uniquely positioned to enhance their performance related to a specific aspect of their life (Momani & Jamous, 2017). Relative advantage is the degree to which an individual believes that specific technology is superior to its predecessor or alternatives (Shih & Fang, 2004). And outcome expectations is the degree to which an individual believes they will experience positive professional or personal consequences by adopting specific technology (Momani & Jamous, 2017).

An extensive review of previous research shows that both an aggregate view of performance expectancy and the underlying components are directly associated with technology adoption. Venkatesh et al. (2003) conducted four longitudinal studies at four different organizations using four different types of technology and found that performance expectancy was the strongest predictor of intention and was significant across all models in the experiment, including TAM, MM, C-TAM-TPB, MPCU, IDT, and SCT. Dwivedi et al. (2011) conducted a meta-analysis that used UTAUT and found that among all analytical constructs, performance expectancy had the largest influence on behavioral intention.

Tamilmani, Rana, and Dwivedi (2021) conducted a meta-analysis that leveraged UTAUT2 and found that performance expectancy was the most used path with the highest level of significance. Beyond the broad definition of performance expectancy, King and He (2006) conducted a meta-analysis that included over 12,000 observations and found that in research leveraging TAM, perceived usefulness had the largest influence on behavioral intention.

Evidence from a variety of studies across fields related to FinTech supports performance expectancy's impact. Yang (2012) found that perceived usefulness was associated with intending to adopt e-commerce websites. Walsh and Lim (2020) found that perceived usefulness was associated with PFM technology adoption. Several studies found evidence to support the relationship between performance expectancy and adoption of internet banking when using UTAUT and UTAUT2 (Al Qeisi & Al-Abdallah, 2014; Daka & Phiri, 2019; Foon & Fah, 2011; Rahi et al., 2018; Tarhini et al., 2016). Additional studies found evidence to support the relationship between perceived usefulness and internet banking adoption when using TAM (McCloskey, 2006; Nasri & Charfeddine, 2012; Pikkarainen et al., 2004; Selamat et al., 2009; Yaghoubi & Bahmani, 2010).

Previous studies also found a relationship between performance expectancy and banking services adoption when participants leveraged mobile applications (Abbas et al., 2018; Savić & Pešterac, 2019; Zhou et al., 2010). And evidence suggests that performance expectancy is associated with newer technology adoption such as mobile peer-to-peer payments and Bitcoin (de Sena Abrahão et al., 2016; Lee & Shin, 2018; Slade, Dwivedi, et al., 2015). This previous literature supports the first hypothesis:

H1: Performance expectancy will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM *technology helps them manage their finances will be more likely to accept and use PFM technology.*

Please see Table 2 for a complete list of all studies that found a statistically significant positive relationship between performance expectancy and consumer FinTech adoption.

Table 2.2

Systematic Literature Review: Performance Expectancy

Focus	Studies
Banking	Abbas et al., 2018; Akter et al., 2021; Al Qeisi & Al-Abdallah, 2014; Alalwan et al., 2016; Alalwan et al., 2017; Alalwan et al., 2018; Albashrawi et al., 2017; Albashrawi et al., 2019; Albashrawi & Motiwalla, 2020; Al-Muhrami et al., 2021; Ammar, 2017; Arenas-Gaitán et al., 2015; Baabdullah et al., 2019; Baptista & Oliveira, 2015; Baptista & Oliveira, 2017; Bouteraa et al., 2022; Daka & Phiri, 2019; Foon & Fah, 2011; Giovanis, Assimakopoulos, et al., 2019; Goularte & Zilber, 2019; Gupta et al., 2019; Hilal & Varela-Neira, 2022; Ivanova & Kim, 2022; Khan et al., 2017; Khan et al., 2022; Li et al., 2022; Malaquias & Silva, 2020; Merhi et al., 2019; Merhi et al., 2021; Nasri, 2021; Oliveira et al., 2014; Penney et al., 2021; Rahi & Abd Ghani, 2018; Rahi et al., 2018; Rahi, Abd. Ghani, et al., 2019; Rahi, Othman Mansour, et al., 2019; Saprikis et al., 2022; Savić & Pešterac, 2019; Solberg Söilen & Benhayoun, 2022; Tarhini et al., 2016; Thaker et al., 2019; Thaker, Thaker, et al., 2022; Thusi & Maduku, 2020; Ur Rashid et al., 2021; Wang et al., 2017; Yi et al., 2020; Yuen et al., 2015; Zhou et al., 2010
Payments	Abubakar et al., 2022; Acharya et al., 2019; Alkhalifah, 2021; Al-Okaily et al., 2020; Al-Sabaawi et al., 2021; Al-Saedi et al., 2020; Chawla & Joshi, 2021; de Sena Abrahão et al., 2016; Giovanis, Kavoura, et al., 2019; Jung et al., 2020; Kang, 2019; Khalilzadeh et al., 2017; Kim & Park, 2020; Kim & Yoo, 2019; Kim & Yoo, 2020; Koenig-Lewis et al., 2015; Lamichhane, 2022; J.-M. Lee, 2019; Leong et al., 2021; H.-Y. Lin et al., 2019; X. Lin et al., 2019; Loncar & Tsai, 2022; Malarvizhi et al., 2022; Morosan & DeFranco, 2016; Nur & Panggabean, 2021; Oliveira et al., 2016; Omar et al., 2022; Ompusunggu & Anugrah, 2021; Purohit & Arora, 2021; Qu et al., 2022; Rahadi et al., 2022; Rahman et al., 2020; Runze & Jongho, 2017; Salamah, 2022; Sivathanu, 2019; Slade et al., 2015; Soodan & Rana, 2020; Soomro, 2019; Suo et al., 2022; Tang et al., 2014; Teo, Tan, Ooi, Hew, et al., 2015; Thaker, Subramaniam, et al., 2022; Thanabordeekij, 2019; Tossy, 2014; Tsai & Loncar, 2022; Upadhyay et al., 2022; Widyanto et al., 2021
Investments	Gan et al., 2021; Kim & Song, 2018; Radic et al., 2022; Tai & Ku, 2013; Wang, 2005; Yeh et al., 2022

Effort Expectancy and Technology Adoption

Effort expectancy relates to the ease associated with the use of a specific technology (Venkatesh et al., 2003). Based on an extensive review of information technology research, Venkatesh et al. (2003) found that effort expectations are represented by four components included in leading information systems theories: effort expectancy (UTAUT), perceived ease of use (TAM), complexity (MPCU), and ease of use (IDT).

In UTAUT2, effort expectancy is an aggregate measure of effort expectations that includes three components from previous research to provide a holistic measure of effort expectations. The three components are the perceived ease of use, complexity, and ease of use (Venkatesh et al., 2012). Perceived ease of use is the degree to which an individual believes that using specific technology would be free from effort (Venkatesh et al., 2003). Complexity is the degree to which an individual perceives specific technology to be challenging to learn, understand, or operate (Shih & Fang, 2004). Ease of use is the degree to which an individual believes that using specific an innovation would be difficult (Momani & Jamous, 2017).

Previous research shows that both an aggregate view of effort expectancy and the underlying components are associated with technology adoption. Venkatesh et al. (2003) found that effort expectancy was significant in the early stages of adoption but becomes nonsignificant. Despite ample support throughout information technology research, the connection between effort expectations and technology adoption is not entirely settled. Ma and Liu's (2004) meta-analysis found evidence to suggest that the relationship between effort expectations and technology acceptance is weak. Moreover, Venkatesh's (2000) meta-analysis found that effort expectations might be moderated by other variables, such as facilitating conditions, motivation, and emotion. Researchers have observed differences in the effort expectations' impact by geographical location (Khechine et al., 2016).

However, and more pertinent to the current study, a variety of studies across fields related to FinTech found evidence to support effort expectations' impact on FinTech adoption. Walsh and Lim (2020) found that perceived ease of use was associated with PFM technology adoption.

Several studies have found evidence to support the relationship between perceived ease of use and the adoption of internet banking and mobile banking when using TAM (Nasri & Charfeddine, 2012; McCloskey, 2006). Additional studies found evidence to support the relationship between effort expectancy and the adoption of internet banking, mobile banking, and mobile payments when using UTAUT and UTAUT2 (Abbas et al., 2018; Daka & Phiri, 2019; de Sena Abrahão et al., 2016; Foon & Fah, 2011; Rahi & Abd Ghani, 2018; Savić & Pešterac, 2019). This previous literature supports the second hypothesis:

H2: Effort expectancy will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that PFM technology is easy to use will be more likely to accept and use PFM technology.

Please see Table 3 for a complete list of all studies that found a statistically significant positive relationship between effort expectancy and consumer FinTech adoption.

Table 2.3

Systematic Literature Review: Effort Expectancy

Focus	Studies
Banking	Abbas et al., 2018; Akter et al., 2021; Alalwan et al., 2017; Alalwan et al., 2018; Albashrawi et al., 2017; Albashrawi et al., 2019; Al-Muhrami et al., 2021; Ammar, 2017; Arenas-Gaitán et al., 2015; Baptista & Oliveira, 2017; Daka & Phiri, 2019; Foon & Fah, 2011; Gupta et al., 2019; Hilal & Varela-Neira, 2022; Ivanova & Kim, 2022; Li et al., 2022; Malaquias & Silva, 2020; Merhi et al., 2019; Merhi et al., 2021; Olasina, 2015; Penney et al., 2021; Rahi & Abd Ghani, 2018; Rahi, Othman Mansour, et al., 2019; Rahi, Abd.Ghani, et al., 2019; Savić & Pešterac, 2019; Thaker et al., 2019; Thaker, Thaker, et al., 2022; Ur Rashid et al., 2021; Wang et al., 2017
Payments	Abubakar et al., 2022; Acharya et al., 2019; Alkhalifah, 2021; Al-Sabaawi et al., 2021; Al-Saedi et al., 2020; Chawla & Joshi, 2021; de Sena Abrahão et al., 2016; Giovanis, Kavoura, et al., 2019; Khalilzadeh et al., 2017; Lamichhane, 2022; Leong et al., 2021; Manrai et al., 2021; Omar et al., 2022; Purohit & Arora, 2021; Qu et al., 2022; Rabaai, 2021; Runze & Jongho, 2017; Salamah, 2022; Sivathanu, 2019; Soodan & Rana, 2020; Soomro, 2019; Tang et al., 2014; Teo, Tan, Ooi, Hew et al., 2015; Teo, Tan, Ooi, & Lin, 2015; Tsai & Loncar, 2022; Upadhyay et al., 2022
Investments	Kim & Song, 2018; Radic et al., 2022; Tai & Ku, 2013; Wang, 2005; Yeh et al., 2022

Social Influence and Technology Adoption

Social influence relates to the degree to which an individual believes others think they should adopt specific technology (Venkatesh et al., 2003). Based on an extensive review of information technology research, Venkatesh et al. (2003) found that social influence is represented by four components included in leading information systems theories: social influence (UTAUT), subjective norm (TPB and DPTB), social factors (MPCU), and image (IDT).

In UTAUT2, social influence is an aggregate measure that includes three components from previous research to provide a holistic measure of social influence. The three components are subjective norm, social factors, and image (Venkatesh et al., 2012). Subjective norm is an individual's perception that influential people in their life believe they should or should not adopt specific technology (Momani & Jamous, 2017). Subjective norm has been included as a key construct of models such as TRA and TPB that analyze intention and subsequent behavior across a variety of disciplines (Venkatesh & Davis, 2000). Social factors represent an individual's internalization of the culture and behavior of a certain group they associate with and the impact that the group's behavior has on their own perceptions (Momani & Jamous, 2017). Image is the degree to which an individual perceives that the use of specific technology will enhance their status within their social circle (Momani & Jamous, 2017).

Venkatesh et al. (2003) found that the impact of social influence was connected to adoption voluntariness. Evidence from a variety of studies across fields related to FinTech has also found evidence to support social influence's impact on technology adoption. Sentosa and Mat (2012) found that subjective norm is associated with intending to adopt e-commerce technology, and Leejoeiwara (2013) found evidence to suggest that peer influence is associated with online learning technology adoption.

Several studies have found evidence to support the association of social influence and internet banking technology adoption when using UTAUT and UTAUT2 (Foon & Fah, 2011; Rahi et al., 2018; Tarhini et al., 2016). Social influence is also associated with the adoption of mobile banking and mobile payment technology (Abbas et al., 2018; de Sena Abrahão et al., 2016; Savić & Pešterac, 2019; Slade, Williams, et al., 2015; Zhou et al., 2010;). Several studies found evidence to support the relationship between subjective norms and the adoption of internet banking and mobile banking when using TAM (Aboelmaged & Gebba, 2013; Nasri & Charfeddine, 2012). Finally, Ramayah et al. (2009) found evidence to suggest that subjective norm has a significant positive relationship with the adoption of online stock trading behavior. This previous literature supports the third hypothesis:

H3: Social influence will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that others think they should use PFM technology will be more likely to accept and use PFM technology.

Please see Table 4 for a complete list of all studies that found a statistically significant positive relationship between social influence and consumer FinTech adoption.

Table 2.4

Systematic Literature Review: Social Influence

Focus	Studies
Banking	Abbas et al., 2018; Akter et al., 2021; Albashrawi et al., 2017; Albashrawi et al., 2019; Al-Muhrami et al., 2021; Baptista & Oliveira, 2017; Dhingra & Gupta, 2020; Foon & Fah, 2011; Giovanis, Assimakopoulos, et al., 2019; Gupta et al., 2019; Hilal & Varela-Neira, 2022; Ivanova & Kim, 2022; Khan et al., 2022; Li et al., 2022; Malaquias & Silva, 2020; Nasri, 2021; Penney et al., 2021; Rahi et al., 2018; Rahi, Abd. Ghani, et al., 2019.; Rahi, Othman Mansour, et al., 2019; Saprikis et al., 2022; Savić & Pešterac, 2019; Solberg Söilen & Benhayoun, 2022; Tarhini et al., 2016; Ur Rashid et al., 2021; Zhou et al., 2010

Payments	Abrahão et al., 2016; Al-Okaily et al., 2020; Al-Sabaawi et al., 2021; Al-Saedi et al., 2020; Giovanis, Kavoura, et al., 2019; Jung et al., 2020; Kang, 2019; Khalilzadeh et al., 2017; Kim & Park, 2020; Kim & Yoo, 2019; Kim & Yoo, 2020; Koenig-Lewis et al., 2015; Lamichhane, 2022; J.-M. Lee, 2019; Leong et al., 2021; X. Lin et al., 2019; Malarvizhi et al., 2022; Moorthy et al., 2022; Morosan & DeFranco, 2016; Nur & Panggabean, 2021; Oliveira et al., 2016; Omar et al., 2022; Ompusunggu & Anugrah, 2021; Purohit & Arora, 2021; Qu et al., 2022; Rahadi et al., 2022; Rahman et al., 2020; Runze & Jongho, 2017; Sivathanu, 2019; Slade et al., 2015; Soodan & Rana, 2020; Suo et al., 2022; Thaker, Subramaniam, et al., 2022; Thanabordeekij, 2019; Tossy, 2014; Widyanto et al., 2021
Investments	Gan et al., 2021; Radic et al., 2022; Tai & Ku, 2013; Wang, 2005; Yeh et al., 2022

Facilitating Conditions and Technology Adoption

Facilitating conditions is the degree to which an individual believes that adoption of specific technology is supported by technical and organizational resources (Venkatesh et al., 2003). In UTAUT2, facilitating conditions is an aggregate measure that includes two components from previous research, perceived behavioral control and compatibility, to provide a holistic measure of facilitating conditions (Venkatesh et al., 2012). Perceived behavioral control is the ease or difficulty an individual perceives with adopting the specific technology (Momani & Jamous, 2017). Perceived internal or external constraints could also affect an individual's perceived behavioral control. Compatibility is the degree to which an individual believes that technology aligns with their beliefs, values, needs, and prior experiences (Shih & Fang, 2004).

Evidence from a variety of studies across fields related to FinTech found evidence to support the impact of facilitating conditions on FinTech adoption. Several studies found evidence to support the relationship between facilitating conditions and the adoption of internet banking and mobile banking when using UTAUT and UTAUT2 (Abbas et al., 2018; Daka & Phiri, 2019; Foon & Fah, 2011; Oliveira et al., 2014; Rahi et al., 2018; Savić & Pešterac, 2019; Zhou et al., 2010). Evidence from several studies suggests that perceived behavioral control is associated with the adoption of e-commerce, online banking, and mobile banking technology

(Kazemi et al., 2013; H.-X. Lin et al., 2019; X. Lin et al., 2019; Yaghoubi & Bahmani, 2010). This previous literature supports the fourth hypothesis:

H4: Facilitating conditions will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that they have the technical and support resources needed to use PFM technology will be more likely to accept and use PFM technology.

Please see Table 5 for a complete list of all studies that found a statistically significant positive relationship between facilitating conditions and consumer FinTech adoption.

Table 2.5

Systematic Literature Review: Facilitating Conditions

Focus	Studies
Banking	Abbas et al., 2018; Akter et al., 2021; Alalwan et al., 2016; Alalwan et al., 2018; Albashrawi & Motiwalla, 2020; Albashrawi et al., 2019; Al-Muhrami et al., 2021; Baabdullah et al., 2019; Bouteraa et al., 2022; Daka & Phiri, 2019; Dhingra & Gupta, 2020; Foon & Fah, 2011; Goularte & Zilber, 2019; Gupta et al., 2019; Hilal & Varela-Neira, 2022; Ivanova & Kim, 2022; Khan et al., 2017; Li et al., 2022; Merhi et al., 2021; Nasri, 2021; Oliveira et al., 2014; Rahi et al., 2018; Rahi, Abd. Ghani, et al., 2019; Rahi, Othman Mansour, et al., 2019; Saprikis et al., 2022; Savić & Pešterac, 2019; Solberg Söilen & Benhayoun, 2022; Thaker et al., 2019; Thaker, Thaker, et al., 2022; Thusi & Maduku, 2020; Ur Rashid et al., 2021; Zhou et al., 2010
Payments	Acharya et al., 2019; Al-Sabaawi et al., 2021; Chawla & Joshi, 2021; Kim & Park, 2020; Kim & Yoo, 2019; Lamichhane, 2022; J.-M. Lee, 2019; Lin et al., 2019; Tsai & Loncar, 2022; Malarvizhi et al., 2022; Manrai et al., 2021; Moorthy et al., 2022; Morosan & DeFranco, 2016; Nur & Panggabean, 2021; Omar et al., 2022; Ompusunggu & Anugrah, 2021; Rabaai, 2021; Rahadi et al., 2022; Rahman et al., 2020; Runze & Jongho, 2017; Sivathanu, 2019; Soodan & Rana, 2020; Soomro, 2019; Tang et al., 2014; Teo, Tan, Ooi, Hew, et al., 2015; Teo, Tan, Ooi, & Lin, 2015; Thaker, Subramaniam, et al., 2022; Thanabordeekij, 2019; Upadhyay et al., 2022; Widyanto et al., 2021
Investments	Radic et al., 2022; Wang, 2005; Yeh et al., 2022

Hedonic Motivation and Technology Adoption

Hedonic motivation is the fun or pleasure derived from using a specific technology and has been found to play an important role in consumer technology adoption. In UTAUT, the focus is on employee adoption of enterprise technology, when motivation is primarily external, as measured by performance expectancy. The shift from enterprise to consumer focus in UTAUT2 introduced the need to consider intrinsic motivation, as measured by hedonic motivation (Venkatesh et al., 2012).

Hedonic motivation is an aggregate measure of three components included in leading information systems theories: hedonic expectancy, perceived enjoyment, and perceived playfulness (Venkatesh et al., 2012). Hedonic expectancy is the degree to which an individual expects that using a specific technology will make their life more interesting, fun, or joyful (Ahn et al., 2016). Perceived enjoyment represents the level of intellectual playfulness an individual experiences from using the technology in a spontaneous or imaginative way (Anandarajan et al., 2002). Perceived playfulness is the pleasure an individual experiences when they actually use the specific technology (Robin et al., 2016).

Tamilmani et al. (2019) conducted a meta-analysis of 53 studies that included hedonic motivation as a construct, while using UTAUT2 as the theoretical framework. The path relationship between hedonic motivation and behavioral intention was significant in 43 of 53 studies (Tamilmani et al., 2019). In the 10 studies that did not find hedonic motivation to be a significant predictor, Tamilmani et al. (2019) found that they focused on mobile payment and learning, in which extrinsic motivation was the dominant factor rather than the intrinsic motivation measured by hedonic motivation.

Intrinsic motivation's impact on technology adoption dates to 1988 when Carrol and Thomas (1988) found that fun and enjoyment were key predictors in consumers' adoption of the Apple Lisa computer. Evidence also suggests that hedonic motivation is associated with technology adoption in a variety of fields such as mobile television (Wong et al., 2014), social media apps (Jarvinen et al., 2016), and personal informatics for health tracking (Pfeiffer et al., 2016). Evidence from a variety of studies across fields related to FinTech found evidence to support hedonic motivation's impact on FinTech adoption. Further, several studies have found evidence to support the relationship between hedonic motivation and the adoption of internet banking (Alalwan et al., 2015; Alalwan et al., 2016) and mobile banking (Alalwan et al., 2017; Baptista & Oliveira, 2015; Baptista & Oliveira, 2017). Evidence from several studies also suggests an association between hedonic motivation and mobile payments (Koenig-Lewis et al., 2015; Oliveira et al., 2016; Slade, Dwivedi, et al., 2015). This previous literature supports the fifth hypothesis:

H5: Hedonic motivation will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology is enjoyable will be more likely to accept and use PFM technology.

Please see Table 6 for a complete list of all studies that found a statistically significant positive relationship between hedonic motivation and consumer FinTech adoption.

Table 2.6

Systematic Literature Review: Hedonic Motivation

Focus	Studies
Banking	Akter et al., 2021; Alalwan et al., 2016; Alalwan et al., 2017; Alalwan et al., 2018; Baabdullah et al., 2019; Baptista & Oliveira, 2015; Baptista & Oliveira, 2017; Dhingra & Gupta, 2020; Khan et al., 2022; Merhi et al., 2021
Payments	Acharya et al., 2019; Khalilzadeh et al., 2017; Kim & Yoo, 2019; Kim & Yoo, 2020; Koenig-Lewis et al., 2015; Lin et al., 2019; Malarvizhi et al., 2022; Morosan & DeFranco, 2016; Nur & Panggabean, 2021; Rabaai, 2021; Rahman et al., 2020; Runze & Jongho, 2017; Sivathanu, 2019; Soodan & Rana, 2020; Tang et al., 2014; Thaker, Subramaniam, et al., 2022

Price Value and Technology Adoption

Price value represents the consumer's perceived tradeoff between the benefits derived from technology and the technology's monetary costs. Price value is important in the consumer context because consumers bear the costs of technology, whereas in the enterprise context, employees do not pay for technology. Price value is positive when the benefits of using technology are greater than the costs of the technology (Venkatesh et al., 2012).

Tamilmani, Rana, Dwivedi, Sahu, et al. (2018) conducted a meta-analysis of 79 studies that leveraged UTAUT2 and found that only 32 of those studies included the price value construct. The primary reason studies excluded the price value construct was that the applicable technology is available to consumers at no cost, such as mobile applications or social networking sites. The remaining studies that included price value as a construct found it was not significantly associated with behavioral intention or use behavior. These findings, contrary to Venkatesh et al.'s (2012), led Tamilmani, Rana, Dwivedi, Sahu, et al. (2018) to advocate for further research on the impact of price value on the acceptance and use of consumer technology. Most PFM tools are available through free applications such as Mint.com or as part of the broader experience with a financial institution (Tajimi, 2021). Therefore, this study will not consider price value as a construct in the models, despite its inclusion in UTAUT2.

Please see Table 7 for a complete list of all studies that found a statistically significant positive relationship between price value and consumer FinTech adoption.

Table 2.7

Systematic Literature Review: Price Value

Focus	Studies
Banking	Akter et al., 2021; Alalwan et al., 2016; Alalwan et al., 2017; Alalwan et al., 2018; Arenas-Gaitán et al., 2015; Baabdullah et al., 2019; Baptista & Oliveira, 2017; Dhingra & Gupta, 2020; Goularte & Zilber, 2019; Khan et al., 2017; Khan et al., 2022; Kwateng et al., 2019; Merhi et al., 2019; Merhi et al., 2021; Penney et al., 2021; Thaker et al., 2019; Thaker, Thaker, et al., 2022; Thusi & Maduku, 2020
Payments	Al-Okaily et al., 2020; Kim & Yoo, 2019; Purohit & Arora, 2021; Qu et al., 2022; Runze & Jongho, 2017; Soodan & Rana, 2020; Suo et al., 2022

Habit and Technology Adoption

Habit represents the extent to which a consumer automatically performs an action. Venkatesh et al. (2012) suggested that habit is an important predictor of consumer technology acceptance and use. In previous research, habit and experience are treated as similar concepts and used interchangeably since prior use is associated with future use (Kim et al., 2005).

The case to treat habit as a unique construct is grounded in psychological research. Ajzen (2002) suggested that simply because an action was taken in the past does not mean it will be performed in the future. Since past behavior does not solely drive future behavior, the concept of habit should be treated as a separate construct (Ajzen, 2002). Ouellette and Wood (1998) noted that habits contain motivational properties that, when combined with repeated exposure, have a direct impact on future performance. Therefore, the frequency of prior actions reflects the habit's strength, which drives future action rather than the prior actions themselves solely driving future action (Ouellette & Wood, 1998).

Liang et al.'s (2007) information systems research found evidence to suggest that habit results from prolonged and repeated exposure to a particular technology, which is strengthened with additional exposure and directly influences both behavioral intention and use behavior directly. This concept challenges the thought that behavioral intention alone predicts use behavior, which is why UTAUT2 includes habit as a construct in consumer technology.

Studies highlight the reasons for excluding habit as a construct. Tamilmani, Rana, and Dwivedi (2018) conducted a meta-analysis of 68 studies that leveraged UTAUT2 and found that only 23 of those studies included the habit construct. When habit was included in the analysis, the path between habit and behavioral intention and use behavior was significant. The meta-analysis found common and valid reasons for the exclusion of habit as a construct, which should influence future research that leverages UTAUT2. First, the most common reason habit was excluded is related to the maturity of the technology. Since habit relies on past repeated behavior, it is not appropriate to consider it as new technology since users would not have had the opportunity for prior exposure. Second, habit is not an appropriate construct when analyzing mandatory technology acceptance and use. For example, students are required to use technology platforms, such as e-learning to complete their education, so it would not be suitable to consider habit in this setting (Tamilmani, Rana, & Dwivedi, 2018).

Limited evidence supports the association between habit and the acceptance and use of FinTech, however. Alalwan et al. (2015) found that habit was a significant predictor of using internet banking but was not related to acceptance of internet banking. Since PFM technology is not brand-new technology and is not mandatory, it will be included in this study. This previous literature supports the sixth hypothesis:

H6: Habit will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology is or would be part of their regular routine will be more likely to accept and use PFM technology.

Please see Table 8 for a complete list of all studies that found a statistically significant positive relationship between habit and consumer FinTech adoption.

Table 2.8

Systematic Literature Review: Habit

Focus	Studies
Banking	Alalwan et al., 2018; Arenas-Gaitán et al., 2015; Baabdullah et al., 2019; Baptista & Oliveira, 2015; Baptista & Oliveira, 2017; Goularte & Zilber, 2019; Khan et al., 2017; Khan et al., 2022; Kwateng et al., 2019; Merhi et al., 2019; Merhi et al., 2021; Penney et al., 2021; Thaker et al., 2019; Thaker, Thaker, et al., 2022

Payments	Acharya et al., 2019; Al-Sabaawi et al., 2021; Manrai et al., 2021; Morosan & DeFranco, 2016; Sivathanu, 2019; Soodan & Rana, 2020; Suo et al., 2022; Tang et al., 2014; Thaker, Subramaniam, et al., 2022; Thanabordeekij, 2019

Trust and Technology Adoption

Trust was the extension included and found statistically significant most often in studies on consumer FinTech adoption using UTAUT or UTAUT2. Trust represents the extent to which an individual believes another party will behave in a dependable, ethical, and socially appropriate manner. When an individual trusts another party, they are in a position of dependency and vulnerability, which makes trust an important social construct. Researchers posit that trust comprises specific beliefs, such as integrity, benevolence, ability, and predictability (Gefen et al., 2003). Beyond playing an integral role in broader society, trust is crucial in economic activities, especially when those activities involve uncertainty, risk, and the possibility of opportunistic behavior (Fukuyama, 1996; Williamson, 1985).

Research suggests that trust also plays an important role in online activity because a consumer's limited experience on a mobile application website does not give them an opportunity to assess trustworthiness as they would in a human interaction (Reichheld & Schefter, 2000). Trust has taken on a more prominent role in online interactions because of privacy and security concerns since vendors could easily misuse consumers' information (Jarvenpaa et al., 1999). Research shows that trust in an online environment can be represented by three components: calculative-based beliefs, structural assurances, and situational normality (Gefen, 2000). Calculative beliefs represent the belief that the vendor will gain nothing by cheating an individual. Structural assurances represent the belief that mechanisms are in place to protect the consumer from the vendor's potential ill intent. Situational normality represents the belief that the experience is consistent with other online experiences and easy to use.

Gefen et al. (2003) found evidence to suggest that trust was as important as other key constructs in information systems research after leveraging TAM to assess the adoption of e-commerce. Sarkar et al. (2020) supported this premise, their meta-analysis on 118 mobile commerce studies found that trust also has a significant positive relationship with attitude, satisfaction, loyalty, and behavioral intention. Gefen et al. (2000; 2003) also found that trust in technology is associated with perceived benefits of technology and behavioral intention to use the technology.

Evidence from a variety of studies across fields related to FinTech found evidence to support the impact of trust on FinTech adoption. Several studies have found evidence to support the relationship between trust and the adoption of internet banking, mobile banking, and mobile payments when using UTAUT and UTAUT2 (Akter et al., 2021; Alalwan et al., 2017; Merhi et al., 2019; Penney et al., 2021; Slade et al., 2013; Slade et al., 2014; Slade, Williams, et al., 2015; Srivastava et al., 2010; Widyanto et al., 2021). This prior literature supports the seventh hypothesis:

H7: Trust will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of trust in the provider offering PFM technology will be more likely to accept and use PFM technology.

Please see Table 9 for a complete list of all studies that found a statistically significant positive relationship between trust and the adoption of consumer FinTech.

Table 2.9

Systematic Literature Review: Trust

Focus	Studies
Banking	Akter et al., 2021; Alalwan et al., 2017; Ammar, 2017; Bouteraa et al., 2022; Dhingra & Gupta, 2020; Foon & Fah, 2011; Giovanis, Assimakopoulos, et al., 2019; Gupta et al., 2019; Ivanova & Kim, 2022; Khan et al., 2022; Kwateng et al., 2019; Li et al., 2022; Malaquias & Silva, 2020; Merhi et al., 2019; Merhi et al., 2021; Olasina, 2015; Oliveira et al., 2014; Penney et al., 2021; Rahi, Abd. Ghani, et al., 2019; Rahi, Othman Mansour, et al., 2019; Tarhini et al., 2016; Thusi & Maduku, 2020; Ur Rashid et al., 2021; Yuen et al., 2015;
Payments	Acharya et al., 2019; Alkhalifah, 2021; Al-Sabaawi et al., 2021; Al-Saedi et al., 2020; Giovanis, Kavoura, et al., 2019; Jung et al., 2020; Kang, 2019; Khalilzadeh et al., 2017; Kim & Park, 2020; Leong et al., 2021; Manrai et al., 2021; Nur & Panggabean, 2021; Rabaai, 2021; Slade et al., 2015; Teo, Tan, Ooi, Hew, et al., 2015; Thaker, Subramaniam, et al., 2022; Tossy, 2014; Widyanto et al., 2021
Investments	Gan et al., 2021

Security and Technology Adoption

Security was the extension included and found statistically significant in the second most amount of studies on consumer FinTech adoption using UTAUT or UTAUT2. In the context of consumer FinTech, the most common representation of security is perceived technology security, which represents an individual's potential feelings and uncertainty about using technology because of the vendor's ability and willingness to protect sensitive information (Cheng et al., 2006; Salisbury et al., 2001). Perceived technology security can be represented by two components: platform security and technology security. Platform security represents the extent to which an individual believes that their personal information is safe when actually using the technology platform. Technology security represents the extent to which an individual believes that their personal information and financial accounts will be protected once a third party has access to the information (Hwang et al., 2021). Thus, perceived technology security plays an important role in the acceptance and use of consumer technology because individuals only become ready to accept new technology once their uncertainty related to security concerns is below their own personal threshold (Lin, Wang, et al., 2019).

Research suggests that this threshold of uncertainty about security concerns is especially important when the technology is related to financial information (Cheng et al., 2006; Salisbury et al., 2001). Security concerns are one of the biggest barriers to consumer adoption of e-commerce, internet usage, and digital banking (Chang, 2014; George, 2002; Hoffman et al., 1999).

Extensive research has been conducted on the impact of perceived technology security on the acceptance and use of FinTech adoption, which supports its inclusion in this study. Evidence from several studies supports a significant positive relationship between the adoption of any FinTech tool and perceived technology security (Al Nawayseh, 2020; Jünger & Mietzner, 2020; Nangin et al., 2020; Ryu, 2018; Tang et al., 2020). Research also supports a relationship between perceived technology security and emerging FinTech tools, such as digital wallets and online trading platforms (Roca et al., 2009; Soodan & Rana, 2020).

Considerable research also shows a significant relationship between perceived technology security and both internet and mobile banking adoption (Akter et al., 2021; Hu et al., 2019; Khan et al., 2017; Merhi et al., 2019; Patel & Patel, 2018; Rahi et al., 2018). Many researchers have also found a significant relationship between the adoption of mobile payment technology and perceived technology security (Hwang et al., 2021; Khalilzadeh et al., 2017; X. Lin et al., 2019; Lubis & Irawan, 2020; Morosan & DeFranco, 2016; Oliveira et al., 2016; Widyanto et al., 2021; Wong & Mo, 2019; Wu & Du, 2012). This previous literature supports the eighth hypothesis:

H8: Perceived technology security will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of certainty related to security will be more likely to accept and use PFM technology.

Please see Table 10 for a complete list of all studies that found a statistically significant positive relationship between security and consumer FinTech adoption.

Table 2.10

Systematic Literature Review: Security

Focus	Studies
Banking	Akter et al., 2021; Ivanova & Kim, 2022; Khan et al., 2017; Merhi et al., 2019; Merhi et al., 2021; Rahi & Ghani, 2018; Saprikis et al., 2022; Ur Rashid et al., 2021
Payments	Al-Okaily et al., 2020; Al-Sabaawi et al., 2021; Chawla & Joshi, 2021; Khalilzadeh et al., 2017; Kim & Park, 2020; X. Lin et al., 2019; Morosan & DeFranco, 2016; Oliveira et al., 2016; Qu et al., 2022; Rahman et al., 2020; Runze & Jongho, 2017; Soodan & Rana, 2020; Widyanto et al., 2021
Investments	Radic et al., 2022; Tai & Ku, 2013

Moderation and Technology Adoption

Venkatesh et al. (2003) posited that the relationship between independent and dependent variables is not constant; rather, it is affected by other variables. When the strength or direction of a relationship between independent and dependent variables is affected by another variable, it is referred to as moderation (Venkatesh, 2003). The four moderators Venkatesh et al. (2003) introduced were age, gender, experience, and voluntariness of use. And including these moderators improved the predictive power of UTAUT (Dwivedi et al., 2020). Performance expectancy was found to be moderated by age and gender. Effort expectancy was found to be moderated by age, gender, and experience. Social influence was found to be moderated by age, gender, experience and voluntariness of use. Facilitating conditions was found to be moderated by age and experience (Venkatesh et al., 2003).

When developing UTAUT2, Venkatesh et al. (2012) eliminated voluntariness of use since consumers are free to choose to adopt technology, therefore, all decisions would be voluntary. Despite removing voluntariness of use, UTAUT2 still includes age, gender, and experience as moderators. Beyond the moderating included in UTAUT, Venkatesh et al. (2012) found that hedonic motivation, price value, and habit were moderated by age, gender, and experience.

Blut et al. (2022) conducted a meta-analysis of studies that leveraged UTAUT and analyzed the inclusion and effect of moderators. This analysis found that most studies that use UTAUT do not include moderation, which Venkatesh et al. (2016) noted is a limitation. When moderators were included, Blut et al. (2022) found that the most significant moderation is age and gender on performance expectancy, with performance expectancy more impactful for adoption of men and younger individuals. The second most significant moderation was the effect of age, gender, and experience on effort expectancy more impactful to adoption among women, older individuals, and more experienced individuals. Beyond the meta-analysis, Venkatesh et al. (2012) found that moderators affected the relationship between all constructs and improved the predictive power of the model. Like Blut et al. (2022), the systematic literature review conducted for this study found that only 25% of studies found a statistically significant moderating effect.

Please see Table 11 for a complete list of all studies that found a statistically significant moderation.

Table 2.11

Systematic Literature Review: Moderation

Focus	Studies
Gender	Akter et al., 2021; Dhingra & Gupta, 2020; Giovanis, Kavoura, et al., 2019; Goularte & Zilber, 2019; Khalilzadeh et al., 2017; Khan et al., 2022; Kwateng et al., 2019; J.-M. Lee, 2019; Merhi et al., 2021; Olasina, 2015; Purohit & Arora, 2021; Qu et al., 2022; Rabaai, 2021; Tai & Ku, 2013; Ur Rashid et al., 2021
Experience	Albashrawi et al., 2017; Albashrawi et al., 2019; Giovanis, Assimakopoulos, et al., 2019; Giovanis, Kavoura, et al., 2019; Goularte & Zilber, 2019; Khalilzadeh et al., 2017; Kim & Yoo, 2020; Kwateng et al., 2019; Olasina, 2015; Teo, Tan, Ooi, Hew, et al., 2015; Ur Rashid et al., 2021
Age	Giovanis et al., 2019b; Goularte & Zilber, 2019; Khalilzadeh et al., 2017; Kwateng et al., 2019; Merhi et al., 2021; Qu et al., 2022; Rabaai, 2021; Tai & Ku, 2013; Ur Rashid et al., 2021
Education	Dhingra & Gupta, 2020; Kwateng et al., 2019; Li et al., 2022; Qu et al., 2022; Slade et al., 2015; Ur Rashid et al., 2021
Personality	Baptista & Oliveira, 2015; Goularte & Zilber, 2019; Khan et al., 2017; Kim & Song, 2018; Soomro, 2019; Wang, 2005
Financial	Li et al., 2022; Qu et al., 2022

The most common moderators identified in this review were age, gender, and experience. Age and gender are relatively straight forward variables that simply reflect the user's age as a continuous variable and the user's gender as a binary variable. Experience, on the other hand, has been operationalized in different ways. Venkatesh et al. (2003, 2012) defined experience as the "opportunity to use a target technology" based on prior information systems research. The most common approach to operationalizing experience is measuring the time between present day and when an individual began using technology, but there may be other factors that affect an individual's opportunity to use technology beyond time (Blut et al., 2022). For example, Walsh and Lim (2020) found that individuals with more complicated financial situations had a greater opportunity to use PFM technology and therefore were more likely to accept and use PFM technology. Additional variables commonly used in personal financial research were considered as moderators such as employment, objective financial knowledge, subjective financial knowledge, confidence, and future orientation. The focus of this research was understanding adoption of PFM technology from an information systems perspective, so the variables included were based on prior research. Future researchers should consider integrating common concepts from personal finance research with information systems research to advance the understanding of FinTech. This previous literature supports the ninth hypothesis:

H9: Age, gender, and number of financial accounts will moderate the effect of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, trust, and perceived technology security on the acceptance and use of PFM technology such that the effect the effect will be weaker as age increases, stronger for males, and stronger for individuals with a higher number of financial accounts.

Beyond the moderating effect of age, gender, and number of financial accounts, previous research suggests these facts have a direct effect on acceptance and use of PFM technology. Younger individuals are more likely than older individuals to adopt PFM technology (Carlin et al., 2017; Walsh & Lim, 2020). Males are more likely than females to adopt PFM technology (Carlin et al., 2017; Walsh & Lim, 2020). As the number of financial accounts increases, more attention is drawn to their finances and they are more likely to adopt PFM technology (Phillips et al., 2013; Walsh & Lim, 2020). This previous literature supports the tenth, eleventh, and twelfth hypotheses:

H10: Age will have a negative relationship with acceptance and use of PFM technology such that as age increases, the likelihood of accepting and using PFM technology will decrease.

H11: Males will be more likely than females to accept and use PFM technology.

H12: Financial accounts will have a positive relationship with acceptance and use of PFM technology such that individuals with a higher number of financial accounts will be more likely to accept and use PFM technology.

Chapter 3 - Methods

The purpose of this study is to develop an understanding of the factors that explain and predict PFM technology adoption. The preceding discussion identified the theory and hypothesized relationships based on both previous information systems research and a systematic literature review of consumer FinTech. UTAUT2 (Venkatesh, 2012) was combined with the hypothesized relationships to form the conceptual framework. To test the hypotheses, measures were identified to best represent each construct of interest before collecting and cleaning primary data. Finally, the empirical model was developed to analyze the complex relationships between constructs. Please see Table 12 for a complete list of the hypothesized relationships tested in this study.

Table 3.1

Hypotheses

#	Hypothesis
H1	Performance expectancy will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology helps them manage their finances will be more likely to accept and use PFM technology.
H2	Effort expectancy will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that PFM technology is easy to use will be more likely to accept and use PFM technology.
H3	Social influence will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that others think they should use PFM technology will be more likely to accept and use PFM technology.
H4	Facilitating conditions will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM is supported by the technical and support resources available will be more likely to accept and use PFM technology.
H5	Hedonic motivation will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology is enjoyable will be more likely to accept and use PFM technology.

H6	Habit will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology is or would be part of their regular routine will be more likely to accept and use PFM technology.
H7	Trust will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of trust in the provider offering PFM technology will be more likely to accept and use PFM technology.
H8	Perceived technology security will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of certainty related to security will be more likely to accept and use PFM technology.
H9	Age, gender, and financial accounts will moderate the effect of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, trust, and perceived technology security on the acceptance and use of PFM technology such that the effect the effect will be weaker as age increases, stronger for males, and stronger for individuals with a higher number of financial accounts.
H10	Age will have a negative relationship with acceptance and use of PFM technology such that as age increases, the likelihood of accepting and using PFM technology will decrease.
H11	Gender will have a positive relationship with acceptance and use of PFM technology, such that males will be more likely than females to accept and use PFM technology.
H12	Financial accounts will have a positive relationship with acceptance and use of PFM technology such that individuals with a higher number of financial accounts will be more likely to accept and use PFM technology.

Conceptual Framework

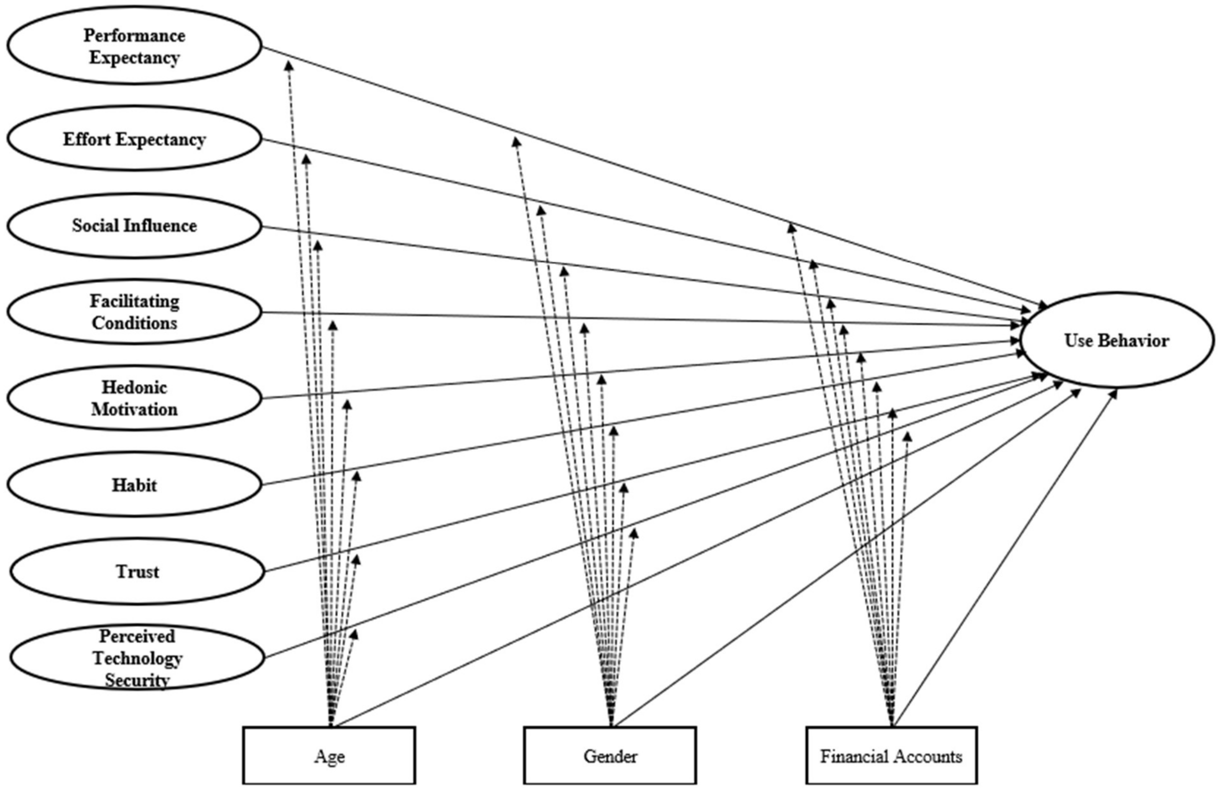
This study leverages an extended UTAUT2 (Venkatesh, 2012) model to identify independent variables that predict PFM technology adoption. UTAUT2 posits that intentions and behaviors can be predicted by an individual's performance expectancy, effort expectancy, social influence, and facilitating conditions, hedonic motivation, price value, and habit. Based on the preceding discussion on the influence of trust and perceived technology security, the base UTAUT2 model is extended to include those constructs as exogenous variables. Since most PFM technology is provided for free through a standalone application or integrated with financial institutions, the price value construct is removed from the model.

The framework in this study includes eight exogenous variables: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, trust, and perceived technology security. The framework will also include three moderating variables: age, gender, and financial accounts. UTAUT2 includes experience as a moderating variable, and it is the second most common moderator in the systematic literature review. As discussed, experience reflects an individual's ability to use technology. Rather than measuring the time an individual has used PFM technology, this study will consider an individual's financial complexity since PFM technology focuses on personal finances. An individual's financial complexity was measured as owning different accounts since owning different accounts affects an individual's opportunity to use specific PFM technology features. For example, someone who has no debt would not have an opportunity to monitor their credit or someone who has no investment accounts would not have an opportunity to track their investments.

Based on UTAUT2, these eight variables, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, trust, and perceived technology security, are hypothesized to influence PFM technology use. Contrary to UTAUT2, the model only includes actual usage as a dependent variable and not intention. Since the study was cross-sectional, no passage of time between surveys would support the inclusion of both intention and use. Actual usage was chosen instead of intention because research suggests it better represents adoption than intention (Wu & Du, 2012). The influence of these eight variables are hypothesized to be moderated by age, gender, and financial accounts. This will serve as the conceptual model of this study and a visual depiction of the model can be found in Figure 3.

Figure 3.1

Conceptual Framework



Measures

To test the hypothesized relationships between constructs, each construct must be operationalized and measured appropriately based on prior information systems research. Returning to Venkatesh et al.'s (2003) initial development of UTAUT and continuing through the systematic literature review described previously, the nine core constructs of the study were treated as latent constructs. Latent constructs are concepts that influence or explain a variable but cannot be measured directly. Common examples of latent constructs are attitudes, perceptions, and feelings. Each latent construct is measured or explained using indicators (Sosik et al., 2009). Therefore, the latent constructs of use behavior, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, trust, and perceived technology security are measured or explained by a series of indicators based on previous research. The moderating or control variables of age, gender, and financial accounts were directly measured.

Use Behavior

Use behavior is a latent construct that serves as the dependent variable in the empirical model. Use behavior is the frequency with which an individual uses PFM technology. This latent construct comprises five formative indicators that assess the use of different PFM features. The two types of indicators are: reflective indicators, which are influenced by the latent construct; and formative indicators, which influence the latent construct (Sosik et al., 2009). Here, the indicators form or influence the latent construct. The five features assessed were net worth tracking, budgeting, credit score monitoring, investment tracking, and goal planning. Each indicator is an ordinal variable ranging from 1 to 5, with 1 representing not currently using, 2 representing several times a year, 3 representing several times a month, 4 representing several times a week, and 5 representing several times a day. Participants were asked about their usage in a survey, and the responses were coded appropriately. In the analysis, each feature was assigned a weighting which, when combined with the participants' responses, formed the use behavior variable. Please see Table 13 for the details of each indicator.

The approach of measuring use by assessing the underlying features and treating these indicators as formative is adapted from Venkatesh et al. (2012). Prior to this study, self-reported use behavior was often represented as a single variable, such as asking about PFM technology adoption in general or analyzing each feature separately. This approach had both conceptual and methodological challenges (Sharma et al., 2009). From a conceptual perspective, a single measure may not accurately reflect the extent, breadth, and variety of using technology (Burton-

Jones & Straub, 2006; Igbaria et al., 1997; Saga & Zmud, 1994; Thong, 1990). Measuring PFM technology use as a latent construct formed by indicators representing each feature overcomes these challenges by incorporating the extent, breadth, and variety of PFM technology use (Venkatesh et al., 2012). From a methodological perspective, a single measure was associated with common method variance (CMV) in TAM and UTAUT based research (Malhotra et al., 2006; Sharma et al., 2009; Burton-Jones & Straub, 2006). Venkatesh et al. (2012) suggested measuring use behavior as a formative latent construct reduced this concern, and most of the studies in the systematic literature review used this approach.

Table 3.2

Measures: Use Behavior

Code	Variable	Variable Type	Scoring	Survey Question
PFM_NW	Net Worth Tracking Use	Ordinal (1-5)	Not currently using (1) Several times a year (2) Several times a month (3) Several times a week (4) Several times a day (5)	How often do you use websites or apps to help manage your finances such as tracking your net worth?
PFM_BUD	Budgeting Use	Ordinal (1-5)	Not currently using (1) Several times a year (2) Several times a month (3) Several times a week (4) Several times a day (5)	How often do you use websites or apps to help manage your finances such as budgeting?
PFM_CSM	Credit Score Monitoring Use	Ordinal (1-5)	Not currently using (1) Several times a year (2) Several times a month (3) Several times a week (4) Several times a day (5)	How often do you use websites or apps to help manage your finances such as monitoring your credit?
PFM_INV	Investment Tracking Use	Ordinal (1-5)	Not currently using (1) Several times a year (2) Several times a month (3) Several times a week (4) Several times a day (5)	How often do you use websites or apps to help manage your finances such as tracking your investments?
PFM_GOAL	Goal Planning Use	Ordinal (1-5)	Not currently using (1) Several times a year (2) Several times a month (3) Several times a week (4) Several times a day (5)	How often do you use websites or apps to help manage your finances such as planning for goals?

Performance Expectancy

Performance expectancy is a latent construct that serves as an independent variable in the empirical model. Performance expectancy is the degree to which an individual believes that using PFM technology will help them manage their finances. This latent construct comprises three reflective indicators since the indicators are influenced by the latent construct. The approach of measuring performance expectancy using these three indicators and treating them as reflective indicators is the standard in UTAUT research since Venkatesh et al. (2003). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the third indicator was reverse coded in the survey to improve data quality. Please see Table 14 for the details of each indicator.

Table 3.3

Measures: Performance Expectancy

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
PE1	Performance Expectancy 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I find it useful in my daily life.	I found it useful in my daily life.	I would find it useful in my daily life.
PE2	Performance Expectancy 2	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Using it helps me accomplish things more quickly.	Using it helped me accomplish things more quickly.	Using it would help me accomplish things more quickly.
PE3	Performance Expectancy 3	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Using it does not increase my productivity.	Using it did not increase my productivity.	Using it would not increase my productivity.

Effort Expectancy

Effort expectancy is a latent construct that serves as an independent variable in the empirical model. Effort expectancy is the degree to which an individual believes that using PFM technology will be easy to use. This latent construct comprises four reflective indicators since the indicators are influenced by the latent construct. The approach of measuring effort expectancy by these four indicators and treating them as reflective indicators is the standard in UTAUT research since Venkatesh et al. (2003). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the third indicator was reverse coded in the survey to improve data quality. Please see Table 15 for the details of each indicator.

Table 3.4

Measures: Effort Expectancy

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
EE1	Effort Expectancy 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Learning how to use it is easy for me.	Learning how to use it was easy for me.	Learning how to use it would be easy for me.
EE2	Effort Expectancy 2	Continuous	2 (Strongly Disagree) to 7 (Strongly Agree)	My interaction with it is clear and understandable.	My interaction with it was clear and understandable.	My interaction with it would be clear and understandable.
EE3	Effort Expectancy 3	Continuous	1 (Strongly Disagree) to 7	I do not find it easy to use.	I did not find it easy to use.	I would not find it easy to use.

			(Strongly Agree)			
EE4	Effort Expectancy 4	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	It is easy for me to become skillful at using it.	It was easy for me to become skillful at using it.	It would be easy for me to become skillful at using it.

Social Influence

Social influence is a latent construct that serves as an independent variable in the empirical model. Social influence is the degree to which an individual believes that others think they should use PFM technology. This latent construct comprises three reflective indicators since the indicators are influenced by the latent construct. The approach of measuring social influence by these three indicators and treating them as reflective indicators is the standard in UTAUT research since Venkatesh et al. (2003). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the second indicator was reverse coded in the survey to improve data quality. Please see Table 16 for the details of each indicator.

Table 3.5

Measures: Social Influence

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
SI1	Social Influence 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	People who are important to me think that I should use it.	People who are important to me thought that I should use it.	People who are important to me think that I should use it.

SI2	Social Influence 2	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	People who influence my behavior do not think that I should use it.	People who influenced my behavior did not think that I should use it.	People who influence my behavior do not think that I should use it.
SI3	Social Influence 3	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	People whose opinions that I value prefer that I use it.	People whose opinions that I valued preferred that I use it.	People whose opinions that I value prefer that I use it.

Facilitating Conditions

Facilitating conditions is a latent construct that serves as an independent variable in the empirical model. Facilitating conditions is the degree to which an individual believes that using PFM technology is supported by the technical and support resources available. This latent construct comprises four reflective indicators since the indicators are influenced by the latent construct. The approach of measuring facilitating conditions by these four indicators and treating them as reflective indicators is the standard in UTAUT research since Venkatesh et al. (2003). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the third indicator was reverse coded in the survey to improve data quality. Please see Table 17 for the details of each indicator.

Table 3.6

Measures: Facilitating Conditions

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
FC1	Facilitating Conditions 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I have the resources necessary to use it.	I had the resources necessary to use it.	I have the resources necessary to use it.
FC2	Facilitating Conditions 2	Continuous	2 (Strongly Disagree) to 7 (Strongly Agree)	I have the knowledge necessary to use it.	I had the knowledge necessary to use it.	I have the knowledge necessary to use it.
FC3	Facilitating Conditions 3	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	It is not compatible with other technologies I use.	It was not compatible with other technologies I used.	It is not compatible with other technologies I use.
FC4	Facilitating Conditions 4	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I can get help from others when I have difficulties using it.	I could get help from others when I had difficulties using it.	I can get help from others when I have difficulties using it.

Hedonic Motivation

Hedonic motivation is a latent construct that serves as an independent variable in the empirical model. Hedonic motivation is the degree to which an individual believes that using PFM technology is enjoyable or fun. This latent construct comprises three reflective indicators since the indicators are influenced by the latent construct. The approach of measuring hedonic motivation by these three indicators and treating them as reflective indicators is the standard in UTAUT2 research since Venkatesh et al. (2012). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the second indicator was reverse coded in the survey to improve data quality. Please see Table 18 for the details of each indicator.

Table 3.7

Measures: Hedonic Motivation

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
HM1	Hedonic Motivation 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Using it is fun.	Using it was fun.	Using it would be fun.
HM2	Hedonic Motivation 2	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Using it is not enjoyable.*	Using it was not enjoyable.*	Using it would not be enjoyable.*
HM3	Hedonic Motivation 3	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Using it is very entertaining.	Using it was very entertaining.	Using it would be very entertaining.

Habit

Habit is a latent construct that serves as an independent variable in the empirical model. Habit is the degree to which an individual believes that using PFM technology is or would be automatic. This latent construct comprises three reflective indicators since the indicators are influenced by the latent construct. The approach of measuring habit by these three indicators and treating them as reflective indicators is the standard in UTAUT2 research since Venkatesh et al. (2012). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the second indicator was reverse coded in the survey to improve data quality. Please see Table 19 for the details of each indicator.

Table 3.8

Measures: Habit

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
HT1	Habit 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	The use of it has become a habit for me.	The use of it became a habit for me.	The use of it would become a habit for me.
HT2	Habit 2	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I am not addicted to using it.	I was not addicted to using it.	I would not get addicted to using it.
HT3	Habit 3	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I must use it.	I felt that I must use it.	I would feel I must use it.

Trust

Trust is a latent construct that serves as an independent variable in the empirical model. Trust is the degree to which an individual believes that the provider for PFM technology is trustworthy. This latent construct comprises three reflective indicators since the indicators are influenced by the latent construct. The approach of measuring trust by these three indicators and treating them as reflective indicators is based on the work of Gefen et al. (2003). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the second indicator was reverse coded in the survey to improve data quality. Please see Table 20 for the details of each indicator.

Table 3.9

Measures: Trust

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
TR1	Trust 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I trust in it.	I trusted in it.	I would trust in it.
TR2	Trust 2	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I do not believe that it is trustworthy.	I did not believe that it was trustworthy.	I do not believe that it is trustworthy.
TR3	Trust 3	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I trust that its providers are honest and keep their promises to users.	I trusted that its providers were honest and kept their promises to users.	I trust that its providers are honest and keep their promises to users.

Perceived Technology Security

Perceived technology security is a latent construct that serves as an independent variable in the empirical model. Perceived technology security is the degree to which an individual has certainty related to the security and safety of their sensitive information. This latent construct comprises four reflective indicators since the indicators are influenced by the latent construct. The approach of measuring perceived technology security by these four indicators and treating them as reflective indicators is based on the work of Salisbury et al. (2001). Each indicator is a continuous variable ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. Participants were asked about their attitudes toward PFM technology in a survey, and the responses were coded appropriately. It is important to note that the questions were phrased slightly differently to improve readability depending on if the participant was a current user, a former user, or never used PFM technology. As discussed in the survey section, the fourth indicator was reverse coded in the survey to improve data quality. Please see Table 21 for the details of each indicator.

Table 3.10

Measures: Perceived Technology Security

Code	Variable	Variable Type	Scoring	Survey Question (Current User)	Survey Question (Past User)	Survey Question (Non User)
PTS1	Perceived Technology Security 1	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I feel secure accessing sensitive information across it.	I felt secure accessing sensitive information across it.	I would feel secure accessing sensitive information across it.
PTS2	Perceived Technology Security 2	Continuous	2 (Strongly Disagree) to 7 (Strongly Agree)	It is a secure means through which to access information.	It was a secure means through which to access information.	It is a secure means through which to access information.
PTS3	Perceived Technology Security 3	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	I feel totally safe providing sensitive information about myself through it.	I felt totally safe providing sensitive information about myself through it.	I feel totally safe providing sensitive information about myself through it.
PTS4	Perceived Technology Security 4	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Overall it is not a safe place to access sensitive information.	Overall it was not a safe place to access sensitive information.	Overall it is not a safe place to access sensitive information.

Age, Gender, and Financial Accounts

Age, gender, and financial accounts represent moderating variables in the empirical model. Age is a continuous variable that reflects the participants response when asked about their age. Gender is a binary variable in which 1 represents a male and 0 represents a female or non-binary individual. Financial accounts is a continuous variable ranging from 0 to 9, where 0 represents no financial accounts and 9 represents nine financial accounts. In the survey, participants were asked whether they owned the following accounts: checking, savings, employer sponsored retirement plan, individual retirement account, brokerage account, credit card with a revolving balance, auto loan, student loan, and mortgage. Their responses were coded appropriately, so the financial accounts variable became an aggregate measure of their number of financial accounts. The survey questions for these variables were adapted from Lin et al. (2022), so the sample could be compared to the general population represented by the 2021 NFCS funded by FINRA. Please see Table 22 for the details of each moderator.

Table 3.11

Measures: Age, Gender, and Financial Accounts

Code	Variable	Variable Type	Scoring	Survey Question (Logic)
AGE	Age	Continuous	Number ranging from 18 to 100	What is your age?
GEN	Male	Binary	Women and Non-Binary (0), Male (1)	What is your gender?
NUM_Accounts	Number of Financial Accounts	Continuous	0 (No Accounts) to 9 (9 Accounts)	Sum of Yes(1) responses to Checking, Savings, Employer Retirement Plan, Individual Retirement Account, Brokerage Account, Credit Card (Revolving), Auto Loan, Student Loan, and Mortgage questions

Data Collection

To test the hypotheses, this study leveraged primary data collection using a survey specifically designed to collect the preceding measures. The following section describes the survey instrument, survey methodology, and quality control procedure applied before analyzing the data. The target population is US adults, so the survey was distributed online via CloudResearch targeting individuals at least 18 years old and living in the United States. After collecting responses, a strict quality control procedure was implemented to ensure high-quality responses were used in the analysis.

Survey Instrument

The survey instrument developed for this study comprised three sections: (1) demographics, (2) PFM use behavior, and (3) attitudes toward PFM technology. The demographics section included twelve questions related to age, gender, occupation, and ownership of different financial accounts. These twelve questions were adapted from Lin et al.

(2022) because the questions are widely used and allowed a quick comparison of the sample to the broader population across demographic characteristics.

The use behavior section included five questions to all respondents and a potential sixth question for respondents that currently use one of five PFM features that asked the respondent to specify how they use the technology. The first five questions were adapted from Venkatesh et al. (2012) and asked the respondent to select one of five options that best describes their usage of net worth tracking, budgeting, credit score monitoring, investment tracking, and goal planning features. The sixth question asked respondents that currently use any of those features to specify if they primarily use that feature through a third party app, third party website, their financial institution’s app, or their financial institution’s website.

The attitudes section included eight sections with 27 total questions across the core constructs of this study. The survey questions related to performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and use behavior were adapted from Venkatesh et al. (2012). Questions related to trust were adapted from Gefen et al. (2003). The survey questions related to perceived technology security were adapted from Salisbury et al. (2001). For each of the 27 questions, respondents were asked Likert scale questions ranging from 1 to 7, with 1 representing strongly disagree and 7 representing strongly agree. The questions were also worded differently depending on whether the respondent was a current user, past user, or never used PFM technology to improve readability. Last, an attention check question was included in the end which asked about their year of birth. This response was compared to the age the respondent provided in the beginning and used in the quality control procedure. For a complete list of all questions and phrasing, please see Appendix A.

Survey Methodology

The survey was built using online questionnaire technology and Qualtrics. Participants were recruited online through CloudResearch, which is a third party website that serves as an intermediary between social science researchers and individuals that complete surveys for a fee. CloudResearch offers researchers access to their own participant pool, similar to M-Turk, and also integrates with M-Turk through a screening procedure shown to improve response quality (Litman & Robinson, 2020).

Previous research suggests that data collected online is as reliable as data collected from traditional survey methods (Buhrmester et al., 2011; Paolacci et al., 2010). CloudResearch was selected to recruit participants rather than M-Turk because while M-Turk is more popular than CloudResearch, M-Turk participants have raised response quality concerns. Response quality concerns began with M-Turk in 2018 when numerous bots were discovered on the platform (Bai, 2018). In response, researchers relied on participants' approval ratings, but rejections are so rare on M-Turk that this approach did not address response quality concerns (Curran, 2016; Litman & Robinson, 2020). Beyond bots, researchers also discovered that the M-Turk population is relatively small and overused, which can lead to samples that do not properly reflect the researcher's target (Chandler et al., 2019; Litman et al., 2017). CloudResearch is also vulnerable to response quality issues, but research suggests their participants provided higher quality data, responded to reverse coded questions more consistently, and passed more attention checks compared to the M-Turk population (Hauser et al., 2022).

CloudResearch recruited 2,513 participants to complete the survey. This target was based on an a priori sample estimate using the number of constructs while considering a minor effect size, desired power of .8, and probability level of .05 (Kock & Hadaya, 2018). Based on those criteria and an empirical model that contains 27 observed variables and 8 latent variables, the recommended sample size is 1,889 and the minimum sample size is 151 (Soper, 2021; Westland, 2007).

Prior to distributing the survey, the number and types of questions were used to estimate a completion time of 5–7 minutes. An informal pilot was conducted and the median response time of the 28 responses was 5 minutes. The target compensation on CloudResearch is $8.50 per hour, so respondents were compensated $1 for survey completion. After collecting the responses, the average duration was 5 minutes and 11 seconds, so the actual hourly compensation was $11.58.

Quality Control

After collecting 2,513 responses, a quality control procedure was conducted that consisted of seven rejection criteria: bot detection, duplicate detection, fraud detection, duration analysis, attention check, straight lining, and survey misconduct. Bot detection, duplicate detection, and fraud detection were identified through the Qualtrics platform, and the remaining items were assessed independently. Bot detection uses Google's reCAPTCHA technology and determines a score between 0 and 1, where a score less than .5 shows the respondent is likely a bot. Duplicate and fraud detection analyze the respondent's metadata to identify likely duplicate and fraud responses. The duration analysis flagged responses that took less than two standard deviations lower than the median duration, which shows the respondent did not actually read the questions. The attention check compared the respondent's provided age with their calculated age based on the year of birth, and responses two or more years apart failed. Straight lining refers to the practice of a respondent mindlessly answering the same number for all questions, and this was detected by reverse coding one question per group. If a respondent input all 1's or all 7's it failed the straight line check. Survey misconduct identified respondents that did not really focus on the questions and was identified by having a standard deviation across all scale items less than .25 since it is extremely unlikely someone would feel that similar across 27 different questions.

After conducting the quality control procedure, the 2,513 responses were reduced to 1,932. A majority of the rejections were because of straight lining. Fraud, bot detection, and duplicates comprised most of the remaining rejections. A combination of various factors contributed to the remaining rejections. Pease see Table 23 for a detailed breakdown of the rejections by reason.

Table 3.12

Summary of Survey Quality Control

Decision	N	%
Approve	1,932	76.88%
Reject For Straight Lining	406	16.16%
Reject for Fraud	74	2.94%
Reject for Captcha	28	1.11%
Reject for Duplicate	20	0.80%
Reject for Survey Misconduct	14	0.56%
Reject for Attention	11	0.44%
Reject For Fraud & Straight Lining	9	0.36%
Reject for Captcha & Fraud	6	0.24%
Reject For Attention & Straight Lining	4	0.16%
Reject for Fraud & Attention	3	0.12%
Reject For Captcha & Straight Lining	2	0.08%
Reject for Duration	2	0.08%
Reject for Captcha & Duplicate	1	0.04%
Reject for Duration & Attention	1	0.04%
Total	2,513	100.00%

Empirical Model

To empirically test the hypotheses using the conceptual model, this study used PLS-SEM. PLS-SEM is a multivariate modeling technique that is a subset of structural equation modeling used to explain and predict complex relationships with both latent and observed variables. PLS-

SEM explains and predicts complex relationships through an iterative algorithm that maximizes the explained variance (Shmueli et al., 2019).

The two types of variables in PLS-SEM are latent constructs and indicators. Latent constructs are concepts that influence or explain but cannot be measured directly. Common examples of latent variables are attitudes, perceptions, and feelings. Observed variables, which can be measured, are associated with latent variables and are known as indicators. Observed variables are measured in various ways, but a common example is a survey response. PLS-SEM has two types of indicators: reflective indicators, which are influenced by the latent variable; and formative indicators, which influence the latent variable (Sosik et al., 2009). But not all indicators are considered equally; rather, the PLS-SEM algorithm automatically varies the weighting and loading based on the influence on the composite score of the latent construct. A weaker relationship between an indicator and a latent construct would have a lower weighting or loading, and a stronger relationship between the two would have a higher weighting (Chin et al., 2003).

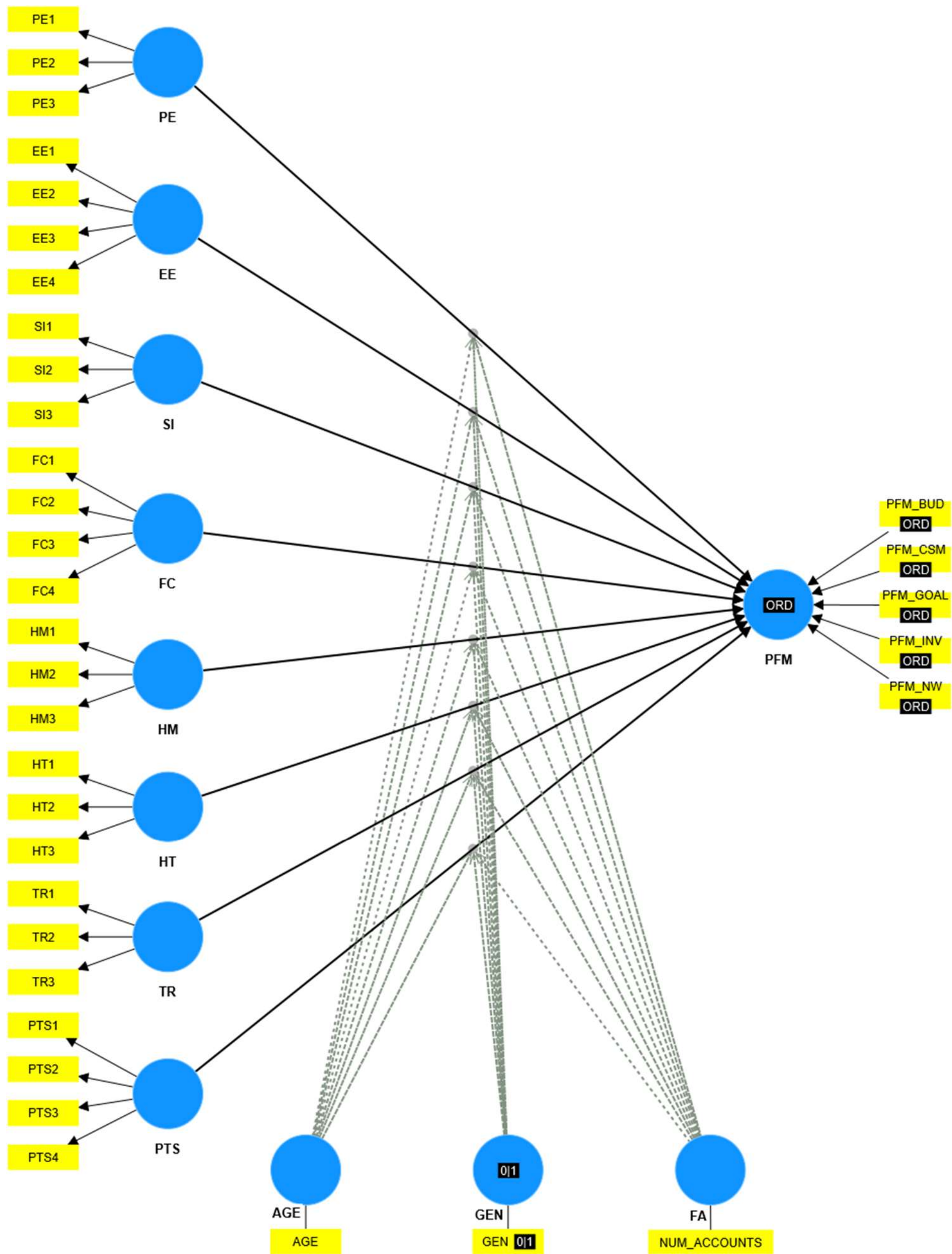
PLS-SEM is similar to ordinary least square (OLS) regression because it generates coefficients of predictor variables on dependent variables. But PLS-SEM also models structural paths or theoretical relationships among latent constructs and paths between latent constructs and indicators. A PLS-SEM model comprises two sub-models: a measurement model and a structural model. The measurement model is the relationship between latent constructs and observed indicators. The structural model is the relationship between the independent and dependent latent constructs. These sub-models might also be known as the outer and inner models (Sosik et al., 2009).

Hair et al. (2011) labeled PLS-SEM a silver bullet to analyze empirical models to estimate predictive relationships. Beyond the ability to explain and predict relationships, PLS-SEM can also be used with relatively small sample sizes (Kock & Hadaya, 2018). PLS-SEM also provides flexibility to researchers when modeling relationships, even if the model is complex and contains both formatively and reflectively measured constructs (Sosik et al., 2009). Based on these advantages, and the less restrictive assumption compared to other advanced modeling techniques, PLS-SEM has quickly become a common statistical analysis method (Hair et al., 2011). PLS-SEM is being used in this study because the conceptual model is complex, the model includes formatively and reflectively measured constructs, previous research suggests that multiple interactions will occur among variables, and the purpose of the study is to both explain and predict PFM technology use and acceptance of (Liang et al., 2007).

Previous information systems research supports this decision. PLS-SEM is widely used through social sciences and information systems research because many key concepts are not directly observable and are inherently latent (Westland, 2007). Information systems research often models complex relationships based on previous theories, which is why PLS-SEM has become one of the more popular statistical approaches in the field (Benitez et al., 2020). Finally, Williams et al. (2011) conducted a literature review on studies that used UTAUT and UTAUT2 and found that SEM and PLS were the two most common approaches. This approach includes Venkatesh et al. (2003, 2012) in the development of UTAUT and UTAUT2. Please see Figure 4 for a visual representation of the empirical model.

Figure 3.2

Empirical Model Using PLS-SEM



Chapter 4 - Results

To empirically test the hypotheses, this study followed the guidelines established by Hair et al. (2019) and started with data cleaning before conducting univariate, bivariate, and multivariate analyses. SPSS 29 was used to conduct the data cleaning, univariate, and bivariate tests. SmartPLS 4.0 was used to conduct the PLS-SEM analysis that included a path analysis, factor analysis, bootstrapping procedure, blindfolding procedure, and IPMA. The following sections detail the procedures used to clean and analyze the data to test the hypotheses.

Data Cleaning

The data cleaning procedure addressed seven areas: missing values, outliers, normality, linearity, homoscedasticity, multicollinearity, and common method bias. The first six areas were based on Tabachnick et al.'s (2007) recommendations and common method bias was added since it occasionally becomes an issue in cross-sectional studies (Juneman, 2013). In the data collection process, participants were required to answer all questions so there was no missing data to address in the data cleaning procedure.

Outliers

Continuous variables in the empirical model were analyzed to identify outliers. Two types of outliers can occur with continuous variables: univariate and multivariate. Univariate outliers occur when there is an extreme value for a single variable, whereas multivariate outliers occur when there is an extremely uncommon combination of responses across different variables that would nearly be statistically impossible. To identify univariate outliers, standardized scores (Z-scores) for the mean values of all latent constructs were compared against a limit of ± 3.29 (Tabachnick et al., 2007). To identify multivariate outliers, the Mahalanobis Distance method was used to estimate the probability of an occurrence based on the Chi-Square distribution.

Responses that had a probability less than .001 were identified as outliers (Tabachnick et al., 2007). Overall, 64 outliers were identified and deleted using these tests, which left 1,868 responses in the sample. Pease see Table 24 for a breakdown of outliers identified by type.

Table 4.1

Summary of Outlier Tests

	N	%
Univariate Outliers	20	1%
Multivariate Outliers	24	1%
Univariate & Multivariate Outliers	20	1%
Total Outliers	64	3%
Remaining Sample	1,868	97%

Normality

The distribution of continuous variables in the empirical model were also assessed for normality. Despite the ability of PLS-SEM to handle non-normal data, research suggests that it can affect the results, so it is best practice to assess normality and transform the data as appropriate (Hair et al., 2010). Normality was assessed by analyzing the skewness and kurtosis of the mean values of all constructs in the empirical model. Please see Table 25 for a breakdown of each construct's skewness and kurtosis. Whether the conservative threshold of ±1 is applied as Hair et al. (2017) suggest or the liberal threshold of ±2 suggested by Garson (2012), the data in this sample are normal.

Table 4.2

Summary of Normality Tests

Variable	Skewness		Kurtosis	
	Statistic	Std. Error	Statistic	Std. Error
Performance Expectancy	-0.449	0.057	0.090	0.113
Effort Expectancy	-0.724	0.057	0.072	0.113
Social Influence	0.336	0.057	-0.273	0.113
Facilitating Conditions	-0.436	0.057	-0.408	0.113
Hedonic Motivation	-0.130	0.057	-0.149	0.113
Habit	0.231	0.057	-0.537	0.113
Trust	-0.611	0.057	0.141	0.113
Perceived Technology Security	-0.462	0.057	-0.096	0.113
PFM Use	0.540	0.057	-0.455	0.113
Age	0.507	0.057	-0.478	0.113
Number of Financial Accounts	-0.090	0.057	-0.482	0.113

Linearity

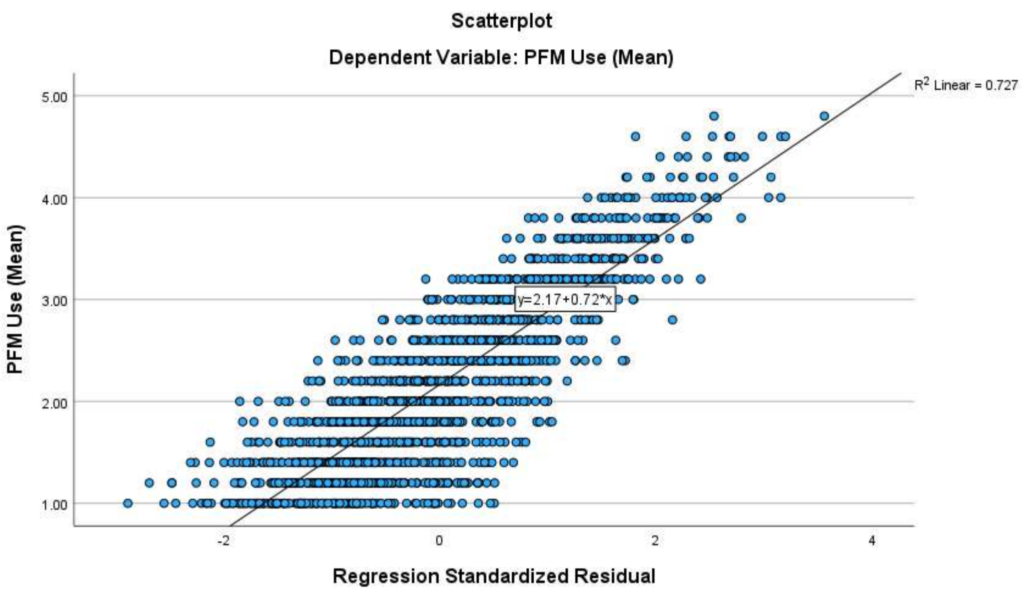
Linearity describes the consistency of the slope of change between independent and dependent variables in a model. Linearity was tested using two methods for the constructs included in the empirical model, an ANOVA test and OLS regression. In the ANOVA tests, the significance values for each construct were greater than .05 showing linearity. In the OLS tests, the significance values for each construct were less than .05 showing linearity. Linearity was validated using both tests, as suggested by Awang et al. (2018).

Homoscedasticity

Homoscedasticity occurs when a variable's residuals indicate consistent variance throughout various values for the variable and should be validated before performing multivariate analyses (Awang et al., 2018). Homoscedasticity was validated using a scatterplot analysis where the dependent variable was the mean of PFM use and the independent variables were the means of the latent constructs in the empirical model. Please see Figure 5 for the scatterplot results. A funnel shape is not observed in the scatterplot and the distances of residuals fit relatively close to the fit line, which validates the assumption of homoscedasticity (Salkind, 2010).

Figure 4.1

Homoscedasticity Test Using Scatterplot



Multicollinearity

The exogenous constructs in the empirical model were tested for multicollinearity by analyzing the tolerance and variance inflation factor (VIF) of the mean values of each construct. Multicollinearity occurs when the variance of an exogenous construct overlaps with another and its presence affects the ability to properly conduct a multivariate analysis (Awang et al., 2018). Please see Table 26 for the tolerance and VIF values for the exogenous constructs included in the empirical model. All VIF values are well below the threshold of 10 suggested by Field (2013), which indicates no multicollinearity issue for the data.

Table 4.3

Summary of Multicollinearity Test

Variable	Tolerance	VIF
Performance Expectancy	0.571	1.753
Effort Expectancy	0.522	1.914
Social Influence	0.725	1.379
Facilitating Conditions	0.532	1.879
Hedonic Motivation	0.666	1.502
Habit	0.748	1.337
Trust	0.381	2.621
Perceived Technology Security	0.402	2.488
Age	0.953	1.049
Number of Financial Accounts	0.957	1.045
Gender	0.975	1.026

Common Method Bias

The last test in the data cleaning procedure was the Harman's single factor test to assess common method bias. This test is suggested for cross-sectional studies such as this study (Juneman, 2013). When common method bias is present, it can affect the validity and reliability of variables in the model (Podsakoff et al., 2012). The Harman's single factor test was conducted using a principal component analysis, where it identified the percentage of variance explained by the first factor. Please see Table 27 for results of the Harman's single factor test. The 32.15% of the variance explained by the first factor is less than the threshold of .5 suggested by Podsakoff et al. (2012), which indicates that common method bias is not present.

Table 4.4

Summary of Common Method Bias Test

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.86	32.15	32.15	3.86	32.15	32.15
2	1.67	13.92	46.07			
3	1.08	8.96	55.03			
4	1.00	8.34	63.36			
5	0.90	7.49	70.86			
6	0.74	6.14	77.00			
7	0.69	5.77	82.76			
8	0.56	4.65	87.41			
9	0.50	4.15	91.56			
10	0.43	3.59	95.15			
11	0.34	2.86	98.01			
12	0.24	1.99	100.00			

Sample Descriptives and Bivariate Tests

After conducting the data cleaning procedure, SPSS was used to develop the sample descriptive statistics and conduct a bivariate analysis using Pearson correlation. The sample descriptive statistics were used to understand the demographics of the sample, how the sample feels about PFM technology, how the sample uses PFM technology, how the sample compares to a broader population, and the relationships between the constructs included in the empirical model.

Sample Demographics and Financial Accounts

Descriptive statistics for the sample demographics are provided in Table 28. From an age perspective, the sample was heavily weighted between ages 25–54, with 29% between ages 25–34, 29% between ages 35–44, and 19% between ages 45–54. The sample did not heavily represent the lower or higher ends of the spectrum, with only 7% between ages 18–24 and 5%

over age 65. Women were better represented in the sample at 55% whereas men represented 44% and non-binary individuals represented 1% of the sample. The occupation with the highest representation in the sample was full-time employees at 52%, followed by self-employed individuals at 15% and part-time employees at 9%. The remaining occupations of homemaker, student, disabled, unemployed, and retired only represented 23% of the sample.

Table 4.5

Sample Demographics

	N	%
Age Category		
Ages 18–24	125	7%
Ages 25–34	538	29%
Ages 35–44	550	29%
Ages 45–54	346	19%
Ages 55–64	208	11%
Ages 65+	101	5%
Gender		
Male	819	44%
Female	1,025	55%
Non-Binary	24	1%
Occupation		
Self-Employed	283	15%
Full-Time Employee	977	52%
Part-Time Employee	168	9%
Homemaker	102	5%
Student	75	4%
Disabled	29	2%
Unemployed	122	7%
Retired	101	5%
Unknown	11	1%

Descriptive statistics for the sample financial accounts are provided in Table 29. From a financial account perspective, nearly each participant in the sample owned a checking account (99%) and a majority owned a savings account (84%). Employer sponsored retirement accounts were the most common investment vehicle (53%), but 32% invested in an individual retirement account and 51% invested in a brokerage account. The most common form of debt was a credit card with a revolving balance, with 70% of the sample indicating they carried a balance on their credit card from month to month. The three remaining types of debt were identified by roughly one-third of the sample, with 31% having an auto loan, 30% having a student loan, and 37% having a mortgage.

Table 4.6

Sample Financial Accounts

	N	%
Checking Account		
Yes	1,841	99%
No	12	1%
Unknown	15	1%
Savings Account		
Yes	1,560	84%
No	288	15%
Unknown	20	1%
Employer Sponsored Retirement Account		
Yes	993	53%
No	848	45%
Unknown	27	1%
Individual Retirement Account		
Yes	604	32%
No	1,218	65%
Unknown	46	2%
Brokerage Account		
Yes	956	51%
No	872	47%
Unknown	40	2%
Credit Card (w/ Revolving Balance)		
Yes	1,305	70%
No	550	29%
Unknown	13	1%
Auto Loan		
Yes	579	31%

No	1,275	68%
Unknown	14	1%
Student Loan		
Yes	562	30%
No	1,293	69%
Unknown	13	1%
Mortgage		
Yes	688	37%
No	1,157	62%
Unknown	23	1%

Sample Attitudes Toward PFM Technology

Descriptive statistics for the sample attitudes toward PFM technology are provided in Table 30. The attitudes toward PFM technology are represented by the survey questions related to performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, trust, and perceived technology security. Effort expectancy had the highest mean score at 5.78 followed closely by facilitating conditions at 5.70, which indicates the sample has positive feelings toward the ease of use and support they currently or would receive while using PFM technology. Habit had the lowest score at 3.36 and Habit 2 was particularly low at 2.39, which was the question related to being addicted to using PFM technology.

Table 4.7

Sample Attitudes Toward PFM Technology

	Min	Max	Mean	Std. Dev
Performance Expectancy (Mean)	1.00	7.00	4.89	1.26
Performance Expectancy 1	1.00	7.00	5.11	1.40
Performance Expectancy 2	1.00	7.00	4.93	1.45
Performance Expectancy 3	1.00	7.00	4.62	1.66
Effort Expectancy (Mean)	2.50	7.00	5.78	0.99
Effort Expectancy 1	2.00	7.00	5.78	1.10
Effort Expectancy 2	1.00	7.00	5.74	1.10
Effort Expectancy 3	1.00	7.00	5.94	1.26

Effort Expectancy 4	1.00	7.00	5.66	1.11
Social Influence (Mean)	1.67	7.00	4.75	1.04
Social Influence 1	1.00	7.00	4.34	1.38
Social Influence 2	1.00	7.00	5.64	1.43
Social Influence 3	1.00	7.00	4.28	1.37
Facilitating Conditions (Mean)	2.75	7.00	5.70	0.89
Facilitating Conditions 1	1.00	7.00	5.98	1.07
Facilitating Conditions 2	1.00	7.00	5.99	1.04
Facilitating Conditions 3	1.00	7.00	5.89	1.35
Facilitating Conditions 4	1.00	7.00	4.93	1.53
Hedonic Motivation (Mean)	1.00	7.00	4.17	1.29
Hedonic Motivation 1	1.00	7.00	3.97	1.48
Hedonic Motivation 2	1.00	7.00	4.85	1.61
Hedonic Motivation 3	1.00	7.00	3.69	1.55
Habit (Mean)	1.00	7.00	3.36	1.40
Habit 1	1.00	7.00	4.30	1.81
Habit 2	1.00	7.00	2.39	1.67
Habit 3	1.00	7.00	3.39	1.77
Trust (Mean)	1.67	7.00	5.51	1.05
Trust 1	1.00	7.00	5.44	1.15
Trust 2	1.00	7.00	5.79	1.24
Trust 3	1.00	7.00	5.32	1.20
Perceived Technology Security (Mean)	1.25	7.00	5.29	1.13
Perceived Technology Security 1	1.00	7.00	5.27	1.27
Perceived Technology Security 2	1.00	7.00	5.37	1.17
Perceived Technology Security 3	1.00	7.00	4.99	1.39
Perceived Technology Security 4	1.00	7.00	5.54	1.35

Sample PFM Technology Use

Descriptive statistics for the PFM technology use sample are provided in Table 31. An overwhelming majority of the sample uses PFM technology with only 8% indicating that they do not currently use PFM technology. Most users use PFM technology several times a month (30%) or several times a week (31%). Use was simplified further to better understand different users by categorizing non-users as individuals who do not currently use PFM technology, regular users as individuals who use PFM technology several times a year or month, and power users as individuals who use PFM technology several times a week or day. The sample is split evenly between regular users at 48% and power users at 44%.

Table 4.8

Sample PFM Technology Use

	Overall PFM Use	
	N	%
PFM Use		
Not Currently Using	149	8%
Several Times a Year	337	18%
Several Times a Month	555	30%
Several Times a Week	582	31%
Several Times a Day	245	13%
PFM User Type		
Non-User	149	8%
Regular User	892	48%
Power User	827	44%

Descriptive statistics for different PFM technology feature use among the sample are provided in Table 32. When participants responded to the survey, they showed their use by specific feature. The most common PFM feature was credit score monitoring with 70% regular users and 10% power users. The most heavily adopted features were budgeting and investment tracking, with each having 23% of the sample classified as power users. The least popular feature was net worth tracking, with 55% of the sample classified as non-users followed closely by goal planning, with 48% of the sample non-users. Budgeting was interesting because it had a relatively large number of non-users but was also tied for the largest number of power users, which indicates that once a user accepts the feature, they use it frequently.

Table 4.9

Sample PFM Technology Use by Feature

	NW	BUD	CSM	INV	GOAL
PFM Use					
Not Currently Using	55%	46%	20%	37%	48%
Several Times a Year	16%	10%	39%	18%	20%
Several Times a Month	16%	21%	30%	21%	19%
Several Times a Week	10%	19%	9%	16%	9%
Several Times a Day	3%	4%	1%	7%	3%
PFM User Type					
Non User	55%	46%	20%	37%	48%
Regular User	32%	30%	70%	40%	39%
Power User	14%	23%	10%	23%	12%

Descriptive statistics for the sample use of PFM technology through different mediums and providers are provided in Table 33. Participants were also asked to identify the medium they used for PFM technology, app or website, along with provider, third party, or financial institution. Numerous participants used a combination of mediums and providers. For the medium, there was no substantial difference in user type between app and website. For providers, using PFM technology through their financial institution was more common than through a third party with a higher percentage of non-users, regular users, and powers users.

Table 4.10

Sample PFM Technology User Types

	Overall	App	Website	3rd Party	Institution
Non User	8%	28%	25%	31%	21%
Regular User	48%	34%	40%	34%	39%
Power User	44%	38%	36%	35%	40%

Comparison of Sample to Broader Population

The survey questions for sample demographics and financial accounts were adapted from the work of Lin et al. (2022), so the sample could be compared to the general population represented by the 2021 NFCS funded by FINRA. Please see Table 34 for a detailed comparison of the sample and 2021 NFCS. Overall, this study's sample is much younger, with only 16% over age 55 compared to 38% of the NFCS over 55. This study's sample is more heavily weighted between ages 25–44, which represents 58% of the sample compared to 33% of the NFCS. The gender distribution between is slightly different with males being underrepresented in the sample compared to the broader population. Consistent with the younger sample, this study only includes 5% retired individuals compared to 21% in the NFCS. The study sample also has higher rates of owning financial accounts across checking (99% vs. 91%), savings (84% vs. 72%), brokerage account (51% vs. 35%), credit card with a revolving balance (70% vs. 30%), and student loans (30% vs. 17%). The biggest difference between the study sample and the NFCS is related to PFM use. Only 8% of the sample were non-users compared to 58% in the NFCS.

Table 4.11

Sample Descriptives Compared to 2021 NFCS

	Sample		2021 NFCS *(Weighted)*	
	N	%	N	%
Age Category				
Ages 18–24	125	7%	3,386	12%
Ages 25–34	538	29%	4,682	17%
Ages 35–44	550	29%	4,322	16%
Ages 45–54	346	19%	4,472	16%
Ages 55–64	208	11%	4,861	18%
Ages 65+	101	5%	5,395	20%
Gender				

Male	819	44%	13,201	49%
Female	1,025	55%	13,917	51%
Non-Binary	24	1%	-	-
Occupation				
Self-Employed	283	15%	2,160	8%
Full-Time Employee	977	52%	10,091	37%
Part-Time Employee	168	9%	2,449	9%
Homemaker	102	5%	1,759	6%
Student	75	4%	888	3%
Disabled	29	2%	1,574	6%
Unemployed	122	7%	2,378	9%
Retired	101	5%	5,819	21%
Unknown	11	1%	0	0%
Checking Account				
Yes	1,841	99%	24,584	91%
No	12	1%	1,860	7%
Unknown	15	1%	674	2%
Savings Account				
Yes	1,560	84%	19,639	72%
No	288	15%	6,708	25%
Unknown	20	1%	771	3%
Employer Sponsored Retirement Account				
Yes	993	53%	13,626	50%
No	848	45%	11,582	43%
Unknown	27	1%	1,910	7%
Individual Retirement Account				
Yes	604	32%	8,286	31%
No	1,218	65%	16,952	63%
Unknown	46	2%	1,880	7%
Brokerage Account				
Yes	956	51%	9,388	35%
No	872	47%	14,932	55%
Unknown	40	2%	2,798	10%
Credit Card (w/ Revolving Balance)				
Yes	1,305	70%	8,181	30%
No	550	29%	18,351	68%
Unknown	13	1%	586	2%
Auto Loan				
Yes	579	31%	7,819	29%
No	1,275	68%	18,718	69%
Unknown	14	1%	581	2%

Student Loan				
Yes	562	30%	4,529	17%
No	1,293	69%	22,589	83%
Unknown	13	1%	0	0%
Mortgage				
Yes	688	37%	7,926	29%
No	1,157	62%	19,016	70%
Unknown	23	1%	176	1%
PFM User Type				
Non-User	149	8%	15,841	58%
Regular User	892	48%	8,328	31%
Power User	827	44%	2,949	11%

Bivariate Relationship Between Latent Constructs

Pearson's correlation was used to assess the strength and direction of the relationship between the mean value of the latent constructs in the empirical model. A Pearson's correlation coefficient ranges from -1 to +1 with values closer to 0 indicating a small relationship between two variables and values closer to -1 or +1 indicating a large relationship between two variables (Cohen, 2008). Cohen (1988) suggested that a coefficient between ± .1 to ± .3 indicates a small relationship, ± .3 to ± .5 indicates a medium relationship, and ± .5 to ± 1 indicates a large relationship. Based on that criteria, performance expectancy, hedonic motivation, habit, and financial accounts have a medium relationship with PFM technology use. Effort expectancy, social influence, facilitating conditions, perceived technology security, age, and gender have a small relationship with PFM technology use. Facilitating conditions do not have a relationship with PFM technology use. Those values are all statistically significant at the .01 or .05 level. Please see Table 35 for the Pearson's correlation results.

Table 4.12

Pearson Correlation

	PE	EE	SI	FC	HM	HT	TR	PTS	AGE	GEN	FA	PFM
PE												
EE	.414**											
SI	.408**	.287**										
FC	.369**	.624**	.364**									
HM	.496**	.310**	.285**	.217**								
HT	.406**	.143**	.240**	.046*	.410**							
TR	.422**	.501**	.390**	.459**	.348**	.224**						
PTS	.382**	.490**	.370**	.464**	.318**	.162**	.755**					
AGE	-.080**	0.002	-.104**	.048*	-.070**	-0.018	.060**	0.023				
GEN	.056*	0.015	0.010	-0.032	.098**	0.043	-0.008	0.035	-.069**			
FA	.158**	.065**	.096**	.096**	.133**	.115**	.100**	.088**	.059*	.070**		
PFM	.428**	.132**	.201**	.097**	.375**	.412**	.156**	.162**	-.160**	.161**	.333**	

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Multivariate Analysis

SmartPLS 4.0 was used to conduct the PLS-SEM analysis to understand the factors that explain and predict PFM technology adoption (Ringle et al., 2022). The analysis followed the steps outlined by Hair et al. (2019), including an evaluation of the measurement model, an evaluation of the structural model, and an assessment of predictor relationships. Since the empirical model included both reflectively and formatively measured latent constructs, the measurement model comprised two parts. The reflective measurement model was evaluated based on construct reliability, construct validity, and discriminant validity. The formative measurement model was evaluated based on an outer model collinearity and outer weight significance test using bootstrapping. The structural model was evaluated based on inner model collinearity, coefficients of determination, predictive relevance, and the standardized root mean square residual. After validating the measurement and structural models, the predictors were assessed based on an inner weight significance test using bootstrapping and an IPMA (Hair et al., 2019).

Evaluation of the Reflective Measurement Model

Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, trust, and perceived technology security were assessed on construct reliability, construct validity, and discriminant validity. Construct reliability assessed the internal consistency of scale items for each latent construct by analyzing Cronbach's alpha and composite reliability. Construct validity assessed whether indicators measured the intended latent construct by analyzing factor loadings and average variance extracted. Discriminant validity assessed whether each latent construct measured unrelated concepts by analyzing the Fornell and Larcker test, the cross loadings, and the heterotrait monotrait ratio (HTMT; Hair et al., 2019).

Cronbach's alpha and composite reliability are both ways to evaluate the consistency among indicators associated with a latent construct. Both approaches are widely used in PLS-SEM research but have slight differences. Cronbach's alpha assumes that factor loadings among the indicators are the same, whereas composite reliability uses each indicator's actual loadings (Hair et al., 2019). Hair et al. (2019) suggest that the true measure of construct reliability lies somewhere between the conservative approach of Cronbach's alpha and the liberal approach of composite reliability. Both tests produce values for each latent construct ranging from 0 to 1, and the value of each construct is compared against the threshold for acceptance of .7 (Hair et al., 2019).

When the test was initially conducted, the Cronbach's alpha of social influence failed to meet the threshold, with a value of .61. Upon further evaluation, social influence 2 indicator was causing the issue since it only had a factor loading of .16, which is much lower than acceptable thresholds discussed later. Since reflective indicators are interchangeable, Hair et al. (2019) suggest removing indicators if their factor loading is below .4 and both the Cronbach's alpha and composite reliability do not exceed the .7 threshold. Social influence 2 was removed, and the tests were run again. Following the removal, all constructs had a Cronbach's alpha and composite reliability that exceeded the thresholds. Please see Table 36 for the Cronbach's alpha and composite reliability of the latent constructs.

Table 4.13

Evaluation of the Measurement Model: Construct Reliability

	Cronbach's alpha	Composite reliability (rho_a)
Performance Expectancy	0.791	0.830
Effort Expectancy	0.892	0.935
Social Influence	0.890	0.892
Facilitating Conditions	0.700	0.789
Hedonic Motivation	0.783	0.857
Habit	0.720	0.765
Trust	0.853	0.956
Perceived Technology Security	0.896	0.959

Factor loadings and average variance extracted (AVE) can evaluate the construct validity. Factor loadings are used to assess how well each indicator reflects the latent construct, while AVE assesses how much of the variance of the latent construct is explained by the indicators (Vinzi et al., 2010). A value of .7 or higher is preferred for factor loadings, but values between .4 and .7 are acceptable if the AVE of the construct is sufficient (Hulland, 1999). The threshold for AVE is .5 to suggest acceptable construct validity. Please see Table 37 for the factor loadings of each indicator. The factor loadings of all indicators exceeded the preferred threshold except for facilitating conditions 4 (.589), hedonic motivation 2 (.629), habit 2 (.685), and perceived technology security 4 (.694). All factor loadings were in the acceptable range, assuming AVE was sufficient. Please see Table 38 for the AVE for each latent construct. The AVE for each construct was well above the acceptable threshold, indicating the reflective measurement model has construct validity.

Table 4.14

Evaluation of the Measurement Model: Construct Validity (Factor Loading)

	PE	EE	SI	FC	HM	HT	TR	PTS
PE1	0.894							
PE2	0.887							
PE3	0.728							
EE1		0.913						
EE2		0.889						
EE3		0.739						
EE4		0.919						
SI1			0.947					
SI3			0.952					
FC1				0.861				
FC2				0.879				
FC3				0.490				
FC4				0.589				
HM1					0.937			
HM2					0.629			
HM3					0.918			
HT1						0.861		
HT2						0.685		
HT3						0.838		
TR1							0.944	
TR2							0.764	
TR3							0.911	
PTS1								0.937
PTS2								0.913
PTS3								0.925
PTS4								0.694

Table 4.15

Evaluation of the Measurement Model: Construct Validity (AVE)

	Average Variance Extracted (AVE)
Performance Expectancy	0.705
Effort Expectancy	0.754
Social Influence	0.901
Facilitating Conditions	0.526
Hedonic Motivation	0.706
Habit	0.638
Trust	0.768
Perceived Technology Security	0.762

Fornell and Larcker, cross loadings, and HTMT can evaluate the discriminant validity. Fornell and Larcker assesses whether indicators associated with a construct better explain that construct than other constructs by comparing the AVE of each construct to the squared correlations between that construct and all other constructs in the reflective model. If the AVE of each construct is greater than the squared correlations for other constructs, the model is assumed to have discriminant validity. Cross loadings assess the same concept differently by comparing the factor loadings of indicators for each latent construct with their loadings of other latent constructs. If the factor loadings of indicators associated with a latent construct are greater than the loadings for all other constructs, the model is assumed to have discriminant validity. HTMT is a newer method to assess discriminant validity by comparing the average heterotrait heteromethod correlations within and across constructs. If the ratio is below .9 the model is assumed to have discriminant validity (Henseler et al., 2015). Please see Table 39 for the Fornell and Larcker results, Table 40 for cross loadings, and Table 41 for HTMT. All three tests passed the thresholds described above and the reflective measurement model was deemed to have discriminant validity.

Table 4.16

Evaluation of the Measurement Model: Discriminant Validity (Fornell & Larcker)

	PE	EE	SI	FC	HM	HT	TR	PTS
PE	**0.840**							
EE	0.426	**0.868**						
SI	0.386	0.220	**0.949**					
FC	0.371	0.663	0.266	**0.725**				
HM	0.501	0.291	0.306	0.194	**0.840**			
HT	0.439	0.175	0.284	0.093	0.433	**0.799**		
TR	0.441	0.503	0.349	0.450	0.342	0.264	**0.877**	
PTS	0.391	0.488	0.333	0.459	0.315	0.198	0.756	**0.873**

Table 4.17

Evaluation of the Measurement Model: Discriminant Validity (Cross Loadings)

	PE	EE	SI	FC	HM	HT	TR	PTS
PE1	**0.894**	0.401	0.367	0.346	0.470	0.438	0.428	0.363
PE2	**0.887**	0.378	0.363	0.324	0.469	0.367	0.381	0.352
PE3	**0.728**	0.280	0.219	0.256	0.297	0.280	0.282	0.257
EE1	0.360	**0.913**	0.181	0.598	0.239	0.141	0.430	0.423
EE2	0.409	**0.889**	0.234	0.599	0.264	0.173	0.500	0.487
EE3	0.309	**0.739**	0.113	0.516	0.226	0.088	0.373	0.348
EE4	0.394	**0.919**	0.211	0.594	0.282	0.181	0.443	0.429
SI1	0.361	0.213	**0.947**	0.246	0.287	0.262	0.328	0.313
SI3	0.372	0.205	**0.952**	0.257	0.294	0.277	0.335	0.318
FC1	0.301	0.577	0.209	**0.861**	0.116	0.062	0.408	0.398
FC2	0.315	0.643	0.180	**0.879**	0.167	0.098	0.386	0.415
FC3	0.226	0.373	0.119	**0.490**	0.089	-0.017	0.332	0.302
FC4	0.244	0.271	0.269	**0.589**	0.181	0.068	0.221	0.225
HM1	0.469	0.259	0.299	0.165	**0.937**	0.436	0.308	0.287
HM2	0.400	0.296	0.167	0.233	**0.629**	0.209	0.318	0.284
HM3	0.409	0.214	0.284	0.128	**0.918**	0.404	0.264	0.247
HT1	0.475	0.271	0.229	0.200	0.400	**0.861**	0.317	0.246
HT2	0.183	-0.018	0.141	-0.100	0.289	**0.685**	0.053	0.015
HT3	0.335	0.099	0.295	0.049	0.335	**0.838**	0.205	0.161
TR1	0.434	0.480	0.352	0.420	0.340	0.284	**0.944**	0.711
TR2	0.318	0.403	0.194	0.358	0.223	0.118	**0.764**	0.572
TR3	0.391	0.441	0.333	0.408	0.312	0.247	**0.911**	0.695
PTS1	0.371	0.458	0.330	0.421	0.305	0.200	0.700	**0.937**
PTS2	0.355	0.459	0.289	0.448	0.255	0.185	0.700	**0.913**
PTS3	0.357	0.423	0.327	0.386	0.331	0.208	0.680	**0.925**
PTS4	0.277	0.382	0.172	0.381	0.163	0.044	0.566	**0.694**

Table 4.18

Evaluation of the Measurement Model: Discriminant Validity (HTMT)

	PE	EE	SI	FC	HM	HT	TR	PTS
PE								
EE	0.498							
SI	0.449	0.239						
FC	0.501	0.818	0.339					
HM	0.637	0.369	0.359	0.285				
HT	0.539	0.193	0.346	0.204	0.548			
TR	0.519	0.576	0.382	0.605	0.426	0.283		
PTS	0.458	0.550	0.358	0.600	0.377	0.216	0.864	

Evaluation of the Formative Measurement Model

PFM technology use was the only formatively measured construct in the model, so it followed different evaluation criteria. The evaluation of formatively measured constructs comprises an outer model collinearity and an outer weights significance test using bootstrapping (Hair et al., 2019). The outer model (also known as the measurement model) was tested for multicollinearity by analyzing the VIF of each indicator. Since formative indicators are not interchangeable, multicollinearity creates issues in the model through overlaps across indicators. The formative indicators were tested for weights and significance because unlike reflective indicators that have loadings, formative indicators have weights since they represent different aspects of the latent construct (Hair, Hult, Ringle, Sarstedt, Danks, et al., 2021). The outer weight and significance test was conducted using a bootstrapping procedure in SmartPLS 4. In a bootstrapping procedure, the sample is randomly divided into sub-samples before estimating relationships. That process repeats 10,000 times to generate standard errors, T statistics, and p values. Formative indicators are significant when the *p*-value is less than .05 (Davison & Hinkley, 1997; Efron & Tibshirani, 1993).

Please see Table 42 for the VIF values for the indicators included in the empirical model. All VIF values are well below the threshold of 10 suggested by Field (2013), which indicates no multicollinearity issue in the measurement model. Please see Table 43 for the outer weight and significance tests. Net worth tracking, budgeting, credit score monitoring, and investment tracking are all statistically significant. Goal planning is not statistically significant but remained in the model. Hair, Hult, Ringle, Sarstedt, Danks, et al. (2021) suggest that removing formative indicators should be an exception because it could bias the latent construct. Formative indicators should not be removed solely for statistical purposes rather should only be removed when there are conceptual justifications (Hair, Hult, Ringle, Sarstedt, Danks, et al., 2021). There is no conceptual justification, so the indicator was kept in the model.

Table 4.19

Evaluation of the Measurement Model: Outer Collinearity

	VIF
Performance Expectancy 1	2.011
Performance Expectancy 2	2.084
Performance Expectancy 3	1.396
Effort Expectancy 1	3.247
Effort Expectancy 2	2.661
Effort Expectancy 3	1.726
Effort Expectancy 4	3.117
Social Influence 1	2.806
Social Influence 3	2.806
Facilitating Conditions 1	2.060
Facilitating Conditions 2	1.919
Facilitating Conditions 3	1.221
Facilitating Conditions 4	1.124
Hedonic Motivation 1	3.321
Hedonic Motivation 2	1.230
Hedonic Motivation 3	3.162
Habit 1	1.497
Habit 2	1.290

Habit 3	1.576
Trust 1	2.884
Trust 2	1.683
Trust 3	2.677
Perceived Technology Security 1	4.362
Perceived Technology Security 2	3.662
Perceived Technology Security 3	3.283
Perceived Technology Security 4	1.576
PFM: Net Worth Tracking	1.384
PFM: Budgeting	1.835
PFM: Credit Score Monitoring	1.186
PFM: Investment Tracking	1.322
PFM: Goal Planning	1.831

Table 4.20

Evaluation of the Measurement Model: Outer Weights and Significance

	Mean	Std. Dev	T Statistic	P Value
PFM: Net Worth Tracking	0.098	0.037	2.707	0.007
PFM: Budgeting	0.338	0.038	8.994	<0.001
PFM: Credit Score Monitoring	0.205	0.032	6.334	<0.001
PFM: Investment Tracking	0.644	0.040	15.980	<0.001
PFM: Goal Planning	0.070	0.040	1.781	0.075

Evaluation of the Structural Model

The structural model was evaluated to understand its ability to explain and predict PFM technology use. The evaluation was based on inner model collinearity, coefficients of determination, predictive relevance, and the standardized root mean square residual. The inner model (also known as the structural model) was tested for multicollinearity by analyzing the VIF of each construct. Please see Table 44 for the VIF values for the indicators included in the empirical model. All VIF values are well below the liberal threshold of 10 suggested by Field (2013), but trust is slightly above the conservative threshold of 5 suggested by Hair et al. (2019).

Table 4.21

Evaluation of the Structural Model: Inner Collinearity

	VIF
Performance Expectancy	3.258
Effort Expectancy	3.601
Social Influence	2.341
Facilitating Conditions	3.566
Hedonic Motivation	2.739
Habit	2.525
Trust	5.130
Perceived Technology Security	4.432
Age	1.088
Gender	1.039
Financial Accounts	1.064

The coefficients of determination, predictive relevance, and standardized root mean square residual were analyzed to assess the model's explanatory power, predictive relevance, and fit. The coefficients of determination (R^2) represent the variance in the endogenous latent construct that is explained by the exogenous latent construct (Hair, Hult, Ringle, & Sarstedt, 2021). Chin (1998) suggested that R^2 values between .19 and .33 represent weak explanatory power, values between .33 and .67 represent moderate explanatory power, and values above .67 represent substantial explanatory power. The R^2 of this model is .414 and the adjusted R^2 is .403 indicating moderate explanatory power.

Since PLS-SEM can both explain and predict relationships, the predictive relevance was assessed by calculating Q^2. This test was run using SmartPLS 4 and using a blindfolding procedure that uses training and holdout groups to iteratively create and evaluate predictions from the model. In the blindfolding procedure, the sample was randomly split into 10 subsets. One subset was treated as the training group and the remaining nine subsets were estimated 10 times each. The output of this procedure is Q^2, which is a number ranging from 0 to 1 that indicates predictive relevance (Geisser, 1974; Ruiz et al., 2009; Stone, 1974). Cohen (1988) suggested that Q^2 values between .02 and .15 represent weak predictive relevance, values between .15 and .35 represent moderate predictive relevance, and values above .35 represent strong predictive relevance. The Q^2 of this model is .35 indicating moderate predictive relevance.

Model fit is an often-debated topic with PLS-SEM but Hu and Bentler (1998) suggest the best measure for approximate model fit is standardized root mean square residual (SRMR). SRMR is based on the square root of the sum of square differences between the model and empirical correlations (Byrne, 2013). SRMR ranges from 0 to 1 with 0 representing a perfectly fit model. Henseler et al. (2014) suggest that the threshold for model fit in PLS-SEM is between .06 and .08. The SRMR of this model is .058 indicating model fit. Please see Table 45 for the evaluation measures of the model.

Table 4.22

Evaluation of the Structural Model: R2, Q^2, and SRMR

	R^2	Adj. R^2	Q^2	SRMR
PFM	0.414	0.403	0.350	0.058

Assessing Predictor Relationships

The relationship and significance between the latent constructs in the model were assessed by calculating inner weights and significance using a bootstrapping procedure. The bootstrapping procedure for the inner model is the same as the procedure previously described for the outer. A latent construct is a significant predictor of another latent construct when the *p*-value is less than .05. Please see Table 46 for the path coefficients, standard deviations, T statistics, and *p*-value for all relationships in the model (Hair et al., 2019).

Seven relationships were statistically significant in the model. Performance expectancy, hedonic motivation, habit, gender, and financial accounts have a positive effect on PFM technology use. Age has a negative effect on PFM technology use and financial accounts has a positive moderating effect on the relationship between habit and PFM technology use.

A one-point increase in performance expectancy leads to a .24 increase in PFM technology use. A one-point increase in hedonic motivation leads to a .11 increase in PFM technology use. A one-point increase in habit leads to a .19 increase in PFM technology use. For every year older an individual is, it leads to a .10 decrease in PFM technology use. Compared to females, males have .31 higher PFM technology use. Each additional financial account an individual owns leads to a .33 increase in PFM technology use. Each additional financial account an individual owns increases the effect of a one-point increase in habit on PFM technology use by .06.

Table 4.23

Assessment of Predictor Relationships

	Coefficient	Std. Dev	T Statistic	*p* Value
PE -> PFM	0.244	0.030	8.219	<0.001
EE -> PFM	-0.036	0.033	1.083	0.279
SI -> PFM	-0.033	0.028	1.185	0.236
FC -> PFM	0.048	0.033	1.411	0.158
HM -> PFM	0.106	0.028	3.708	<0.001
HT -> PFM	0.192	0.029	6.667	<0.001
TR -> PFM	-0.068	0.040	1.713	0.087
PTS -> PFM	0.025	0.036	0.714	0.475
AGE -> PFM	-0.103	0.020	5.200	<0.001
GEN -> PFM	0.305	0.044	6.984	<0.001
FA -> PFM	0.330	0.021	15.558	<0.001
AGE x PE -> PFM	-0.002	0.022	0.079	0.937
AGE x EE -> PFM	0.030	0.025	1.127	0.260
AGE x SI -> PFM	0.017	0.021	0.826	0.409
AGE x FC -> PFM	-0.006	0.025	0.185	0.853

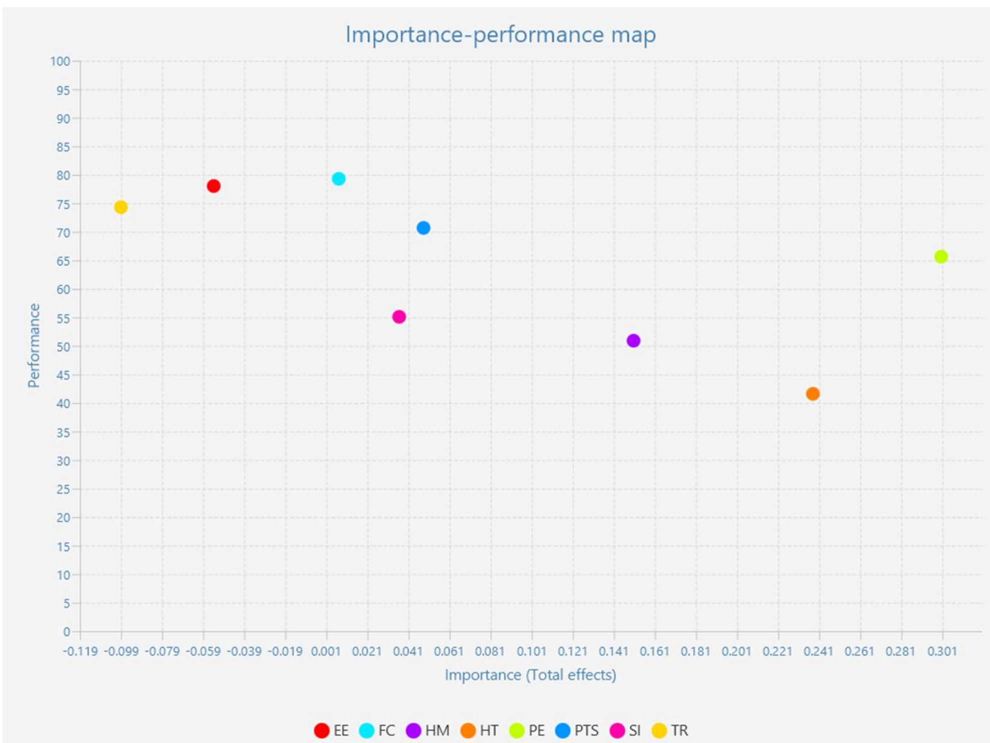
AGE x HM -> PFM	-0.035	0.023	1.544	0.123
AGE x HT -> PFM	-0.040	0.021	1.897	0.058
AGE x TR -> PFM	0.030	0.030	1.081	0.280
AGE x PTS -> PFM	-0.006	0.029	0.245	0.806
GEN x PE -> PFM	0.034	0.048	0.733	0.464
GEN x EE -> PFM	-0.008	0.054	0.095	0.925
GEN x SI -> PFM	0.050	0.043	1.183	0.237
GEN x FC -> PFM	-0.058	0.052	1.201	0.230
GEN x HM -> PFM	0.018	0.046	0.373	0.709
GEN x HT -> PFM	0.036	0.046	0.806	0.420
GEN x TR -> PFM	-0.030	0.062	0.489	0.625
GEN x PTS -> PFM	0.037	0.059	0.610	0.542
FA x PE -> PFM	0.028	0.023	1.261	0.207
FA x EE -> PFM	0.018	0.026	0.706	0.480
FA x SI -> PFM	-0.021	0.020	1.011	0.312
FA x FC -> PFM	-0.010	0.026	0.427	0.669
FA x HM -> PFM	0.010	0.021	0.466	0.641
FA x HT -> PFM	0.060	0.022	2.678	0.007
FA x TR -> PFM	-0.027	0.030	0.938	0.348
FA x PTS -> PFM	-0.010	0.027	0.380	0.704

Besides conducting the PLS path analysis described above, an IPMA was used to better understand the predictors of PFM technology use. An IPMA provides information on the relative performance of the exogenous latent constructs in the model, which allows researchers to draw conclusions on two dimensions, importance and performance (Hair et al., 2017). An IPMA is common for marketing and managerial analyses since it provides a practical perspective that identifies the most important areas to focus on. This analysis was conducted in SmartPLS 4, and the visual output is presented in Figure 6.

A common way to interpret the output is separating the graph into quadrants (Ringle & Sarstedt, 2016). The top left quadrant represents areas where PFM technology providers are overdoing it since the relative importance is low but the performance of the constructs is high. Trust, effort expectancy, facilitating conditions, perceived technology security, and social influence fall into this quadrant. The top right quadrant represents areas where PFM technology providers are doing a good job since the relative importance and performance are both high. Performance expectancy falls in this quadrant. The bottom right quadrant represents the opportunities for PFM technology providers to better serve consumers since the relative importance is high but the performance is low. Hedonic motivation and habit fall in this quadrant.

Figure 4.2

Importance Performance Map Analysis



Chapter 5 - Discussion

The purpose of this study was to develop an understanding of the factors that explain and predict adoption of PFM technology. This exploratory study focused on PFM technology because research suggests it shows promise of being a scalable and low-cost intervention that improves users' financial behavior (Kersten-van Dijk et al., 2017; Walsh & Lim, 2020). Despite the promise of PFM technology, little peer-reviewed research examines what influences the acceptance and use of these digital tools, and no studies have applied leading information systems research to evaluate other forms of consumer FinTech. This study based the research design and hypotheses on UTAUT2 and extended it based on the findings of a systematic literature review on consumer FinTech adoption. After collecting primary data designed to evaluate the key constructs of the model, a robust analysis was conducted to identify statistically significant constructs that explain and predict PFM technology use. The following sections will discuss key research findings, the findings' practical implications, the study's limitations, and future research opportunities to grow the body of knowledge on PFM technology.

Review of Research Findings

The preceding chapter discussed the results of the study from a technical perspective, but it is important to provide context and compare these results with prior research. The following sections will discuss key observations on PFM adoption, a summary of hypothesis testing, and a discussion on the results of each hypothesis.

Insights on PFM Adoption

A benefit of collecting the data required to conduct the analysis is insight into the current adoption of PFM technology among the sample. Broad surveys such as the NFCS collect responses on general PFM use, but this survey also gathered data on use by feature, channel, and provider. An overwhelming majority of the sample uses PFM technology with only 8% indicating that they do not currently use PFM technology. Most users use PFM technology several times a month (30%) or several times a week (31%). The high adoption among the sample is interesting, but how they use PFM technology is compelling.

Only 45% of the sample used net worth tracking and when someone used this feature, it was infrequent with 32% of the sample using it several times a month or year. The lack of interest in monitoring net worth is inconsistent with traditional economic theories, such as Life-Cycle Hypothesis (LCH) and Behavioral Life-Cycle Hypothesis (BLCH). LCH posits individuals will attempt to smooth consumption by borrowing during periods of low income, saving during periods of high income, and spending in retirement (Ando & Modigliani, 1963). BLCH built on LCH by introducing the concepts of self-control, mental accounting, and framing (Shefrin & Thaler, 1988). Based on LCH it is reasonable to assume that individuals would pay attention to their net worth as it would help them understand their life stage and progress toward consumption smoothing. Based on BLCH it is reasonable to assume that individuals would pay attention to their net worth as they view accounts differently and this would affect their decisions. The low adoption of net worth tracking indicates these theories may not fully explain how PFM users approach their finances.

Rather than approaching finances rationally, Olafsson and Pagel (2017) suggested that individuals approach their finances by paying attention when things they care about change. Their rationale is that even the act of checking on finances costs time and emotional energy, so individuals will only spend energy when it is worth it to them (Olafson & Pagel, 2017). The adoption of PFM technology by feature among the sample aligns more with this view rather than the views of LCH or BLCH prioritizing the importance of net worth.

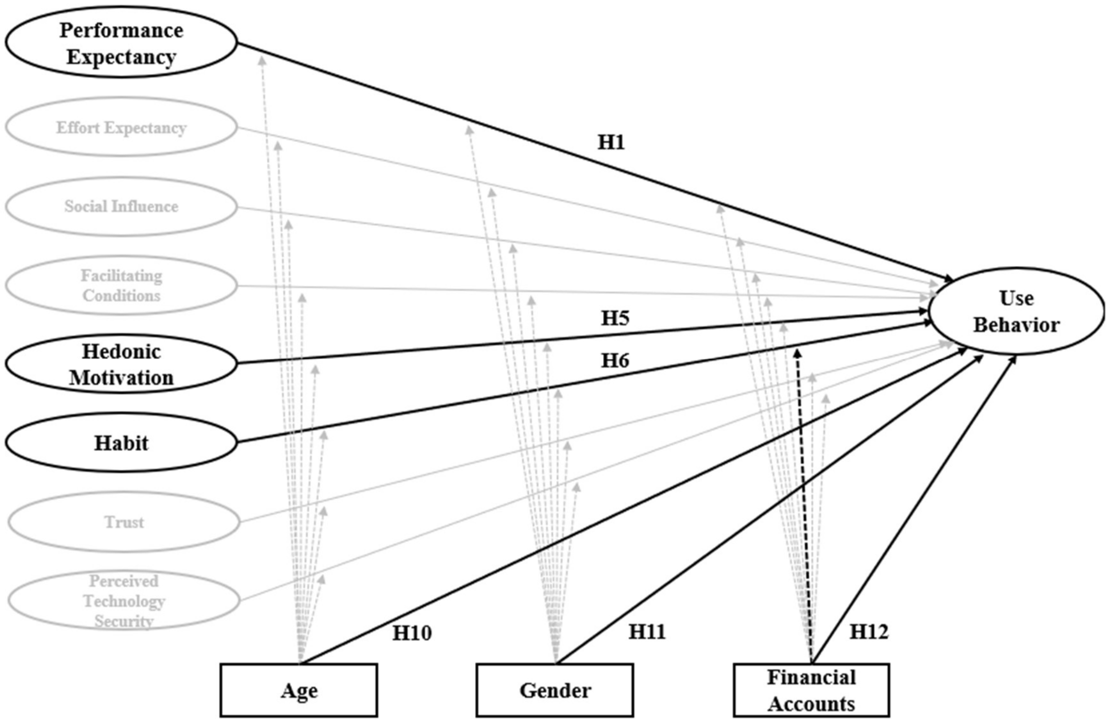
Net worth tracking and goal planning were the least accepted features, and usage was infrequent. Conversely, credit score monitoring was the most accepted feature, but usage also was infrequent. Budgeting and investment tracking were moderately accepted features and usage was frequent. These observations seem to align with the views of Olafsson and Pagel (2017) since the frequency of changes aligns with each feature's usage. Changes to net worth, goal progress, and credit scores take time, whereas changes to investment positions and budgets occur more frequently. Frequent usage of budgeting and investment tracking combined with infrequent usage of net worth tracking, credit score monitoring, and goal planning align with the idea that individuals pay attention to their finances when changes occur.

Summary of Hypotheses Testing

Based on a multivariate analysis using PLS-SEM, seven statistically significant relationships were in the conceptual framework. Please see Figure 7 for a visual representation of these relationships.

Figure 5.1

Hypothesis Testing Within Conceptual Framework



The estimated relationships were used to test the study's hypotheses. Six of the study's twelve hypotheses were supported by the multivariate analysis. Performance expectancy, hedonic motivation, and habit are constructs from UTAUT2 that positively affect PFM technology use. Age negatively affects PFM technology use, males are more likely to use PFM technology, and the number of financial accounts positively affects PFM technology use. Effort expectancy, social influence, facilitating conditions, trust, and perceived technology security do not affect PFM technology use. As moderators, age, gender, and financial accounts do not affect the relationship between predictors in this model and PFM technology use outside of the moderating effect of financial accounts on habit. The summary of hypothesis testing is presented in Table 47.

Table 5.1

Summary of Hypothesis Testing

Hypothesis	Relationship	Result
H1	Performance expectancy is positively related to PFM use	Supported
H2	Effort expectancy is positively related to PFM use	Not supported
H3	Social influence is positively related to PFM use	Not supported
H4	Facilitating Conditions is positively related to PFM use	Not supported
H5	Hedonic motivation is positively related to PFM use	Supported
H6	Habit is positively related to PFM use	Supported
H7	Trust is positively related to PFM use	Not supported
H8	Perceived technology security is positively related to PFM use	Not supported
H9	Age, gender, and financial accounts moderates PFM use	Not supported
H10	Age is negatively related to PFM use	Supported
H11	Gender is positively related to PFM use	Supported
H12	Financial accounts is positively related to PFM use	Supported

H1 Performance Expectancy

The hypothesis related to performance expectancy was:

H1: Performance expectancy will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology helps them manage their finances will be more likely to accept and use PFM technology.

Performance expectancy has a positive effect on the acceptance and use of PFM technology. This finding is consistent with Walsh and Lim's (2020) previous research on PFM adoption, which found a significant relationship between perceived usefulness and PFM adoption. It is also consistent with nearly 93% of studies in the systematic literature review that found a significant relationship between performance expectancy and the use of consumer FinTech when the variable was included in the analysis. The indicators associated with the performance expectancy latent construct with the highest loadings are PE1 and PE2. Within the survey, the statement for PE1 was "I find it useful in my daily life" and the statement for PE2 was "Using it helps me accomplish things quickly." Based on the significant positive relationship of the construct and high loadings, the effectiveness and efficiency improvement in managing personal finances provided by PFM technology has a strong influence on the technology's acceptance and use.

H2 Effort Expectancy

The hypothesis related to effort expectancy was:

H2: Effort expectancy will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that PFM technology is easy to use will be more likely to accept and use PFM technology.

This hypothesis was not supported since the relationship between effort expectancy and PFM technology use was not statistically significant. Despite effort expectancy being significant in 59% of the studies in the systematic literature that included the variable, the insignificant relationship is not entirely surprising. A review of prior information systems research suggests the relationship between effort expectancy and technology adoption is mixed, especially among younger users or those who have high experience using technology. The contributing factors of this study that explain the insignificant result are the age of the sample, experience of the sample, and design of the study.

Among the studies in the systematic literature that included effort expectancy but did not find evidence to suggest a significant relationship, most of them had a sample that was much younger than the general population (Al-Okaily et al., 2020; Baabdullah et al., 2019; Baptista & Oliveira, 2015; Bouteraa et al., 2022; Gan et al., 2021; H.-Y. Lin et al., 2019; J.-M. Lee, 2019; Kang, 2019; Moorthy et al., 2022; Rahadi et al., 2022; Thusi & Maduku, 2020). This is consistent with the current study, which has a much younger sample compared to the general population. Growing up as digital natives, it is reasonable to assume that effort expectancy may be less important to younger individuals, since using technology is more common and has been a part of their lives since their developmental years.

With 92% of the sample using PFM technology, they have much more experience using the technology compared to the general population. Venkatesh et al. (2003) suggested that effort expectancy becomes less important and eventually becomes insignificant as experience increases. As experience increases, the technology becomes more familiar and the baseline of effort expectancy increases. This is observed in the sample's mean score for effort expectancy of 5.78 on a scale of 1 to 7. Generally, a high effort expectancy score and significant experiences indicates someone has high information literacy, which makes effort expectancy less important.

The current study included all relevant UTAUT2 variables and use behavior as the dependent variable. Among studies in the systematic literature review with use behavior as the dependent variable rather than behavioral intention, only 31% found a significant relationship between effort expectancy and adoption when the variable was included in the model. Including all, rather than some, of the UTAUT2 variables also reduced the percentage finding a significant relationship from 59% to 56%. It is likely that the study design explains some of the reason for this hypothesis not being supported, but the age and experience of the sample explain most of the findings.

H3 Social Influence

The hypothesis related to social influence was:

H3: Social influence will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that others think they should use PFM technology will be more likely to accept and use PFM technology.

This hypothesis was not supported since the relationship between social influence and PFM technology use was not statistically significant. Despite social influence being significant in 66% of the studies in the systematic literature that included the variable, the insignificant relationship is not entirely surprising. A review of prior information systems research suggests the relationship between social influence and technology adoption is mixed, especially among those who have high experience using technology or when the technology is personal in nature. The contributing factors of this study that explain the insignificant result are the experience of the sample, type of technology, effect of COVID, and study design.

With 92% of the sample using PFM technology, they have much more experience using the technology compared to the general population. Venkatesh et al. (2003) suggested that social influence becomes less important and eventually becomes insignificant as experience increases. As experience increases, the technology becomes more familiar and what others think becomes less important.

Venkatesh et al. (2003) and Davis et al. (1989) suggested that the type of technology affects the importance of social influence. Using PFM technology is voluntary and a personal experience since it contains financial information that many individuals prefer to be confidential. Venkatesh et al. (2003) suggested that voluntary technology adoption was influenced less by social influence than mandatory technology adoption. Davis et al. (1989) suggested that technology that is used independently that is personal in nature is naturally going to be influenced less by social influence. The voluntary and personal nature of PFM technology supports the insignificant finding.

Another possibility for the contradiction between this study and prior research is the effect of COVID-19 (COVID). Hightower and Hagmann (1995) found that social influence is less important in remote settings compared to in-person settings. Sahut and Lissilour (2023) also found that social influence was not significant in the adoption of remote platforms following COVID lockdowns. Researchers cannot ignore broader societal influences on individuals, so it may be worth exploring the ongoing relationship between social influence and technology adoption as society readjusts to life after COVID.

The current study included all relevant UTAUT2 variables. Including all, rather than some, of the UTAUT2 variables reduced the percentage finding a significant relationship from 66% to 43%. It is likely that the study design explains some of the reason for this hypothesis not being supported, but the experience with PFM technology, personal nature of PFM technology, and impact of COVID explain most of the findings.

H4 Facilitating Conditions

The hypothesis related to facilitating conditions was:

H4: Facilitating conditions will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that they have the technical and support resources needed to use PFM technology will be more likely to accept and use PFM technology.

This hypothesis was not supported since the relationship between facilitating conditions and PFM technology was not statistically significant. Despite facilitating conditions being significant in 71% of the studies in the systematic literature that included the variable, the insignificant relationship is not entirely surprising. A review of prior information systems research suggests the relationship between facilitating conditions and technology adoption is mixed, especially among younger users or those who have high experience using technology. The contributing factors of this study that explain the insignificant result are the age of the sample, experience of the sample, and design of the study.

Among the studies in the systematic literature that included facilitating conditions but did not find evidence to suggest a significant relationship, most of them had a sample that was much younger than the general population (Al-Okaily et al., 2020; Baptista & Oliveira, 2015; Gan et al., 2021; H.-Y. Lin et al., 2019; J.-M. Lee, 2019; Khalilzadeh et al., 2017). This is consistent with the current study, which has a much younger sample compared to the general population. Growing up as digital natives, it is reasonable to assume that facilitating conditions may be less important to younger individuals since they feel confident they can either figure out how to use technology or know where to turn for help.

With 92% of the sample using PFM technology, they have much more experience using the technology compared to the general population. Venkatesh et al. (2003) suggested that facilitating conditions become less important and eventually become insignificant as experience increases. As experience increases, the technology becomes more familiar and the baseline of facilitating conditions increases. This is observed in the sample's mean score for facilitating conditions of 5.70 on a scale of 1 to 7.

The current study included all relevant UTAUT2 variables. Including all, rather than some, of the UTAUT2 variables reduced the percentage finding a significant relationship from 71% to 63%. It is likely that the study design explains some of the reason for this hypothesis not being supported, but the age and experience of the sample explain most of the findings.

H5 Hedonic Motivation

The hypothesis related to hedonic motivation was:

H5: Hedonic motivation will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology is enjoyable will be more likely to accept and use PFM technology.

Hedonic motivation has a positive effect on the acceptance and use of PFM technology. This finding is consistent with Tamilmani et al.'s (2019) meta-analysis but was contrary to only 23% of studies in the systematic literature review finding a significant relationship between hedonic motivation and consumer FinTech adoption. The indicators associated with the hedonic motivation latent construct with the highest loadings are HM1 and HM3. Within the survey, the statement for HM1 was "Using it is fun." and the statement for HM3 was "Using it is very entertaining." Based on the significant positive relationship of the construct and high loadings, the fun and enjoyment users experience is nearly as important as the measurable results they experience measured by performance expectancy.

H6 Habit

The hypothesis related to habit was:

H6: Habit will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of belief that using PFM technology is or would be part of their regular routine will be more likely to accept and use PFM technology.

Habit has a positive effect on the acceptance and use of PFM technology. This finding is consistent with Liang et al.'s (2007) and the systematic literature review on consumer FinTech adoption. The indicators associated with the habit latent construct with the highest loadings are

HT1 and HT3. Within the survey, the statement for HT1 was "The use of it has become a habit for me" and the statement for HT3 was "I must use it." Based on the significant positive relationship of the construct and high loadings, making PFM technology use a habit is influential on the level of adoption.

H7 Trust

The hypothesis related to trust was:

H7: Trust will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of trust in the provider offering PFM technology will be more likely to accept and use PFM technology.

This hypothesis was not supported since the relationship between trust and PFM technology use was not statistically significant. This was contrary to trust being significant in 96% of the studies in the systematic literature review when the variable was included in the analysis and Sarker et al.'s (2020) meta-analysis, which focused on e-commerce. A review of prior information systems research suggests the relationship between trust and technology adoption is complex, especially in the distinction between acceptance and use in the UTAUT framework. Within UTAUT, acceptance is whether an individual adopts the technology at all and use is how frequently an individual adopts the technology once they accept it (Venkatesh et al., 2012). Since 92% of the sample uses PFM technology, they have already accepted the technology and most of the distinction in this study is related to their use of PFM technology. It is also worth noting that the mean score for trust for the sample was 5.51 on a scale of 1 to 7. This was the third highest mean among the constructs, which may indicate that the sample was already satisfied by the trust related to PFM technology and therefore it did not have an incremental effect on the use of PFM technology.

That distinction is important, since trust is generally not considered to play a constant role over time. Historically, trust was posited to grow over time by starting low and gradually increasing. This view was challenged when Kramer (1994) was surprised by the level of trust by individuals early in their journey, which suggested that trust may need to reach a sufficient level to consider a behavior before being relatively consistent beyond that point. This led to an emphasis on studying initial trust as an antecedent to accepting new or innovative technology (Benbasat & Wang, 2005).

Initial trust occurs when an individual does not have any prior experience with a particular technology, so they rely on other sources and personal intuition (McKnight, 1998; 2002). Two major factors of initial trust are an individual’s disposition to trust and institution based trust. Disposition to trust is an individual’s natural tendency to depend on others, whereas institution based trust is an individual’s belief in the provider to act in an ethical manner (Shapiro, 1987; Zucker, 1986). Once initial trust is sufficient to accept technology, the underlying factors are sufficient to support continued use (McKnight, 2002). This supports the concept that initial trust is an antecedent to accepting new technology, but may not play a prominent role in the use beyond acceptance.

Since an overwhelming majority of the sample already uses PFM technology, the insignificant relationship between trust and adoption is likely attributable to the design of the study. Future research may consider recruiting more individuals that do not currently use PFM technology, treating trust as an antecedent to acceptance, and distinguishing between third party and financial institution providers. Recruiting more individuals without prior PFM technology experience could allow researchers to better compare the differences in trust between users and non-users. Treating trust as an antecedent could allow researchers to understand the level of trust required for an individual to accept PFM technology. Distinguishing between third party and financial institution providers could allow researchers to assess the importance of institution based trust in the context of initial trust and the acceptance of PFM technology.

H8 Perceived Technology Security

The hypothesis related to perceived technology security was:

H8: Perceived technology security will have a positive relationship with acceptance and use of PFM technology, such that individuals with a higher degree of certainty related to security will be more likely to accept and use PFM technology.

This hypothesis was not supported since the relationship between perceived technology security and PFM technology use was not statistically significant. This was contrary to security being significant in 82% of the studies in the systematic literature review when the variable was included in the analysis. A review of prior information systems research suggests the relationship between perceived technology security and technology adoption is complex, similar to trust. Consistent with the preceding discussion, that an overwhelming majority of the sample uses PFM technology is likely a major contributor to the insignificant finding. Using perceived technology security to represent the construct of security was appropriate, since an individual's subjective perception of risk is more important than an objective measure (Klang, 2001).

It is natural that an individual without experience will have greater anxiety and higher perception of the risk related to security than an individual with experience (Nangin et al., 2020). This concept is supported by online shopping research suggesting that perceived technology security plays a larger role in acceptance compared to use (Ranganathan & Ganapathy, 2002; Lian & Lin, 2008). Since an overwhelming majority of the sample already uses PFM technology, the insignificant relationship between security and adoption is likely attributable to the design of the study. Future research may consider recruiting more individuals that do not currently use PFM technology, treating perceived technology security as an antecedent to acceptance, and recruiting more male respondents. Recruiting more individuals without prior PFM technology experience could allow researchers to better compare the differences in perceived technology security between users and non-users. Treating perceived technology security as an antecedent could allow researchers to understand the level required for an individual to accept PFM technology. Recruiting more males could affect outcomes since females typically have more concern about security than males (Undale, Kulkarni, & Patil, 2021).

The effect of COVID also cannot be ignored related to perceived technology security. COVID lockdowns forced individuals to adopt technology across every aspect of their lives and dramatically sped up the digital transformation (Hashem, 2020). It is worth investigating if the effect of perceived technology security is diminished in an age where nearly everything is digital.

H9 Moderation of Age, Gender, and Financial Accounts

The hypothesis related to moderation was:

H9: Age, gender, and financial accounts will moderate the effect of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, trust, and perceived technology security on the acceptance and use of PFM technology such that the effect the effect will be weaker as age increases, stronger for males, and stronger for individuals with a higher number of financial accounts.

This hypothesis was not supported since only one of the 24 moderating relationships in the model was statistically significant. This finding is contrary to Venkatesh et al. (2012) but consistent with 25% of studies in the systematic literature review finding significant moderation.

H10 Age

The hypothesis related to age was:

H10: Age will have a negative relationship with acceptance and use of PFM technology such that as age increases, the likelihood of accepting and using PFM technology will decrease.

Age has a negative effect on PFM technology acceptance and use such that younger individuals are more likely to accept and use PFM technology than older individuals. This finding is consistent with prior information systems research and the findings by Carlin et al. (2017) and Walsh and Lim (2020) related to PFM technology. It is worth noting that this study's sample overrepresented young people, which is a limitation that may affect this relationship.

H11 Gender

The hypothesis related to gender was:

H11: Males will be more likely than females to accept and use PFM technology.

Gender has a positive effect on PFM technology acceptance and use such that males are more likely to accept and use PFM technology than females. This finding is consistent with prior information systems research and the findings by Carlin et al. (2017) and Walsh and Lim (2020) related to PFM technology.

H12 Financial Accounts

The hypothesis related to financial accounts was:

H12: Financial accounts will have a positive relationship with acceptance and use of PFM technology such that individuals with a higher number of financial accounts will be more likely to accept and use PFM technology.

The number of financial accounts has a positive effect on PFM technology acceptance and use. This finding is consistent with prior information systems research and the findings by Phillips et al. (2013) and Walsh and Lim (2020) related to PFM technology.

Practical Implications

Leveraging research findings to uncover practical implications is an important step in strengthening the relationship between academia and the private sector. This relationship should enable private sector companies to make data-driven decisions to serve consumers while providing academics a platform to see the real-world impact of their research. Three important practical implications from this study could have a positive effect on financial institutions and consumers. First, PFM technology providers should use gamification to improve hedonic motivation and make using PFM technology a habit. Second, PFM technology providers should communicate both the financial and intrinsic benefits of using PFM technology when acquiring consumers. Third, financial institutions should invest in PFM technology, as it attracts consumers with more financial accounts that are more likely to be a fit for a variety of financial products.

Improving Hedonic Motivation and Habit Through Gamification

Based on the PLS-SEM path analysis and IPMA, hedonic motivation and habit are important predictors of PFM technology use with room for improvement. Positive and negative reinforcements condition individuals and encourage continued behavior (Skinner, 1938). Gamification is a concept that has gained popularity across digital tools but has been subject to both praise and criticism (Gatautis et al., 2016). At its core, gamification is a digital strategy that provides positive reinforcements to make the user experience more enjoyable and encourage continued use (Dale, 2014). Deterding et al. (2011) defined gamification as using design elements from gaming in a non-gaming environment. Ideally, the design of gamification aligns the provider's priorities with the consumer's intrinsic motivation (Rodrigues et al., 2016). Previous research on gamification suggests that a well-implemented approach can make using technology more enjoyable and the combination of repeated exposure and increased enjoyment creates stronger habits (Duhigg, 2014; Rodrigues et al., 2016; Rodrigues et al., 2017). Since hedonic motivation and habit significantly affect PFM technology use, leveraging gamification to improve both constructs should help PFM provider increase acceptance and use on their platform.

Marketing the Financial and Intrinsic Benefits of PFM Technology

Based on the PLS-SEM path analysis, performance expectancy and hedonic motivation are significant predictors of PFM technology acceptance. Performance expectancy relates to the extrinsic benefits that come from using PFM technology, whereas hedonic motivation relates to the intrinsic benefits that come from using PFM technology (Venkatesh et al., 2012). As PFM providers market their offerings to attract consumers, they may benefit from adjusting their value propositions to include both the extrinsic and intrinsic benefits. Messaging that focuses on the usefulness, ability to accomplish things quicker, and the enjoyment of using PFM technology should resonate well with consumers based on the model's significant relationships and factor loadings. Since younger individuals and males are more likely to use PFM technology, PFM providers' marketing efforts may be more cost effective by targeting younger males compared to campaigns distributed to a broader audience.

Investing in PFM Technology to Attract More Complex Consumers

Based on the PLS-SEM path analysis, the number of financial accounts owned by an individual significantly affects their PFM technology use. The beta of the number of financial accounts was the highest in the model, indicating it has the strongest effect of any construct. This outcome is supported by previous research showing that as the number of financial accounts increase, more of an individual's attention is drawn to their finances (Phillips et al., 2013; Walsh & Lim, 2020). In theory, individuals with more financial accounts are also more profitable for financial institutions that serve a variety of needs through diversified products. This combination presents a unique opportunity for financial institutions to attract and better serve customers that benefit them the most. Additionally, descriptive statistics suggest individuals prefer using PFM technology through their financial institution compared to a third party. The most popular features among the sample were credit score monitoring, budgeting, and investment tracking which suggests these could be features that institutions focus on as they build their capabilities. This outcome supports the business case for financial institutions to either add a PFM offering to their broader experience or invest in making their existing PFM offering more compelling.

Limitations and Future Research

As an exploratory study, which should be viewed as the start toward a better understanding of PFM technology, there are important limitations to consider when interpreting the results. These limitations, combined with key findings, can also serve as a guide for future research that can build on the body of knowledge related to PFM technology.

Limitations

This study was designed as cross-sectional rather than longitudinal to keep costs and complexity to an acceptable level. The cross-sectional design did not support the collection or analysis of behavioral intent or attitudinal changes over time. This design is consistent with studies included in the systematic literature review, but inconsistent with Venkatesh et al. (2003, 2012). The study also used a survey that assessed use based on self-reported metrics from the participants. Self-reported use may differ from actual use, so it may be helpful for PFM providers to conduct research on this topic as they can assess actual use behavior. When collecting responses from participants, the survey did not specifically ask if the participant was the primary decision maker in their household. This is consistent with studies included in the systematic literature review, but is not consistent with personal finance research. Since the focus of this study was on PFM technology adoption, prior information systems research was prioritized but future research should better integrate concepts from both information systems and personal finance research.

When analyzing the data, there were clear differences between this study's sample and the sample from the 2021 NFCS. The study sample was much younger, had much more revolving credit card use, more financial accounts, and much more PFM use compared to the NFCS' sample. The biggest difference is PFM technology use. The study sample comprised 8% non-users, 48% regular users, and 44% power users. The NFCS sample comprised 58% non-users, 31% regular users, and 11% power users (Lin et al., 2022). Part of the difference can be attributed to the study sample's age and financial accounts since both significantly affect PFM technology use, or to how the use questions were asked in each survey. The 2021 NFCS asked, "How often do you use websites or apps to help with financial tasks such as budgeting, saving, or credit management (e.g., GoodBudget, Mint, Credit Karma, etc.)?" This study asked about use based on Venkatesh et al.'s (2012) suggestions, which asked about the use for each specific feature. These are fundamentally different approaches to gathering data on a similar concept. The 2021 NFCS provides specific examples of third parties that provide PFM technology, whereas this study focused on the features before asking if they used a third party or their financial institution. PFM technology use by the study sample with a third party is lower at 31% non-user, 34% regular user, and 35% power user. So, use with a third party falls between broader use among the study sample and use among the 2021 NFCS sample. The most likely scenario is that the combination of a younger sample with more financial accounts and the phrasing of the questions led to the difference (Lin et al., 2022).

Future Research

As researchers further investigate PFM technology based on this exploratory study, opportunities for future research can help academics and private companies better serve consumers through technology. First, this study assessed PFM technology use based on the overall use of the individual, but different features within PFM technology are used in different ways. Future research should compare the differences between net worth tracking, budgeting, credit score monitoring, investment tracking, and goal planning to understand what influences the acceptance and use of those specific features. Additionally, comparisons between use on apps and websites or with a third party and financial institution could provide interesting insights.

Second, this study used PLS-SEM to both explain and predict relationships, but an experimental design could take it further. Researchers should leverage experiments to test the effect of different marketing messages on PFM technology acceptance based on UTAUT2's key constructs. Researchers can also leverage experiments to test the effect of different engagement tactics aligned with key constructs to test the effect on PFM use. Third, this study focused on what causes individuals to accept and use PFM technology but did not assess the effectiveness of PFM technology in driving financial behavior. An experimental design with proper treatment and control groups could objectively assess the effect PFM technology has on an individual's financial decisions.

Fourth, there are several opportunities to better integrate information systems and personal finance research into the conceptual framework and analysis. Since the focus of this research was understanding the adoption of PFM technology as an information system, the conceptual framework and operationalization was largely driven by information systems research. Since FinTech is a combination of finance and technology, future research should continue to integrate research from both fields. Demographic, attitude, and knowledge variables that are commonly considered in personal finance research should be integrated into information systems models. Demographic variables, such as employment, income, household status, education attained, amount of assets, and cash flow, could serve as potential control variables or moderators. Attitudes, such as financial confidence, financial stress, financial anxiety, risk tolerance, and future orientation, could serve as potential exogenous variables. Types of knowledge, such as objective financial knowledge, subjective financial knowledge, objective investment knowledge, and subjective investment knowledge, could serve as potential control variables, moderators, or exogenous variables.

Conclusion

As researchers explore interventions to improve financial decisions beyond financial education and access to financial advisors, experts believe that technology will reshape the financial services industry by democratizing access to insights in real time (Lee & Shin, 2018). PFM technology is a type of FinTech with the opportunity to influence responsible financial behavior at scale, as it enhances consumer awareness and provides targeted recommendations (Li & Forlizzi, 2010). PFM technology includes common features, such as net worth tracking, budgeting, credit score monitoring, investment tracking, and goal planning. PFM technology collects, consolidates, and presents financial data in a concise user interface on a website or through a mobile application (Dorfleitner et al., 2016). Consumers access PFM technology through standalone tools such as Mint.com or as an integrated feature provided by their financial institution (Tajimi, 2021). From an information systems perspective, PFM technology can be classified as personal informatics. Personal informatics enable users to collect, review, and act on relevant information. The basic premise of personal informatics is that self-tracking drives insights, and those insights change behavior (Kersten-van Dijk et al., 2017).

PFM technology can only drive change if individuals accept and use this innovative technology. So, understanding the factors that influence this specific technology adoption is critical to the development of future innovations. This study leverages UTAUT2, which enhanced the UTAUT for consumer technology (Venkatesh et al., 2012). Since PFM technology is a consumer FinTech, this study also conducted a systematic literature review of studies that used UTAUT or UTAUT2 to identify key variables that influenced consumer FinTech adoption that are both part of UTAUT2 and extensions. The combination of the broader information systems review and concentrated focus on consumer FinTech was the foundation for the conceptual framework, hypotheses, and analysis.

To test the hypotheses, this study leveraged primary data collection using a survey specifically designed to collect the preceding measures. The target population is American adults, so the survey was distributed online via CloudResearch targeting individuals that are at least 18 years old and living in the United States. After collecting responses, a strict quality control procedure was implemented to ensure high-quality responses were used in the PLS-SEM analysis. The analysis followed the steps outlined by Hair et al. (2019), including an evaluation of the measurement model, an evaluation of the structural model, and an assessment of predictor relationships. Since the empirical model included both reflectively and formatively measured latent constructs, the measurement model comprised two parts. The reflective measurement model was evaluated based on construct reliability, construct validity, and discriminant validity. The formative measurement model was evaluated based on an outer model collinearity and outer weight significance test using bootstrapping. The structural model was evaluated based on inner model collinearity, coefficients of determination, predictive relevance, and the SRMR. After validating the measurement and structural models, the predictors were assessed based on an inner weight significance test using bootstrapping and an IPMA. By assessing the predictors, the study's twelve hypotheses were tested (Hair et al., 2019).

Seven relationships were statistically significant in the model. Performance expectancy, hedonic motivation, habit, gender, and financial accounts have a positive effect on PFM technology use. Age has a negative effect on PFM technology use and financial accounts has a positive moderating effect on the relationship between habit and PFM technology use. An IPMA found that hedonic motivation and habit are important predictors of PFM technology use that have room for improvement. Three important practical implications from this study could have a positive effect on financial institutions and consumers. First, PFM technology providers should use gamification to improve hedonic motivation and make using PFM technology a habit. Second, PFM technology providers should communicate both the financial and intrinsic benefits of using PFM technology when acquiring consumers. Third, financial institutions should invest in PFM technology, as it attracts consumers with more financial accounts that are more likely to be a fit for a variety of financial products.

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Appendix A - Survey Instrument

Start of Block: Demographics

Q1 What is your age?

____

Q2 What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary (3)

Q3 Which of the following best describes your current employment or work status?

- ○ Self-employed (1)
- ○ Work full-time for an employer (2)
- ○ Work part-time for an employer (3)
- ○ Homemaker (4)
- ○ Full-time student (5)
- ○ Permanently sick, disabled, or unable to work (6)
- ○ Unemployed (7)
- ○ Retired (8)
- ○ Prefer not to say (9)

Q4 Please select whether have, don't have, or prefer not to say related to the following types of accounts:

	Have (1)	Don't have (2)	Prefer not to say (3)
Checking account (1)	○	○	○
Savings account, money market account, or CDs (2)	○	○	○
Any retirement plans through a current or previous employer, like a pension plan, a Thrift Savings Plan (TSP), or a 401(k) (3)	○	○	○
Any other retirement accounts NOT through an employer, like an IRA, Keogh, SEP, or any other type of retirement account that you have set up yourself (4)	○	○	○
Not including retirement accounts, do you have any investments in stocks, bonds, mutual funds, or other securities (5)	○	○	○

Q5 Please select whether you have, don't have, or prefer not to say related to the following types of debt:

	Have (1)	Don't have (2)	Prefer not to say (3)
Credit card (with a balance at the end of the month) (1)	○	○	○
Auto loan (2)	○	○	○
Student loan (3)	○	○	○
Mortgage (4)	○	○	○

End of Block: Demographics

Start of Block: PFM Adoption

Q6 How often do you use websites or apps to help manage your finances such as tracking your net worth, budgeting, monitoring your credit, tracking your investments, or planning for goals?

	Several times a day (1)	Several times a week (2)	Several times a month (3)	Several times a year (4)	Do not currently use but did in the past (5)	Never used (6)
Tracking your net worth (1)	○	○	○	○	○	○
Budgeting (2)	○	○	○	○	○	○
Monitoring your credit score (3)	○	○	○	○	○	○
Tracking your investments (4)	○	○	○	○	○	○
Planning for goals (5)	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your net worth [Several times a day]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your net worth [Several times a week]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your net worth [Several times a month]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your net worth [Several times a year]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your net worth [Do not currently use but did in the past]

Q7a Which of the following describe how you access(ed) net worth tracking? (check all that apply)

- ☐ Third party mobile app (such as Mint, Credit Karma, YNAB) (1)
- ☐ Third party website (such as Mint, Credit Karma, YNAB) (2)
- ☐ Financial institution mobile app (institution you have an account(s) with) (3)
- ☐ Financial institution website (institution you have an account(s) with) (4)

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... = Budgeting [Several times a day]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Budgeting [Several times a week]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Budgeting [Several times a month]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Budgeting [Several times a year]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Budgeting [Do not currently use but did in the past]

Q7b Which of the following describe how you access(ed) budgeting? (check all that apply)

- ☐ Third party mobile app (such as Mint, Credit Karma, YNAB) (1)
- ☐ Third party website (such as Mint, Credit Karma, YNAB) (2)
- ☐ Financial institution mobile app (institution you have an account(s) with) (3)
- ☐ Financial institution website (institution you have an account(s) with) (4)

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... = Monitoring your credit score [Several times a day]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Monitoring your credit score [Several times a week]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Monitoring your credit score [Several times a month]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Monitoring your credit score [Several times a year]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Monitoring your credit score [Do not currently use but did in the past]

Q7c Which of the following describe how you access(ed) credit score monitoring? (check all that apply)

- ☐ Third party mobile app (such as Mint, Credit Karma, YNAB) (1)
- ☐ Third party website (such as Mint, Credit Karma, YNAB) (2)
- ☐ Financial institution mobile app (institution you have an account(s) with) (3)
- ☐ Financial institution website (institution you have an account(s) with) (4)

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your investments [Several times a day]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your investments [Several times a week]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your investments [Several times a month]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your investments [Several times a year]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Tracking your investments [Do not currently use but did in the past]

Q7d Which of the following describe how you access(ed) investment tracking? (check all that apply)

- ☐ Third party mobile app (such as Mint, Credit Karma, YNAB) (1)
- ☐ Third party website (such as Mint, Credit Karma, YNAB) (6)
- ☐ Financial institution mobile app (institution you have an account(s) with) (3)
- ☐ Financial institution website (institution you have an account(s) with) (4)

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... = Planning for goals [Several times a day]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Planning for goals [Several times a week]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Planning for goals [Several times a month]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Planning for goals [Several times a year]

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... = Planning for goals [Do not currently use but did in the past]

Q7e Which of the following describe how you access(ed) goal planning? (check all that apply)

▢ Third party mobile app (such as Mint, Credit Karma, YNAB) (1)

▢ Third party website (such as Mint, Credit Karma, YNAB) (2)

▢ Financial institution mobile app (institution you have an account(s) with) (3)

▢ Financial institution website (institution you have an account(s) with) (4)

End of Block: PFM Adoption

Start of Block: PE Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q8a (Current User) The next few statements will explore how much an app/website helps you manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I find it useful in my daily life. (1)	○	○	○	○	○	○	○
Using it helps me accomplish things more quickly. (2)	○	○	○	○	○	○	○
Using it does not increase my productivity. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >= 1

Q8b (Past User) The next few statements will explore how much an app/website helped you manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I found it useful in my daily life. (1)	○	○	○	○	○	○	○
Using it helped me accomplish things more quickly. (2)	○	○	○	○	○	○	○
Using it did not increase my productivity. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q8c (Never User) The next few statements will explore how much an app/website could help you manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I would find it useful in my daily life. (1)	○	○	○	○	○	○	○
Using it would help me accomplish things more quickly. (2)	○	○	○	○	○	○	○
Using it would not increase my productivity. (3)	○	○	○	○	○	○	○

End of Block: PE Questions

Start of Block: EE Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q9a (Current User) The next few statements will explore how much effort it takes to use an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
Learning how to use it is easy for me. (1)	○	○	○	○	○	○	○
My interaction with it is clear and understandable. (2)	○	○	○	○	○	○	○
I do not find it easy to use. (3)	○	○	○	○	○	○	○
It is easy for me to become skillful at using it. (4)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >= 1

Q9b (Past User) The next few statements will explore how much effort it took to use an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
Learning how to use it was easy for me. (1)	o	o	o	o	o	o	o
My interaction with it was clear and understandable. (2)	o	o	o	o	o	o	o
I did not find it easy to use. (3)	o	o	o	o	o	o	o
It was easy for me to become skillful at using it. (4)	o	o	o	o	o	o	o

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q9c (Never User) The next few statements will explore how much effort it could take to use an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
Learning how to use it would be easy for me. (1)	○	○	○	○	○	○	○
My interaction with it would be clear and understandable. (2)	○	○	○	○	○	○	○
I would not find it easy to use. (3)	○	○	○	○	○	○	○
It would be easy for me to become skillful at using it. (4)	○	○	○	○	○	○	○

End of Block: EE Questions

Start of Block: SI Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q10a (Current User) The next few statements will explore how people you know feel about using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
People who are important to me think that I should use it. (1)	○	○	○	○	○	○	○
People who influence my behavior do not think that I should use it. (2)	○	○	○	○	○	○	○
People whose opinions that I value prefer that I use it. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >= 1

Q10b (Past User) The next few statements will explore how people you knew felt about using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
People who are important to me thought that I should use it. (1)	○	○	○	○	○	○	○
People who influenced my behavior did not think that I should use it. (2)	○	○	○	○	○	○	○
People whose opinions that I valued preferred that I use it. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q10c (Never User) The next few statements will explore how people you know feel about using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
People who are important to me think that I should use it. (1)	○	○	○	○	○	○	○
People who influence my behavior do not think that I should use it. (2)	○	○	○	○	○	○	○
People whose opinions that I value prefer that I use it. (3)	○	○	○	○	○	○	○

End of Block: SI Questions

Start of Block: FC Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q11a (Current User) The next few statements will explore things that support or get in the way of using an app/website to manage your finances.   Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I have the resources necessary to use it. (1)	○	○	○	○	○	○	○
I have the knowledge necessary to use it. (2)	○	○	○	○	○	○	○
It is not compatible with other technologies I use. (3)	○	○	○	○	○	○	○
I can get help from others when I have difficulties using it. (5)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >= 1

Q11b (Past User) The next few statements will explore things that supported or got in the way of using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I had the resources necessary to use it. (1)	○	○	○	○	○	○	○
I had the knowledge necessary to use it. (2)	○	○	○	○	○	○	○
It was not compatible with other technologies I used. (3)	○	○	○	○	○	○	○
I could get help from others when I had difficulties using it. (5)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q11c (Never User) The next few statements will explore things that could support or get in the way of using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I have the resources necessary to use it. (1)	○	○	○	○	○	○	○
I have the knowledge necessary to use it. (2)	○	○	○	○	○	○	○
It is not compatible with other technologies I use. (3)	○	○	○	○	○	○	○
I can get help from others when I have difficulties using it. (5)	○	○	○	○	○	○	○

End of Block: FC Questions

Start of Block: HM Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q12a (Current User) The next few statements will explore the enjoyment you experience using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
Using it is fun. (1)	○	○	○	○	○	○	○
Using it is not enjoyable. (2)	○	○	○	○	○	○	○
Using it is very entertaining. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >= 1

Q12b (Past User) The next few statements will explore the enjoyment you experienced using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
Using it was fun. (1)	○	○	○	○	○	○	○
Using it was not enjoyable. (2)	○	○	○	○	○	○	○
Using it was very entertaining. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q12c (Never User) The next few statements will explore the enjoyment you could experience using an app/website to manage your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
Using it would be fun. (1)	○	○	○	○	○	○	○
Using it would not be enjoyable. (2)	○	○	○	○	○	○	○
Using it would be very entertaining. (3)	○	○	○	○	○	○	○

End of Block: HM Questions

Start of Block: HT Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q13a (Current User) The next few statements will explore how much using an app/website to manage your finances has become a habit. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
The use of it has become a habit for me. (1)	○	○	○	○	○	○	○
I am not addicted to using it. (2)	○	○	○	○	○	○	○
I must use it. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >= 1

Q13b (Past User) The next few statements will explore how much using an app/website to manage your finances became a habit. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
The use of it became a habit for me. (1)	o	o	o	o	o	o	o
I was not addicted to using it. (2)	o	o	o	o	o	o	o
I felt that I must use it. (3)	o	o	o	o	o	o	o

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q13c (Never User) The next few statements will explore how much using an app/website to manage your finances could become a habit. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
The use of it would become a habit for me. (1)	o	o	o	o	o	o	o
I would not get addicted to using it. (2)	o	o	o	o	o	o	o
I would feel I must use it. (3)	o	o	o	o	o	o	o

End of Block: HT Questions

Start of Block: TR Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q14a (Current User) The next few statements will explore how much you trust an app/website you use for managing your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I trust in it. (1)	○	○	○	○	○	○	○
I do not believe that it is trustworthy. (2)	○	○	○	○	○	○	○
I trust that its providers are honest and keep their promises to users. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >=

Q14b (Past User) The next few statements will explore how much you trusted an app/website you use for managing your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I trusted in it. (1)	○	○	○	○	○	○	○
I did not believe that it was trustworthy. (2)	○	○	○	○	○	○	○
I trusted that its providers were honest and kept their promises to users. (3)	○	○	○	○	○	○	○

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q14c (Never User) The next few statements will explore how much you could trust an app/website you use for managing your finances. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I would trust in it. (1)	○	○	○	○	○	○	○
I do not believe that it is trustworthy. (2)	○	○	○	○	○	○	○
I trust that its providers are honest and keep their promises to users. (3)	○	○	○	○	○	○	○

End of Block: TR Questions

Start of Block: PTS Questions

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) >= 1

Or How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) >= 1

Q15a (Current Users) The next few statements will explore your uncertainty about using an app/website to manage your finances because of the security protecting your sensitive information. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I feel secure accessing sensitive information across it. (1)	o	o	o	o	o	o	o
It is a secure means through which to access information. (2)	o	o	o	o	o	o	o
I feel totally safe providing sensitive information about myself through it. (3)	o	o	o	o	o	o	o
Overall it is not a safe place to access sensitive information. (6)	o	o	o	o	o	o	o

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) >= 1

Q15b (Past Users) The next few statements will explore your uncertainty about an app/website you used to manage your finances because of the security protecting your sensitive information. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I felt secure accessing sensitive information across it. (1)	o	o	o	o	o	o	o
It was a secure means through which to access information. (2)	o	o	o	o	o	o	o
I felt totally safe providing sensitive information about myself through it. (3)	o	o	o	o	o	o	o
Overall it was not a safe place to access sensitive information. (6)	o	o	o	o	o	o	o

Display This Question:

If How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a day] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a week] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a month] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Several times a year] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Do not currently use but did in the past] (Count) = 0

And How often do you use websites or apps to help manage your finances such as tracking your net wort... [Never used] (Count) >= 1

Q15c (Never Users) The next few statements will explore your potential uncertainty about using an app/website to manage your finances because of the security protecting your sensitive information. Please read the following sentences and rate on a scale of 1-7, how much you agree. 1 being strongly disagree, and 7 being strongly agree.

	1 - Strongly Disagree (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 - Strongly Agree (7)
I would feel secure accessing sensitive information across it. (1)	◯	◯	◯	◯	◯	◯	◯
It is a secure means through which to access information. (2)	◯	◯	◯	◯	◯	◯	◯
I feel totally safe providing sensitive information about myself through it. (3)	◯	◯	◯	◯	◯	◯	◯
Overall it is not a safe place to access sensitive information. (6)	◯	◯	◯	◯	◯	◯	◯

End of Block: PTS Questions

Start of Block: Attention Check

Q16 What year were you born?

____

Appendix B - Dependent Variable Coding

Code	Role	Variable Type	Scoring	Details
PFM	Latent Construct	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	Factor weightings of PFM_NW, PFM_BUD, PFM_CSM, PFM_INV, PFM_GOAL
PFM_NW	Formative Indicator	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(USE_NW=6,1, IF(USE_NW=5,1, IF(USE_NW=4,2, IF(USE_NW=3,3, IF(USE_NW=2,4, IF(USE_NW=1,5))))))
PFM_BUD	Formative Indicator	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(USE_BUD=6,1, IF(USE_BUD=5,1, IF(USE_BUD=4,2, IF(USE_BUD=3,3, IF(USE_BUD=2,4, IF(USE_BUD=1,5))))))
PFM_CSM	Formative Indicator	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(USE_CSM=6,1, IF(USE_CSM=5,1, IF(USE_CSM=4,2, IF(USE_CSM=3,3, IF(USE_CSM=2,4, IF(USE_CSM=1,5))))))
PFM_INV	Formative Indicator	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(USE_INV=6,1, IF(USE_INV=5,1, IF(USE_INV=4,2, IF(USE_INV=3,3, IF(USE_INV=2,4, IF(USE_INV=1,5))))))
PFM_GOAL	Formative Indicator	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(USE_GOAL=6,1, IF(USE_GOAL=5,1, IF(USE_GOAL=4,2, IF(USE_GOAL=3,3, IF(USE_GOAL=2,4, IF(USE_GOAL=1,5))))))

Appendix C - Independent Variable Coding

Code	Role	Variable Type	Scoring	Details
PE	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of PE1, PE2, PE3
PE1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(PE1_A, PE1_B, PE1_C)
PE2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(PE2_A, PE2_B, PE1_C)
PE3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(MAX(PE1_A,PE1_B,PE1_C))
EE	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of EE1, EE2, EE3, EE4
EE1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(EE1_A, EE1_B, EE1_C)
EE2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(EE2_A, EE2_B, EE2_C)
EE3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(MAX(EE3_A, EE3_B, EE3_C))
EE4	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(EE4_A, EE4_B, EE4_C)
SI	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of SI1, SI2, SI3
SI1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(SI1_A, SI1_B, SI1_C)
SI2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(max(SI2_A, SI2_B, SI2_C))
SI3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(SI3_A, SI3_B, SI3_C)
FC	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of FC1, FC2, FC3, FC4
FC1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(FC1_A, FC1_B, FC1_C)
FC2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(FC2_A, FC2_B, FC2_C)
FC3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(MAX(FC3_A, FC3_B, FC3_C))
FC4	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(FC4_A, FC4_B, FC4_C)
HM	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of HM1, HM2, HM3
HM1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(HM1_A, HM1_B, HM1_C)

HM2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(MAX(HM2_A, HM2_B, HM2_C))
HM3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(HM3_A, HM3_B, HM3_C)
HT	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of HT1, HT2, HT3
HT1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(HT1_A, HT1_B, HT1_C)
HT2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(MAX(HT2_A, HT2_B, HT2_C))
HT3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(HT3_A, HT3_B, HT3_C)
TR	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of TR1, TR2, TR3
TR1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(TR1_A, TR1_B, TR1_C)
TR2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(MAX(TR2_A, TR2_B, TR2_C))
TR3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(TR3_A, TR3_B, TR3_C)
PTS	Latent Construct	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	Factor Loadings of PTS1, PTS2, PTS3, PTS4
PTS1	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(PTS1_A, PTS1_B, PTS1_C)
PTS2	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(PTS2_A, PTS2_B, PTS2_C)
PTS3	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	MAX(PTS3_A, PTS3_B, PTS3_C)
PTS4	Reflective Indicator	Continuous	1 (Strongly Disagree) to 7 (Strongly Agree)	8-(MAX(PTS4_A, PTS4_B, PTS4_C))

Appendix D - Moderating Variable Coding

Code	Role	Variable Type	Scoring	Details
AGE	Moderating Variable	Continuous	Number ranging from 18 to 100	Q1. What is your age?
GEN	Moderating Variable	Binary	Male (1), All Other (0)	IF(GENDER=1,1,0)
NUM_ACCOUNTS	Moderating Variable	Continuous	0 (No Accounts) to 9 (9 Accounts)	COUNTIFS(CHK:SAV:RETIRE:IRA:BROKER:CREDIT:AUTO:STULOAN:MORT,0)

Appendix E - Sample Descriptive Variable Coding

Code	Role	Variable Type	Scoring	Details
PFM_GENERAL	Sample Descriptive	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	MAX(PFM_NW, PFM_BUD, PFM_CSM, PFM_INV, PFM_GOAL)
PFM_APP	Sample Descriptive	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(MEDIUM_APP=1, PFM_GENERAL, 1)
PFM_WEB	Sample Descriptive	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(MEDIUM_WEB=1,PFM_GENERAL, 1)
PFM_3RD	Sample Descriptive	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(PROVIDER_3RD=1,PFM_GENERAL, 1)
PFM_FI	Sample Descriptive	Ordinal	Not currently using (1), Several times a year (2), Several times a month (3), Several times a week (4), Several times a day (5)	IF(PROVIDER_FI=1,PFM_GENERAL, 1)
PFM_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_GENERAL=1,1, IF(PFM_GENERAL=2,2, IF(PFM_GENERAL=3,2, IF(PFM_GENERAL=4,3, IF(PFM_GENERAL=5,3)))))
APP_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_APP=1,1, IF(PFM_APP=2,2, IF(PFM_APP=3,2, IF(PFM_APP=4,3, IF(PFM_APP=5,3)))))
WEB_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_WEB=1,1, IF(PFM_WEB=2,2, IF(PFM_WEB=3,2, IF(PFM_WEB=4,3, IF(PFM_WEB=5,3)))))
3RD_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_3RD=1,1, IF(PFM_3RD=2,2, IF(PFM_3RD=3,2, IF(PFM_3RD=4,3, IF(PFM_3RD=5,3)))))
FI_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_FI=1,1, IF(PFM_FI=2,2, IF(PFM_FI=3,2, IF(PFM_FI=4,3, IF(PFM_FI=5,3)))))

NW_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_NW=1,1, IF(PFM_NW=2,2, IF(PFM_NW=3,2, IF(PFM_NW=4,3, IF(PFM_NW=5,3)))))
BUD_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_BUD=1,1, IF(PFM_BUD=2,2, IF(PFM_BUD=3,2, IF(PFM_BUD=4,3, IF(PFM_BUD=5,3)))))
CSM_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_CSM=1,1, IF(PFM_CSM=2,2, IF(PFM_CSM=3,2, IF(PFM_CSM=4,3, IF(PFM_CSM=5,3)))))
INV_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_INV=1,1, IF(PFM_INV=2,2, IF(PFM_INV=3,2, IF(PFM_INV=4,3, IF(PFM_INV=5,3)))))
GOAL_USERTYPE	Sample Descriptive	Categorical	Non user (1), Regular User (2), Power User (3)	IF(PFM_GOAL=1,1, IF(PFM_GOAL=2,2, IF(PFM_GOAL=3,2, IF(PFM_GOAL=4,3, IF(PFM_GOAL=5,3)))))
FEATURES_USED	Sample Descriptive	Continuous	0 (No Features) to 5 (5 Features)	COUNTIFS(PFM_NW:PFM_BUD:PFM_CSM:PFM_INV:PFM_GOAL,2,3,4,5)
AGE_CAT	Sample Descriptive	Categorical	Age 18-24 (1), Age 25-34 (2), Age 35-44 (3), Age 45-54 (4), Age 55-64 (5), Age 65+ (6)	IF(AND(AGE>=18, AGE<=24),1, IF(AND(AGE>=25,AGE<=34),2, IF(AND(AGE>=35,AGE<=44),3, IF(AND(AGE>=45, AGE<=54),4, IF(AND(AGE>=55,AGE<=64),5, IF(AGE>=65,6,))))))
GENDER	Sample Descriptive	Categorical	Male (1), Female (2), Non-binary (3)	Q2. What is your gender?
CHK	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q4_1. Please select whether have, don't have, or prefer not to say related to the following types of accounts: Checking account
SAV	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q4_2. Please select whether have, don't have, or prefer not to say related to the following types of accounts: Savings account
RETIRE	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q4_3. Please select whether have, don't have, or prefer not to say related to the following types of accounts: Employer retirement plan
IRA	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q4_4. Please select whether have, don't have, or prefer not to say related to the following types of accounts: Individual retirement account
BROKER	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q4_5. Please select whether have, don't have, or prefer not to say related to the following types of accounts: Brokerage account

CREDIT	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q5_1. Please select whether you have, don't have, or prefer not to say related to the following types of debt: Credit card
AUTO	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q5_2. Please select whether you have, don't have, or prefer not to say related to the following types of debt: Auto loan
STULOAN	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q5_3. Please select whether you have, don't have, or prefer not to say related to the following types of debt: Student loan
MORT	Sample Descriptive	Categorical	Yes (1), No (2), Unknown (3)	Q5_4. Please select whether you have, don't have, or prefer not to say related to the following types of debt: Mortgage
JOB	Sample Descriptive	Categorical	Self-employed (1), Full-time (2), Part-time (3), Homemaker (4), Student (5), Disabled (6), Unemployed (7), Retired (8), Unknown (9)	Q3. Which of the following best describes your current employment or work status?

Appendix F - Working Variable Coding

Code	Role	Variable Type	Scoring	Details
USE_NW	Working Variable	Likert Scale	Several times a day (1), Several times a week (2), Several times a month (3), Several times a year (4), Do not currently use but did in the past (5), Never used (6)	Q6_1. How often do you use websites or apps to help manage your finances such as tracking your net worth?
USE_BUD	Working Variable	Likert Scale	Several times a day (1), Several times a week (2), Several times a month (3), Several times a year (4), Do not currently use but did in the past (5), Never used (6)	Q6_2. How often do you use websites or apps to help manage your finances such as budgeting?
USE_CSM	Working Variable	Likert Scale	Several times a day (1), Several times a week (2), Several times a month (3), Several times a year (4), Do not currently use but did in the past (5), Never used (6)	Q6_3. How often do you use websites or apps to help manage your finances such as monitoring your credit?
USE_INV	Working Variable	Likert Scale	Several times a day (1), Several times a week (2), Several times a month (3), Several times a year (4), Do not currently use but did in the past (5), Never used (6)	Q6_4. How often do you use websites or apps to help manage your finances such as tracking your tracking your investments?
USE_GOAL	Working Variable	Likert Scale	Several times a day (1), Several times a week (2), Several times a month (3), Several times a year (4), Do not currently use but did in the past (5), Never used (6)	Q6_5. How often do you use websites or apps to help manage your finances such as planning for goals?
MEDIUM_APP	Working Variable	Binary	No (0), Yes (1)	IF((COUNTIFS(MEDIUM_NW:MEDIUM_BUD; MEDIUM_CSM; MEDIUM_INV; MEDIUM_GOAL,1)+COUNTIFS(MEDIUM_NW:MEDIUM_BUD; MEDIUM_CSM; MEDIUM_INV; MEDIUM_GOAL,3)>=1),1,0)
MEDIUM_WEB	Working Variable	Binary	No (0), Yes (1)	IF((COUNTIFS(MEDIUM_NW:MEDIUM_BUD; MEDIUM_CSM; MEDIUM_INV; MEDIUM_GOAL,2)+COUNTIFS(MEDIUM_NW:MEDIUM_BUD; MEDIUM_CSM; MEDIUM_INV; MEDIUM_GOAL,3)>=1),1,0)

PROVDER_3RD	Working Variable	Binary	No (0), Yes (1)	IF((COUNTIFS(PROVIDER_NW:PROVIDER_BUD; PROVIDER_CSM; PROVIDER_INV; PROVIDER_GOAL,1)+COUNTIFS(PROVIDER_NW:PROVIDER_BUD; PROVIDER_CSM; PROVIDER_INV; PROVIDER_GOAL,3)>=1),1,0)
PROVIDER_FI	Working Variable	Binary	No (0), Yes (1)	IF((COUNTIFS(PROVIDER_NW:PROVIDER_BUD; PROVIDER_CSM; PROVIDER_INV; PROVIDER_GOAL,2)+COUNTIFS(PROVIDER_NW:PROVIDER_BUD; PROVIDER_CSM; PROVIDER_INV; PROVIDER_GOAL,3)>=1),1,0)
MEDIUM_NW	Working Variable	Categorical	App (1), Web (2), Both (3)	IF(ACCESS_NW=1,1,IF(ACCESS_NW=3,1,IF(ACCESS_NW="1,3",1, IF(ACCESS_NW=2,2,IF(ACCESS_NW=4,2, IF(ACCESS_NW="2,4",2, IF(ACCESS_NW="1,2",3, IF(ACCESS_NW="2,3",3, IF(ACCESS_NW="1,4",3,IF(ACCESS_NW="3,4",3,IF(ACCESS_NW="1,2,3,4",3, IF(ACCESS_NW="1,2,3",3, IF(ACCESS_NW="1,2,4",3, IF(ACCESS_NW="2,3,4",3, IF(ACCESS_NW="1,3,4",3,0)))))))))))))))
PROVIDER_NW	Working Variable	Categorical	Third Party (1), Financial Institution (2), Both (3)	IF(ACCESS_NW=1,1,IF(ACCESS_NW=3,2, IF(ACCESS_NW="1,3",3, IF(ACCESS_NW=2,1, IF(ACCESS_NW=4,2, IF(ACCESS_NW="2,4",3, IF(ACCESS_NW="1,2",1, IF(ACCESS_NW="2,3",3, IF(ACCESS_NW="1,4",3, IF(ACCESS_NW="3,4",2, IF(ACCESS_NW="1,2,3,4",3, IF(ACCESS_NW="1,2,3",3, IF(ACCESS_NW="1,2,4",3, IF(ACCESS_NW="2,3,4",3, IF(ACCESS_NW="1,3,4",3,0)))))))))))))))
ACCESS_NW	Working Variable	Multiple Choice	Third party mobile app (1), Third party website (2), Financial institution mobile app (3), Financial institution website (4)	Q7a. Which of the following describe how you access(ed) net worth tracking? (check all that apply)

MEDIUM_BUD	Working Variable	Categorical	App (1), Web (2), Both (3)	IF(ACCESS_BUD=1,1,IF(ACCESS_BUD=3,1, IF(ACCESS_BUD="1,3",1, IF(ACCESS_BUD=2,2, IF(ACCESS_BUD=4,2,IF(ACCESS_BUD="2,4",2, IF(ACCESS_BUD="1,2",3, IF(ACCESS_BUD="2,3",3, IF(ACCESS_BUD="1,4",3,IF(ACCESS_BUD="3,4",3, IF(ACCESS_BUD="1,2,3,4",3, IF(ACCESS_BUD="1,2,3",3, IF(ACCESS_BUD="1,2,4",3, IF(ACCESS_BUD="2,3,4",3, IF(ACCESS_BUD="1,3,4",3,0)))))))))))))))
PROVIDER_BUD	Working Variable	Categorical	Third Party (1), Financial Institution (2), Both (3)	IF(ACCESS_BUD=1,1, IF(ACCESS_BUD=3,2, IF(ACCESS_BUD="1,3",3, IF(ACCESS_BUD=2,1, IF(ACCESS_BUD=4,2,IF(ACCESS_BUD="2,4",3, IF(ACCESS_BUD="1,2",1, IF(ACCESS_BUD="2,3",3, IF(ACCESS_BUD="1,4",3, IF(ACCESS_BUD="3,4",2, IF(ACCESS_BUD="1,2,3,4",3, IF(ACCESS_BUD="1,2,3",3, IF(ACCESS_BUD="1,2,4",3, IF(ACCESS_BUD="2,3,4",3, IF(ACCESS_BUBUD="1,3,4",3,0)))))))))))))))
ACCESS_BUD	Working Variable	Multiple Choice	Third party mobile app (1), Third party website (2), Financial institution mobile app (3), Financial institution website (4)	Q7b. Which of the following describe how you access(ed) budgeting? (check all that apply)

MEDIUM_CSM	Working Variable	Categorical	App (1), Web (2), Both (3)	IF(ACCESS_CSM=1,1, IF(ACCESS_CSM=3,1, IF(ACCESS_CSM="1,3",1, IF(ACCESS_CSM=2,2, IF(ACCESS_CSM=4,2,IF(ACCESS_CSM="2,4",2, IF(ACCESS_CSM="1,2",3, IF(ACCESS_CSM="2,3",3, IF(ACCESS_CSM="1,4",3, IF(ACCESS_CSM="3,4",3, IF(ACCESS_CSM="1,2,3,4",3, IF(ACCESS_CSM="1,2,3",3, IF(ACCESS_CSM="1,2,4",3, IF(ACCESS_CSCSM="2,3,4",3, IF(ACCESS_CSM="1,3,4",3,0)))))))))))))))
PROVIDER_CSM	Working Variable	Categorical	Third Party (1), Financial Institution (2), Both (3)	IF(ACCESS_CSM=1,1, IF(ACCESS_CSM=3,2, IF(ACCESS_CSM="1,3",3, IF(ACCESS_CSM=2,1, IF(ACCESS_CSM=4,2,IF(ACCESS_CSM="2,4",3, IF(ACCESS_CSM="1,2",1, IF(ACCESS_CSM="2,3",3, IF(ACCESS_CSM="1,4",3, IF(ACCESS_CSM="3,4",2, IF(ACCESS_CSM="1,2,3,4",3, IF(ACCESS_CSM="1,2,3",3, IF(ACCESS_CSM="1,2,4",3, IF(ACCESS_CSM="2,3,4",3, IF(ACCESS_CSM="1,3,4",3,0)))))))))))))))
ACCESS_CSM	Working Variable	Multiple Choice	Third party mobile app (1), Third party website (2), Financial institution mobile app (3), Financial institution website (4)	Q7c. Which of the following describe how you access(ed) credit score monitoring? (check all that apply)

MEDIUM_INV	Working Variable	Categorical	App (1), Web (2), Both (3)	IF(ACCESS_INV=1,1, IF(ACCESS_INV=3,1, IF(ACCESS_INV="1,3",1, IF(ACCESS_INV=2,2, IF(ACCESS_INV=4,2, IF(ACCESS_INV="2,4",2, IF(ACCESS_INV="1,2",3, IF(ACCESS_INV="2,3",3, IF(ACCESS_INV="1,4",3, IF(ACCESS_INV="3,4",3, IF(ACCESS_INV="1,2,3,4",3, IF(ACCESS_INV="1,2,3",3, IF(ACCESS_INV="1,2,4",3, IF(ACCESS_INV="2,3,4",3, IF(ACCESS_INV="1,3,4",3,0)))))))))))))))
PROVIDER_INV	Working Variable	Categorical	Third Party (1), Financial Institution (2), Both (3)	IF(ACCESS_INV=1,1, IF(ACCESS_INV=3,2, IF(ACCESS_INV="1,3",3, IF(ACCESS_INV=2,1, IF(ACCESS_INV=4,2, IF(ACCESS_INV="2,4",3, IF(ACCESS_INV="1,2",1, IF(ACCESS_INV="2,3",3, IF(ACCESS_INV="1,4",3, IF(ACCESS_INV="3,4",2, IF(ACCESS_INV="1,2,3,4",3, IF(ACCESS_ININV="1,2,3",3, IF(ACCESS_INV="1,2,4",3, IF(ACCESS_INV="2,3,4",3, IF(ACCESS_INV="1,3,4",3,0)))))))))))))))
ACCESS_INV	Working Variable	Multiple Choice	Third party mobile app (1), Third party website (2), Financial institution mobile app (3), Financial institution website (4)	Q7d. Which of the following describe how you access(ed) investment tracking? (check all that apply)

MEDIUM_GOAL	Working Variable	Categorical	App (1), Web (2), Both (3)	IF(ACCESS_GOAL=1,1, IF(ACCESS_GOAL=3,1, IF(ACCESS_GOAL="1,3",1, IF(ACCESS_GOAL=2,2, IF(ACCESS_GOAL=4,2, IF(ACCESS_GOAL="2,4",2, IF(ACCESS_GOAL="1,2",3, IF(ACCESS_GOAL="2,3",3, IF(ACCESS_GOAL="1,4",3, IF(ACCESS_GOAL="3,4",3, IF(ACCESS_GOAL="1,2,3,4",3, IF(ACCESS_GOAL="1,2,3",3, IF(ACCESS_GOAL="1,2,4",3, IF(ACCESS_GOAL="2,3,4",3, IF(ACCESS_GOAL="1,3,4",3,0)))))))))))))))
PROVIDER_GOAL	Working Variable	Categorical	Third Party (1), Financial Institution (2), Both (3)	IF(ACCESS_GOAL=1,1, IF(ACCESS_GOAL=3,2, IF(ACCESS_GOAL="1,3",3, IF(ACCESS_GOAL=2,1, IF(ACCESS_GOAL=4,2, IF(ACCESS_GOAL="2,4",3, IF(ACCESS_GOAL="1,2",1, IF(ACCESS_GOAL="2,3",3, IF(ACCESS_GOAL="1,4",3, IF(ACCESS_GOAL="3,4",2, IF(ACCESS_GOAL="1,2,3,4",3, IF(ACCESS_GOAL="1,2,3",3, IF(ACCESS_GOAL="1,2,4",3, IF(ACCESS_GOAL="2,3,4",3, IF(ACCESS_GOAL="1,3,4",3,0)))))))))))))))
ACCESS_GOAL	Working Variable	Multiple Choice	Third party mobile app (1), Third party website (2), Financial institution mobile app (3), Financial institution website (4)	Q7e. Which of the following describe how you access(ed) goal planning? (check all that apply)
PE1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8a (Current User)_1. I find it useful in my daily life.
PE2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8a (Current User)_2. Using it helps me accomplish things more quickly.
PE3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8a (Current User)_3. Using it does not increase my productivity.
PE1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8b (Past User)_1. I found it useful in my daily life.
PE2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8b (Past User)_2. Using it helped me accomplish things more quickly.

PE3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8b (Past User)_3. Using it did not increase my productivity.
PE1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8c (Never User)_1. I would find it useful in my daily life.
PE2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8c (Never User)_2. Using it would help me accomplish things more quickly.
PE3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q8c (Never User)_3. Using it would not increase my productivity.
EE1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9a (Current User)_1. Learning how to use it is easy for me.
EE2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9a (Current User)_2. My interaction with it is clear and understandable.
EE3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9a (Current User)_3. I do not find it easy to use.
EE4_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9a (Current User)_4. It is easy for me to become skillful at using it.
EE1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9b (Past User)_1. Learning how to use it was easy for me.
EE2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9b (Past User)_2. My interaction with it was clear and understandable.
EE3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9b (Past User)_3. I did not find it easy to use.
EE4_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9b (Past User)_4. It was easy for me to become skillful at using it.
EE1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9c (Never User)_1. Learning how to use it would be easy for me.
EE2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9c (Never User)_2. My interaction with it would be clear and understandable.
EE3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9c (Never User)_3. I would not find it easy to use.
EE4_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q9c (Never User)_4. It would be easy for me to become skillful at using it.
SI1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10a (Current User)_1. People who are important to me think that I should use it.
SI2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10a (Current User)_2. People who influence my behavior do not think that I should use it.
SI3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10a (Current User)_3. People whose opinions that I value prefer that I use it.
SI1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10b (Past User)_1. People who are important to me thought that I should use it.

SI2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10b (Past User)_2. People who influenced my behavior did not think that I should use it.
SI3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10b (Past User)_3. People whose opinions that I valued preferred that I use it.
SI1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10c (Never User)_1. People who are important to me think that I should use it.
SI2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10c (Never User)_2. People who influence my behavior do not think that I should use it.
SI3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q10c (Never User)_3. People whose opinions that I value prefer that I use it.
FC1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11a (Current User)_1. I have the resources necessary to use it.
FC2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11a (Current User)_2. I have the knowledge necessary to use it.
FC3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11a (Current User)_3. It is not compatible with other technologies I use.
FC4_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11a (Current User)_4. I can get help from others when I have difficulties using it.
FC1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11b (Past User)_1. I had the resources necessary to use it.
FC2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11b (Past User)_2. I had the knowledge necessary to use it.
FC3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11b (Past User)_3. It was not compatible with other technologies I used.
FC4_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11b (Past User)_4. I could get help from others when I had difficulties using it.
FC1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11c (Never User)_1. I have the resources necessary to use it.
FC2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11c (Never User)_2. I have the knowledge necessary to use it.
FC3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11c (Never User)_3. It is not compatible with other technologies I use.
FC4_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q11c (Never User)_4. I can get help from others when I have difficulties using it.
HM1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12a (Current User)_1. Using it is fun.
HM2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12a (Current User)_2. Using it is not enjoyable.
HM3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12a (Current User)_3. Using it is very entertaining.

HM1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12b (Past User)_1. Using it was fun.
HM2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12b (Past User)_2. Using it was not enjoyable.
HM3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12b (Past User)_3. Using it was very entertaining.
HM1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12c (Never User)_1. Using it would be fun.
HM2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12c (Never User)_2. Using it would not be enjoyable.
HM3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q12c (Never User)_3. Using it would be very entertaining.
HT1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13a (Current User)_1. The use of it has become a habit for me.
HT2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13a (Current User)_2. I am not addicted to using it.
HT3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13a (Current User)_3. I must use it.
HT1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13b (Past User)_1. The use of it became a habit for me.
HT2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13b (Past User)_2. I was not addicted to using it.
HT3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13b (Past User)_3. I felt that I must use it.
HT1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13c (Never User)_1. The use of it would become a habit for me.
HT2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13c (Never User)_2. I would not get addicted to using it.
HT3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q13c (Never User)_3. I would feel I must use it.
TR1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14a (Current User)_1. I trust in it.
TR2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14a (Current User)_2. I do not believe that it is trustworthy.
TR3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14a (Current User)_3. I trust that its providers are honest and keep their promises to users.
TR1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14b (Past User)_1. I trusted in it.
TR2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14b (Past User)_2. I did not believe that it was trustworthy.

TR3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14b (Past User)_3. I trusted that its providers were honest and kept their promises to users.
TR1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14c (Never User)_1. I would trust in it.
TR2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14c (Never User)_2. I do not believe that it is trustworthy.
TR3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q14c (Never User)_3. I trust that its providers are honest and keep their promises to users.
PTS1_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15a (Current Users)_1. I feel secure accessing sensitive information across it.
PTS2_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15a (Current Users)_2. It is a secure means through which to access information.
PTS3_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15a (Current Users)_3. I feel totally safe providing sensitive information about myself through it.
PTS4_A	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15a (Current Users)_4. Overall it is not a safe place to access sensitive information.
PTS1_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15b (Past Users)_1. I felt secure accessing sensitive information across it.
PTS2_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15b (Past Users)_2. It was a secure means through which to access information.
PTS3_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15b (Past Users)_3. I felt totally safe providing sensitive information about myself through it.
PTS4_B	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15b (Past Users)_4. Overall it was not a safe place to access sensitive information.
PTS1_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15c (Never Users)_1. I would feel secure accessing sensitive information across it.
PTS2_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15c (Never Users)_2. It is a secure means through which to access information.
PTS3_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15c (Never Users)_3. I feel totally safe providing sensitive information about myself through it.
PTS4_C	Working Variable	Scale (1-7)	1 (Strongly Disagree) to 7 (Strongly Agree)	Q15c (Never Users)_4. Overall it is not a safe place to access sensitive information.