ADOPTION OF AI-ENABLED ROBO-ADVISORS IN FINTECH: SIMULTANEOUS EMPLOYMENT OF UTAUT AND THE THEORY OF REASONED ACTION

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ABSTRACT

In fintech, robo-advisors are a helpful technology for users desiring to use financial services remotely; as such, robo-advisors are being used by an increasing number of users. However, service providers of this artificial intelligence (AI)-based technology still have challenges to solve, such as issues with security, privacy, and distrust. In addition to technological benefits, we argue that if the service providers were to consider the risk-sensing behavioral attitudes of users toward AI-based robo-advisors, then more users may be attracted to this technology. By simultaneously employing the unified theory of acceptance and use of technology (UTAUT) and the theory of reasoned action (TRA), we develop a conceptual model and propose a series of hypotheses related to users' adoption of robo-advisors in fintech services. Specifically, we argue that the antecedents (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) affect the positive attitudes that individual investors hold toward robo-advisors, and we claim that the TRA-related factors (i.e., perceived security, perceived privacy, and trust) play vital roles in encouraging the use of robo-advisors. Using large-scale survey data from 638 Chinese users having experience with robo-advisor services, we empirically tested our framework using the structural equation modeling approach. The results clearly support the proposed hypotheses concerning the direct and indirect effects of various predictors, such as performance expectancy, effort expectancy, social influence, facilitating conditions, perceived security, and perceived privacy, on user attitudes toward robo-advisors and their intention to adopt such fintech services. In addition, our results demonstrate that the majority of these relationships are indirect by virtue of the mediating roles of attitude, trust, and facilitating conditions. This study contributes to the understanding of users' adoption of robo-advisors by combining UTAUT and TRA, which is useful for exploring the relationships between attitudes and behavioral intentions to use as well as the interrelationships among security, privacy, and trust.

Keywords: Robo-advisor; Perceived security; Perceived privacy; Trust; China

1. Introduction

Fintech is a compound word formed using "finance" and "technology" that captures the changes occurring in financial services and industries through the convergence of financial services and information technology. According to KPMG (2022), there were 5,684 global fintech investments in 2021, with the combined investment amount equal to about 210 billion dollars, representing a 68% increase over the investment of 124.9 billion dollars from the previous

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year. Given the increasing volatility of the capital markets, such as concerns involving the COVID-19 pandemic, fluctuations in virtual currencies, and inflation, there is increasing demand for long-term investments based on increases in stable asset management. Online wealth management services called robo-advisors constitute one of the technological fields attracting attention owing to the upsurge in demand for non-face-to-face fintech since the first outbreak of COVID-19 (Goh, 2020). The scale of robo-advisors in the global market is expected to grow to about USD 2552 billion in 2023 from USD 543 billion in 2018 (Statista, 2022). Further, the number of users of robo-advisors increased rapidly from 42 million in 2017 to 292 million in 2021. Despite this popularity, Deloitte (2017) noted that robo-advisor technologies have inherent risks that customers may experience (e.g., technology, operation, and business risks), which may cause biased asset concentration, failure to respond to unexpected rapid changes, and reduced protection of financial assets. Ultimately, earning consumer trust is the most urgent priority for firms that provide artificial intelligence (AI)-enabled fintech services. Within the fintech industry, Belanche et al. (2019) proposed exploring the mechanism by which trust plays a role in specific areas where innovative technologies are likely to evolve (Roh, Yang, et al., 2022). Considering this background, we believe that it is crucial to examine the antecedent factors that are related to trust for robo-advisor users. We define trust as "... the individual or group's willingness to be vulnerable to the other party" (Cheng et al., 2021, p. 500; Shin, 2019, p. 2). Cheng et al. (2021) emphasized the importance of trust between humans and robots (e.g., chatbots) rather than interpersonal interactions, given the increasing proliferation of tools and opportunities for people to interact with technology.

Robo-advisors pursue efficient customer analysis and asset management based on technologies, such as AI, robot process automation, and machine learning (Belanche et al., 2019; Shanmuganathan, 2020). In this study, a robo-advisor is defined as an "AI-enabled fintech that has both robot and advisory capabilities as a technology in which a program makes investment decisions and asset allocations through a preprogrammed algorithm." Similarly, Cheng et al. (2021) defined a chatbot, a type of robo-advisor, as a computerized chat system that uses casual language to communicate with people. Aided by extensive data analysis, a robo-advisor provides a comprehensive service that composes, rebalances, and manages a customized portfolio by identifying each customer's unique risk appetite, investment propensity, financial situation, and financial plan. Fintech robo-advisors can also simultaneously cater to numerous consumers' financial demands (e.g., target profitability, risk, and investment period), thus increasing customer support, satisfaction, and relational effectiveness.

There are three main theoretical motives for this study with the aim of extending the focus of existing literature on robo-advisors. The first two are related to the attributes of fintech (i.e., technological innovation and distrust in conservative financial managers), and the last is related to the psychology of fintech users. First, although existing research on fintech is mainly focused on the acceptance of innovation in technology, intention to use it, and mobile payments of consumers, there is scant research examining the preconditions that can induce positive attitudes and intentions among users to adopt robo-advisors, which is one of the key attributes of fintech. Attitudes toward behavior refer to one's personal beliefs in carrying out specific behaviors, and intention to use refers to a given behavior in which a strong intention to perform that behavior leads to a higher likelihood of that behavior (Fishbein and Ajzen, 1975, 2010). For example, in a study examining the acceptance of robo-advisors among potential users in North America, the UK, and Portugal with a focus on the effects of technology acceptance on attitude, Belanche et al. (2019) found that subjective norms served as external factors. Given that potential users may not fully reflect the intentions and attitudes of users who have actually used a particular technology, it is imperative to expand existing literature by exploring the antecedent factors that prompt users to augment their attitudes and intentions to use robo-advisors. Further, most prior research on fintech has furnished essential lessons on the factors influencing user adoption (Lee and Kim, 2020; Mombeuil, 2020; Ryu, 2018; Singh et al., 2020, 2021; Wang et al., 2019); user motives regarding financial technology adoption have mostly been explored from a technological perspective (Singh et al., 2020).

Second, because individual investors have suffered as a result of private equity firms engaging in illegal activities (e.g., yield manipulation, fraudulent transactions, and toxic asset purchases), negative perceptions of funds sold in the financial sector have spread, leading to reduced trust in the traditional financial products and managers (Tokic, 2018). Although robo-advisors are driving innovation in financial services using AI technologies, it is nearly impossible for financial services to operate without customer trust. In other words, even enthusiastic fintech users will not entrust their valuable assets to untrustworthy asset advisors. Fintech research and studies on how trust affects attitudes and adoption of fintech services are still in their infancy, and there is a need for more extensive work (Roh, Yang, et al., 2022; Singh et al., 2020, 2021). Similarly, the behavioral precedents supporting or opposing the use of robo-advisor technology are insufficiently studied. Using fintech technologies involves an intricate interplay of information technology and user behaviors (Roh, Yang, et al., 2022; Ryu, 2018). However, very few studies have attempted to examine the use and acceptance of robo-advisors in terms of the unified technology acceptance theory and behavior-based theory. Therefore, there is a need to elucidate the preceding factors for robo-advisors from a divergent theoretical approach.

Third, although trust-related factors are conventionally considered in these technologies, we believe that considering a combination of these factors with users' psychological cognitive processes may help increase the understanding and technology acceptance of robo-advisors. Based on extant literature on fintech services (Belanche et al., 2019; Roh, Yang, et al., 2022; Singh et al., 2020), users' psychological obstacles may prevent them from adopting such AI-enabled financial tools. Thus, we considered how trust is influenced by privacy and security, which are subjectively expected norms from the perspective of the theory of reasoned action (TRA), to better understand why AI-enabled fintech services are technologically accepted. In adopting robo-advisors in fintech, the unified theory of acceptance and use of technology (UTAUT) focuses on the antecedents and expected effects of user technology, while the TRA weights the psychological factors behind the user's desired outcomes. In this regard, our understanding of robo-advisors can be further improved by simultaneously considering these complementary theories.

To address these gaps in literature, we extend existing studies to explore the antecedents that stimulate the actual use of robo-advisors through two theoretical approaches. To this end, the present study presents a trust-based robo-advisor introduction model based on UTAUT and TRA as the crucial theoretical lenses. UTAUT suggests the formative antecedent factors of specific technology users whereas TRA concentrates on the cognitive and behavioral features of service use. This study presents the idea of UTAUT as a precedent for technology acceptance and introduces a trust-based model for robo-advisors by integrating TRA in accordance with consumer cognitive behaviors. Therefore, our all-embracing research question is as follows: *what are the antecedents for the adoption of robo-advisors, and what roles do trust-related factors play in adopting such fintech?* Using questionnaire survey data acquired from fintech-experienced users in China, we investigate the trust that has emerged from the perceived security and privacy based on acceptance of integrated technologies for robo-advisors, with specific focus on the attitudes and intentions regarding the use of fintech services, through partial least-squares structural equation modeling (PLS-SEM).

By addressing the above research gaps, we contribute to research on robo-advisors in fintech literature by proposing a theoretical dual model with UTAUT as the technology-acceptance-based theory and TRA as the behavioral-based theory, while focusing on the role of cognitive trust interwoven with perceived privacy and security. First, we explore the antecedent factors affecting the attitudes regarding and usage of robo-advisors as fintech services. As most of the existing research focuses on cognitive behaviors for general-purpose fintech (e.g., mobile payments, blockchain, and O2O applications), our insights into robo-advisors are expected to provide in-depth theoretical and practical implications. Second, we empirically identify the importance of the interplay between perceived security, perceived privacy, and trust among fintech service users who have accepted robo-advisors as the TRA simultaneously with UTAUT. Third, we contribute to more diverse awareness regarding robo-advisors and fintech by analyzing the implications from both behavioral and technological perspectives.

Through structural equation testing, this study confirmed several findings. First, all hypotheses regarding the UTAUT factors for user adoption of fintech robo-advisors were supported. Second, the perceived security and privacy affecting user trust formation in the fintech robo-advisor were found to be statistically significant. Third, among the hypotheses on simultaneous consideration of UTAUT and TRA, perceived privacy positively affected the facilitating conditions and attitudes toward fintech robo-advisors, while trust, which was influenced by such perceived security and privacy, affected attitude and intention to use. However, the effects of perceived security on the facilitating conditions and attitudes were insignificant. These results imply that Chinese users are likely to have positive attitudes toward fintech robo-advisors by reacting more sensitively to privacy than perceived security. Therefore, it would be reasonable for Chinese fintech-related managers to emphasize various protective instruments that prevent consumer privacy problems rather than highlighting security issues.

The remainder of this paper is structured as follows: the theoretical background and previous literature are reviewed in the next section. Our hypotheses and framework are established in the third section, and the methodology and empirical findings are respectively provided in the fourth and fifth sections. Then, the conclusion section describes the findings as well as the theoretical and managerial implications, limitations, and future research directions.

2. Theoretical Background

2.1. Robo-advisor

Robo-advisors conduct accurate analyses of the financial situations of customers wishing to invest from an advisory point of view; however, the pursuit of high return is not necessarily a winning strategy for all investors (Jung et al., 2018). For some people, preserving their principal may be the biggest goal, while others may be in situations where they must withdraw all their money to make large-scale purchases in the following year. Robo-advisors should be able to understand the various financial needs of these customers and take them into account while planning their trading strategies (Chen et al., 2022; Senyo and Osabutey, 2020; Wang et al., 2019). Mathematically, this is like solving an optimization problem with the customer's financial needs as the constraint. To generate a return on investment, the three values of "what, when, and how much to buy and sell" must be considered appropriately. In calculating the optimal value, AI-enabled data mining is performed with substantial amounts of pricing data. While humans can do such investment deliberations intuitively, they can also be automated through suitable investment robots. A robo-advisor automatically makes the above three decisions according to changing market conditions (Tokic, 2018). The global COVID-19 pandemic has led to an inevitable surge in the contactless market as a megatrend. Given the growing market volatility and uncertainty, scholarly interest in robo-advisors that allow stable financial investments based on objective data analyses and verified algorithmic strategies is thriving. Extant studies on robo-advisors in fintech have often examined why such technologies are attracting attention (Belanche et al., 2019), which robo-advisors are popularly chosen by consumers for use (Shanmuganathan, 2020) and investments (Jung et al., 2018), and the future of such technologies (Tokic, 2018). Since these studies have focused on the technological usefulness of robo-advisors and their benefits to users, there has been less attention on the cognitive barriers that cause intrinsic psychological anxiety in consumers from the viewpoint of attitudes or intentions to use such technology. More importantly, to the best of our knowledge, very few works have dealt with factors shaping the expected outcomes of user attitudes toward robo-advisors or intention to adopt such services. UTAUT can explain the expected outcomes of why consumers show positive attitudes and intentions toward robo-advisors, and TRA can improve the understanding of how subjective psychological norms affect consumers who are likely to adopt the technology. Literature on technology acceptance by users begins with the technology acceptance model (TAM) based on perceived usefulness and ease of use as the key antecedents (Davis, 1989). Fintech has been studied in various fields, such as mobile payments (Iman, 2018), crypto payments (Jonker, 2019), e-wallets, and e-commerce (Tripathy and Jain, 2020), in terms of user technology adoption. In addition, as a different analytic approach from the structural equations of previous studies, Huarng and Yu (2022) used the fuzzy set qualitative comparative analysis (fsQCA) to verify that innovation, technology, entrepreneurship, and economic development have causality with fintech adoption based on a sample of 30 countries. Jünger and Mietzner (2020) verified the extent to which traditional bank users could move to fintech by focusing on literature related to switching behaviors. However, in existing literature on fintech, there is lack of research on a model in which consumers psychologically consider a specific, reasoned action together with technology regarding intention to use when they come across a robo-advisor. In this regard, our study is a pilot effort to formally examine these important questions on what shapes the attitudes of users regarding the use of robo-advisors and their intention to adopt such fintech services; this is also a pioneering empirical research that provides clear evidence of the support for the proposed hypotheses concerning the direct or indirect effects of various factors, such as performance expectancy, effort expectancy, social influence, facilitating conditions, perceived security, and perceived privacy on users' attitudes toward or intention to adopt robo-advisors.

2.2. Unified Theory of Acceptance and Use of Technology

Venkatesh et al. (2003) reviewed the ground-breaking research examining information systems (IS) acceptance to identify the theoretical and contextual similarities and differences between the theories on technology acceptance from three research perspectives—social psychology, IS management, and behavioral psychology—to provide a comprehensive understanding of technology adoption. Venkatesh et al. (2003) found a limitation in that the predictive powers of existing models for acceptance intention were mostly under 50%. In response, they devised an integrated model called the UTAUT, which they added to TAM to overcome these constraints; the common aspects of existing technology acceptance models that were typically overlooked were sample simplification, exclusion of complex ITs, and variance in explanatory power according to IT system and context (Brown et al., 2015; Jeong and Roh, 2017). To address these issues and ensure the extensive implications of the models, eight previous models were synthesized and combined to create the UTAUT, namely the TRA, TAM, motivational model, theory of planned behavior, model of PC utilization, diffusion of innovation theory, and social cognitive theory. UTAUT aims to explain user intentions for using information systems and their usage behaviors; it proposes four central components, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. In general, the first three factors directly affect attitude or intention to use, while the fourth factor directly or indirectly influences user behaviors.

There are several empirical studies that consider UTAUT as the theoretical basis. For example, Im et al. (2011) investigated the uptake of two technologies by Korean and American users, i.e., MP3 players and Internet banking, to observe how culture affects the relationships between the components in the UTAUT model. In a study examining the impact of mobile banking adoption, Yu (2012) assessed that an individual's intention to adopt mobile banking is affected by social influence, perceived financial cost, performance expectancy, and perceived credibility. Hoque and Sorwar (2017) validated the UTAUT model's suitability in terms of mHealth services for the elderly in emerging nations like Bangladesh. Chao (2019) included perceived enjoyment, mobile self-efficacy, satisfaction, and trust in the traditional UTAUT with regard to the behavioral intention to use m-learning from the consumer's point of view; they also employed perceived risk as a moderator. With the social isolation caused by the COVID-19 pandemic, Erjavec and Manfreda (2022) found that herd behavior is a potentially innovative phenomenon that affects the behavioral intentions of online purchases in decision-making scenarios based on the UTAUT model. They also verified that social influence did not significantly affect behavioral intention to adopt online shopping and that fears concerning COVID-19 did not affect behavioral intentions to adopt online shopping.

2.3. Theory of Reasoned Action

The TRA plays a notable role in predicting the actions that an individual will perform in the future according to their preceding attitudes and behavioral intentions, and it seeks to explain the relationships between attitudes and behaviors within human actions (Doswell et al., 2011; Fishbein and Ajzen, 1975). The consequence that a person expects after engaging in a particular behavior informs their decision for the behavior (Fishbein and Ajzen, 1975). Having evolved from psychosocial literature on the attitude–behavior association, the TRA postulates that socially relevant behaviors are under the control of the will and that an individual's intention to perform a behavior is both an immediate determinant and the best single predictor of that behavior (Fishbein and Ajzen, 1975, 2010). According to the TRA, people are more likely to undertake a proposed behavior when they assess the behavior favorably (attitude) and believe that others should also follow it (subjective norm), which results in higher intention (motivation). For instance, a person will have a positive attitude toward a given action if they believe that engaging in that action would result in beneficial outcomes (Albarracin and Ajzen, 2007). Attitudes are viewed as a function of the sum of a person’s vital behavioral beliefs about the results of their actions that are weighted by how they perceive the results. Subjective norms result from a person’s opinions about how a specific person or group of people should behave. Anyone who believes that the essential referent should take action will be aware of the societal pressures involved. Subjective norms result from a person's salient normative views about reference items, each of which is weighted on the basis of the person's desire to adhere to that object.

As discussed above, the TRA has traditionally increased the understanding of identifying individual tendencies toward certain behaviors; this theory has recently been combined with other theoretical models to achieve more complex interpretations, thereby providing in-depth theoretical/practical implications. In a study jointly considering the information systems success model (ISSM) and TRA, Roh, Yang, et al. (2022) proposed a set of assumptions about consumer adoption of fintech services; they found that the consumers' perceptions of security and privacy are positively associated with trust, thus promoting both favorable attitudes and their intentions to use those services. Roh, Seok, et al. (2022) integrated the theory of consumption value (TCV) and TRA to examine the consumption of organic foods from the perspective of an extended research model; specifically, they examined whether TCV affected consumer decisions to consume organic food for sustainability, and they explored the extended TRA, which was designed to incorporate trust and perceived knowledge in the research model. Drawing on the diffusion of innovation (DOI) theory and TRA, Kwon et al. (2021) examined how external forces and organizational cultures of openness and learning affected perceived usefulness and the hurdles involved in social media usage decisions of small business owners under the COVID-19 situation. Considering the possibility of grafting to various contexts, the outcomes of the above studies suggest that TRA is one of the theoretically well-rounded lenses that may be applicable to contemporary studies of consumer behavior decision-making.

3. Hypothesis Development

3.1. UTAUT-related Factors

An attitude is commonly defined as “a positive or negative view of an ‘attitude object’: a person, a behavior, or an event” (Bernstein et al., 2000). In this study, we argue that users’ attitudes toward adopting fintech such as robo-advisors influence adoption behaviors via their influences on intentions to adopt such systems or services. In this regard, the attitudes of users in this study reflect more their beliefs, feelings, values, and dispositions toward adopting robo-advisor services (cf. Shin, 2019). The degree to which a person expects that using a system will improve their job performance is known as their performance expectancy, which is an important factor in both voluntary and required settings as well as the best predictor of intent to use (Venkatesh et al., 2003). From the viewpoint of technology acceptance, the level at which technology aids users in carrying out particular tasks implies performance expectancy; people are typically drawn to technologies that have several advantages. Compared to traditional asset managers, robo-advisors as a fintech service (e.g., in the form of a mobile application) offer the advantages of ease, accessibility, and quicker transactions (Belanche et al., 2019). The ease of system usability is used to determine effort expectancy, which refers to the degree to which users find a technology to be simple to use. AI-enabled technologies select and show the key financial indicators of the most readily available alternatives to investors by using customized algorithms (e.g., exchange-traded funds) (Chen et al., 2022). Social influence is defined as the degree to which close friends and family members of a user believe that they embrace new technology, which affects the user's decision. As the use of a particular technology becomes increasingly pervasive, individuals adopt it to facilitate interpersonal interactions within social ties regardless of their personal preferences (e.g., mobile banking) (Senyo and Osabutey, 2020). In this study, the facilitating conditions, defined as “the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system” (Venkatesh et al., 2003, p. 453), represent the users' perceptions of the assistance and feasibility of using robo-advisors. Users who plan financial investments through robo-advisors expect certain target returns on their investments. Since the investment guidance provided by traditional a financial planner is complex and difficult to understand, fintech service users inevitably use the beneficial functions provided by robo-advisors (e.g., transparent profit data disclosure, portfolio reorganization by time and situation, and low fees). Further, the reluctance toward face-to-face financial services owing to COVID-19 also enhances individual investors' interests in asset management through fintech services and robo-advisors. Altogether, robo-advisor users accustomed to fintech services can easily access remittances, shopping, currency exchange, and stocks on any platform (e.g., social network service, mobile application, and online). Therefore, we suggest the following hypotheses.

H1a: Performance expectancy positively affects users' attitudes toward adopting robo-advisors.

H1b: Effort expectancy positively affects users' attitudes toward adopting robo-advisors.

H1c: Social influence positively affects users' attitudes toward adopting robo-advisors.

H1d: Facilitating conditions positively affect users' attitudes toward adopting AI-enabled robo-advisors.

Behavioral intention is commonly defined as "the degree to which a person has formulated conscious plans to perform or not perform some specific future behavior" (Warshaw and Davis, 1985, p. 214). Consistent with literature, we conceptualize and operationalize the intentions of users to adopt robo-advisors as the likelihood of their robo-advisor adoption (Warshaw and Davis, 1985). The mindset that a person has while performing a specific action affects their conduct. Behavioral attitudes play significant roles in determining intention to use. The psychological manifestation of one's preparedness to carry out a certain action as a previous behavioral factor is referred to as their behavioral intention. UTAUT defines a person's attitude toward a target behavior as their desire to appropriately carry out that action (Khalilzadeh et al., 2017). It is expected that the UTAUT assumption can be applied to the robo-advisor context because it has been extensively used in multifaceted technological backgrounds based on computerized devices. Since the main variables in the original UTAUT model are attitudinal aspects, considering attitudes as a distinct construct might pose problems in terms of discriminant validity. Nevertheless, the four antecedents of UTAUT were developed under the premise that attitudes were the main mediating factors in conceiving predictors and behavioral intentions. In particular, facilitating conditions are highly likely to affect attitudes and behavioral intentions under UTAUT (Khalilzadeh et al., 2017). In a study using the UTAUT while focusing on mobile users in the US, Yang (2010) found that both facilitating conditions and attitudes had direct effects on behavioral intentions. Therefore, we propose attitude and intention to use in terms of the following hypotheses.

H2a: Attitude positively affects users' intentions to adopt robo-advisors.

H2b: Facilitating conditions positively affect users' intentions to adopt robo-advisors.

3.2. TRA Model Expansion: Perceived Security, Perceived Privacy, and Trust

In the specific context of robo-advisors pertaining to fintech, perceived security, privacy, and trust have all been noted as alternative but considerable TRA factors. According to Shin (2019), perceived security refers to how confidently and safely customers believe they can utilize a service under certain conditions. A user's preferences regarding the handling and customization of information may be seen as being reflected in their perceived security (Shin, 2019; Shin, 2010). The technological security of a robo-advisor determines its perceived security, thus affecting the trust-based actions of users who conduct transactions using the robo-advisor (Belanche et al., 2019; Kim et al., 2021). Although robo-advisors deliver customized information to customers, it may be difficult for users to identify whether such financial products are optimized for them. Thus, maintaining high security of robo-advisor services through regular updates can drive user adoption of their services. These systemic security protocols may improve customer perceptions of security and make them more receptive to the facilitating conditions related to the robo-advisor's overall infrastructure and resources (Kim and Yun, 2007; Shin, 2010). Moreover, establishing a technological infrastructure for verification and authentication while routinely assessing the security of a robo-advisor from a customer-centric standpoint can improve personal attitudes (e.g., blockchain) (Shin, 2019; Shin, 2013). A robo-advisor can instantly verify whether the user's requested financial information is being handled appropriately, which also improves attitude. For example, users may consider robo-advisors favorably if they believed that it was safe to trust their investment and portfolio restructuring recommendations (Lee and Kim, 2020; Senyo and Osabutey, 2020). In conclusion, very few studies have used the TRA to examine how perceived security affects the trust, facilitating conditions, and attitudes concerning robo-advisors. Consequently, we anticipate the following associations:

H3a: Perceived security positively affects users' trust toward adopting robo-advisors.

H3b: Perceived security positively affects users' facilitating conditions toward adopting robo-advisors.

H3c: Perceived security positively affects users' attitudes toward adopting robo-advisors.

User perceptions regarding the protection and non-misuse of their personal information are collectively defined as perceived privacy (Al-Okaily et al., 2020; Balapour et al., 2020; Parasuraman et al., 1988; Smith et al., 2011). In this study, we define perceived privacy as the user's ability to control when, how, and to what extent their personal information is disclosed to, communicated to, and protected by fintech systems or services such as robo-advisors (Casaló et al., 2007; Shin, 2019). Positive privacy may help users address dangers and prepare for situations in which private information is collected and handled (Kim et al., 2021; Rios et al., 2018). It is crucial for financial services prone to privacy issues to safeguard their customers against potential losses or fraud. Similarly, investors in the financial sector will have more confidence in and positive opinions about fintech services with fewer privacy concerns (Miyazaki and Fernandez, 2001; Shin, 2011). Access to personal information is a must for robo-advisors since they offer investors a range of financial portfolios based on algorithms by considering such personal information (Belanche et al., 2019; Senyo and Osabutey, 2020). Given this, the precision of the robo-advisor's system could guarantee that the customer has psychological stability without compromising their personal information. A robo-advisor that calculates algorithms based on the big data of all investors through an infinite loop offers the most suitable solution for individual investors when they decide to invest; by contrast, conventional financial planners with bounded rationality recommend financial investments to people based on the amount of relevant information they have available (Shanmuganathan, 2020). Rather than depending on an investor's personal information, robo-advisors utilize stored information comprising existing investors' assets, portfolios, and returns on investment as resources to leverage when and how new investments are being made. These explanations lead to the following hypotheses.

H4a: Perceived privacy positively affects users' trust toward adopting robo-advisors.

H4b: Perceived privacy positively affects users' facilitating conditions toward adopting robo-advisors.

H4c: Perceived privacy positively affects users' attitudes toward adopting robo-advisors.

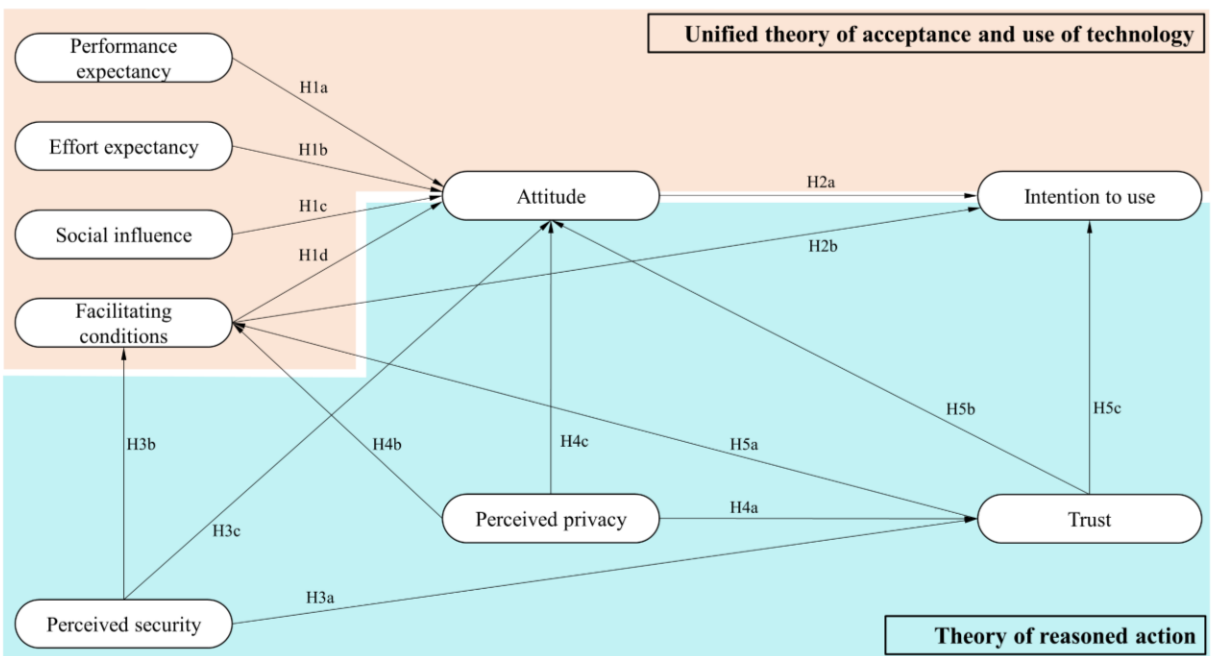

Figure 1: Research Model

Since trust is a crucial component of the TRA, it has attracted substantial attention from various angles and depths of analyses. Trust plays a pivotal role in reducing the risk of uncertainty associated with the parties in a financial transaction relationship, particularly in an online ecosystem such as fintech services (de Matos et al., 2020). Since there is a need for an established level of trust before users feel secure about conducting financial investments through fintech services, doubts about robo-advisor services could be alleviated by a data-based objective recommendation system involving accumulated AI-enabled asset capabilities (e.g., account, fund, and portfolio management). Therefore, users' attitudes and behavioral intentions toward robo-advisors are influenced by their trust or confidence levels. For example, fintech users often feel uncertain about the outcomes of payments using mobile applications or online vendors. Therefore, as financial transaction vehicles, robo-advisors should help customers overcome their hesitation by establishing trust in payment and banks through real-time synchronization of the transaction details. The above values of trust could allow robo-advisor users to be aware of stabilization mechanisms, which will affect their positive attitudes and intentions to use. Hence, we propose the following hypotheses.

H5a: Trust positively affects users' facilitating conditions toward adopting robo-advisors.

H5b: Trust positively affects users' attitudes toward adopting robo-advisors.

H5c: Trust positively affects users' intentions to adopt robo-advisors.

4. Methodology

4.1. Research Context and Sample

To empirically examine our hypothesized relationships, we implemented a structural equation model test after collecting samples from China. We believe that Chinese consumers' financial activities and decision making provide a suitable research setting to explore consumer attitudes and behaviors toward the fast-paced fintech industry for the following reasons. First, as one of the fastest-growing global economy and the largest global consumer market, China is now leading the global fintech development race, having undoubtedly emerged as the hub of global fintech innovation and adoption. According to data reported by KPMG China, fintech investments in China have increased dramatically over the last few years, specifically having increased by 252% since 2010, reaching USD8.8 billion and accounting for the largest share of global investments in this sector. It is expected that digital technologies will be widely applied in the Chinese financial sector and that such digital transformation is anticipated to help fintech firms attract new customers while improving their customer experiences in many ways. Moreover, as one of the leading digital technologies, AI technology is expected to play the most important role in driving future fintech development. Stanford University's AI Index suggests that China ranks in the top-three economies for advancing AI globally; as a result, AI has been widely adopted in many ways throughout the Chinese finance sector. Specifically, China is expected to emerge as the largest robo-advisor market in the world according to a report released by CreditEase Corp and Bloomberg LP. Lufax and consultant iResearch stated that the robo-advisor service market in China is expected to reach 737 billion yuan by 2022 (approximately USD114 billion according to the official 2021 exchange rate). Finally, China has the largest fintech ecosystem in the world as well as the highest penetration rate of fintech services among major economies; the adoption rate of consumer fintech in China reached 87% in 2019, according to EY's Global Fintech Adoption Index 2019. More importantly, with the rapid development of the Chinese robo-advisory market, Chinese consumers are increasingly interested in using various robo-advisor services. For example, as evidenced by a 2020 survey conducted by Kagan, a research division within S&P Global Market Intelligence, approximately 38% of Chinese internet users are currently using robo-advisor services, and roughly 68% of non-internet users are also showing increased interest in using such robo-advisor services.

Using a survey approach, we collected data from Chinese consumers in two major regions: Beijing and Shanghai. According to the 2021 China Leading Fintech 50 and Future 50 Report released by KPMG, a global business services firm, Beijing and Shanghai dominate the landscape of fintech in China, with more than half of fintech firms clustered in these two regions as of 2021. Moreover, the two regions still ranked among the top in China for fintech technology development and attracted approximately 62% of all Chinese fintech investments in 2021, demonstrating that both leading fintechs and investment were heavily concentrated in these two regions. Before administering the survey, we carefully developed and designed the questionnaire to ensure that it had good reliability and validity according to several guidelines. We first developed an English questionnaire, translated it into Chinese with the assistance of two independent bilingual researchers who are capable of speaking both Chinese and English, and finally had it translated back into English by two additional independent bilingual translators to ensure equivalence of the concepts (cf. Park and Xiao, 2020; Xiao et al., 2021). To assess the validity of our measurements, we recruited eight raters who were PhD candidates in marketing and international business at a research university. We refined some items that were incorrectly classified by the eight raters in two rounds of sorting. To assess the clarity of the measurement items and ensure validity of the measures included in the study as well as comprehensiveness of the focal phenomenon, we pretested the questionnaire by recruiting 50 users enrolled in an MBA program at a Chinese university and organized on-site interviews with more than 20 additional Chinese users. During the pretest and interviews, we asked the respondents to help us check the applicability and clarity of the elements used in the survey, and we further refined and modified some items slightly for accuracy and completeness.

To collect data that better reflect consumers' perceptions, attitudes, and behaviors toward application of AI robo-advisors in fintech services, we used a street-intercept survey approach wherein we distributed hard copies of the questionnaire in crowded public spaces within the two chosen areas. As prior studies have argued for the particular importance of building strong trust and close relationships to enhance survey participation rate and maintain high-quality responses from respondents in China (Park and Xiao, 2021), we distributed the survey by recruiting a renowned locally esteemed market research institution. Through careful design of the data-gathering stages, we compiled 669 responses, thus achieving as overall response rate of 79.6%. After eliminating 31 returns with incomplete or excessively missing data on the key scales used in the study, we assembled 638 useful responses. The respondents were majority male (52.4%) and mostly aged between 20 and 39 years (66%). Further, most of the respondents were married (61.8%), and nearly 70% has bachelor's degrees.

4.2. Bias Testing

As nonresponse bias may occur in survey research, we assessed whether this influenced our empirical results by comparing the earliest responding and latest responding consumers based on important sample attributes (e.g., age and education level) (Armstrong and Overton, 1977). We compared the first and fourth quartiles of the respondents in terms of age and education level, and the results showed no significant differences ($p > 0.05$); therefore, nonresponse bias was considered less likely to be a serious concern influencing the empirical statistical results. Specifically, we did not find a significant difference between the first and fourth quartiles of respondents for age, with early respondents averaging 2.70 and late respondents averaging 2.55 for chronological age measured through a grouping variable (1 = below 20 years, 2 = 20−29 years, 3 = 30−39 years, 4 = 40−49 years, 5 = over 50 years). Similarly, we did not find a significant difference between the first and fourth quartiles of respondents for education level, with early respondents averaging 4.01 and late respondents averaging 3.93 for a chronological education level measured through a grouping variable (1 = middle school and below, 2 = high school, 3 = college, 4 = bachelor's degree, 5= master's degree or above). Further, our survey-based study may also suffer from potential common method variance (CMV). However, we believe that CMV is not a significant problem in our data for the following reasons. First, in the cover letter attached to the questionnaires, we assured the respondents that their responses would only be used for the purpose of research analysis in this study and that they would be fully confidential. Second, to reduce the possibility of a simple "straight line" response leading to CMV bias (Chang et al., 2020; Johnson et al., 2011), we attentively devised the question items by including measurements of the main latents under different subcategories in the questionnaire and using other compositions. Lastly, we randomized the order in which the items in the questionnaire were presented by employing survey software and reversing the scaling on several key construct items in the questionnaire. Still, following the recommendation of Podsakoff et al. (2003), we evaluated this possible doubt by conducting an exploratory factor analysis with the questions on all multi-selective scales. The results of Harman's one-factor analysis suggest that the first factor only explains 48% of the total variance in the data (i.e., not more than a cutoff of 50%) and that no single factor emerged or was dominant in the unrotated factor structure. Therefore, we believe that CMV is not a significant concern in our study.

4.3. Measures

In this study, unless explicitly mentioned otherwise, we measured all constructs using multiple-item, seven-point Likert scales by asking the respondents to indicate the extent to which they agreed or disagreed with each statement (1 = "strongly disagree" to 7 = "strongly agree"). All items used to measure the independent and dependent variables in this study were adopted from well-developed scales that have been proven to be reliable and valid in literature, after slight modifications for the specific purpose of our study. Table 1 summarizes the detailed measurement of variables. We also incorporated several control variables into the analysis: user age, gender, marital status, and education level. We used a grouping variable to measure user age (i.e., 1 = below 20 years, 2 = 20−29 years, 3 = 30−39 years, 4 = 40−49 years, 5 = over 50 years). To measure user gender, we created a dummy variable (0 = female users, 1 = male users). We used a dummy variable to indicate marital status (1 = users being married, 0 = users being single). We measured user education as a chronological education level reflected through a grouping variable (i.e., 1 = middle school and below, 2 = high school, 3 = college, 4 = bachelor's degree, 5 = master's degree or above).

5. Empirical Analyses and Results

To empirically test the conceptual framework, we used the partial least-squares structural equation modeling (Richter et al., 2016; Venaik et al., 2005; Zott and Amit, 2008). Before testing the hypothesized relationships, we first checked the reliability and validity of the constructs by estimating the measurement model.

5.1. Reliability and Validity Checking

As presented in Table 1, all Cronbach's alpha values and composite reliabilities are higher than 0.80 and therefore clearly over the threshold value of 0.70 (Fornell and Larcker, 1981). Further, the factor loadings of all constructs are statistically significant, and their coefficients are all larger than 0.80, further demonstrating that the measurement model and constructs are reliable and valid (Chin, 1998; Hulland, 1999). To assess the convergence validity of the constructs, we checked the average variance extracted (AVE), whose results suggest that the AVE values for all constructs are greater than 0.70, far exceeding the threshold of 0.5. These results suggested appropriate convergent validity and reliability (Fornell and Larcker, 1981). To investigate the discriminant validity between constructs, we compared the correlations between each of the constructs and other constructs in the model as well as the square root of AVE of each construct. As presented in Table 2, each construct's square root of AVE is significantly larger than the correlation between that construct and the other constructs. These results provide evidence of acceptable discriminant validity of the measures (Fornell and Larcker, 1981). We also checked the discriminant validity by comparing the loading value of each indicator with its cross-loading with other indicators, and the results indicate that the factor loading of each indicator is higher for its designated construct than the respective cross-loadings, thus providing further evidence of adequate discriminant validity (Chin, 1998). Moreover, we verified the heterotrait–monotrait (HTMT) ratios of the correlations, and the results showed that all HTMT values were under the threshold of 0.85, providing further evidence of adequate discriminant validity between the constructs in the model (Henseler et al., 2015; Kline, 2011). Finally, we examined the predictive validity of the latent constructs in the model using Stone–Geisser's Q^2 test (Geisser, 1975; Stone, 1974); the results demonstrated that both the cross-validated community and redundancy values were all greater than the threshold of zero, indicating that the model was relevant for prediction (Fornell and Cha, 1994).

Table 1: Descriptive Statistics and Validity Assessments

Construct and indicators	Mean	STD	Outer loadings
Performance expectancy (AVE=0.822, alpha=0.928, CR=0.949) (Venkatesh et al., 2003; Venkatesh et al., 2012)			
I find fintech useful in my daily life.	5.063	1.491	0.912
Using fintech increases my chances of achieving things that are important to me.	5.102	1.402	0.905
Using fintech helps me accomplish things more quickly.	5.207	1.434	0.903
Using fintech increases my productivity.	5.135	1.508	0.906
Effort expectancy (AVE=0.768, alpha=0.904, CR=0.930) (Venkatesh et al., 2003; Venkatesh et al., 2012)			
Learning to use fintech is easy for me.	5.422	1.464	0.819
My interactions with fintech are clear and understandable.	5.237	1.467	0.881
I find fintech easy to use.	4.876	1.485	0.903
It is easy for me to become skillful at using fintech.	4.980	1.540	0.899
Social influence (AVE=0.756, alpha=0.838, CR=0.903) (Venkatesh et al., 2003; Venkatesh et al., 2012)			
People who are important to me think that I should use fintech.	4.991	1.457	0.894
People who influence my behaviors think that I should use fintech.	5.121	1.451	0.891
People whose opinions I value prefer that I use fintech.	4.014	1.099	0.822
Facilitating conditions (AVE=0.820, alpha=0.927, CR=0.948) (Venkatesh et al., 2003; Venkatesh et al., 2012)			
I have the resources necessary to use fintech.	4.868	1.401	0.907
I have the knowledge necessary to use fintech.	4.813	1.283	0.909
Fintech is compatible with other technologies I use.	4.865	1.293	0.900
I can get help from others when I have difficulties using fintech.	4.895	1.399	0.906
Perceived security (AVE=0.827, alpha=0.896, CR=0.935) (Shin, 2019; Shin, 2010)			
I believe the information I provide to fintech will be handled by appropriate processes.	4.676	1.464	0.917
I am confident that the private information I provide will be secure.	4.478	1.481	0.897
I believe that only legitimate parties view the information I provide to fintech.	4.466	1.665	0.916
Perceived privacy (AVE=0.851, alpha=0.912, CR=0.945) (Kim et al., 2019; Shin, 2019)			
I am confident that I am aware of all the parties collecting the information I provide when using fintech.	4.100	1.750	0.927
I am aware of the exact nature of information being collected during the use of fintech.	4.149	1.677	0.926
I am not concerned that the information I submit to fintech could be misused.	3.940	1.846	0.914
Trust (AVE=0.785, alpha=0.931, CR=0.948) (Geebren et al., 2021; Gefen, 2002)			
Fintech keeps its promises.	4.897	1.592	0.886
Fintech services meet my needs.	5.182	1.463	0.888
Fintech is trustworthy.	4.909	1.479	0.892
I think fintech is concerned with the present and future interests of users.	5.348	1.471	0.868
Overall, I trust fintech.	4.835	1.497	0.895
Attitude (AVE=0.849, alpha=0.911, CR=0.944) (Shin, 2017; Shin, 2019; Venkatesh et al., 2003)			
I have positive feelings toward fintech in general.	4.868	1.488	0.918
The thought of using fintech is appealing to me.	4.886	1.520	0.922
It would be a good idea to use fintech.	4.937	1.442	0.925

Intention to use (AVE=0.843, alpha=0.907, CR=0.942) (Shin, 2017; Shin, 2019; Venkatesh et al., 2012; Vijayasarathy, 2004)			
I intend to use fintech in the future.	4.892	1.348	0.925
I intend to visit fintech sites as much as possible.	4.760	1.470	0.909
I intend to continue using fintech in the future.	4.831	1.356	0.920

Note: N = 638, AVE=average variance extracted, alpha= Cronbach's alpha, CR=composite reliability, STD=standard deviation.

Table 2: Correlations and Discriminant Validity

Constructs	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Gender	–												
2. Age	0.11	–											
3. Education level	-0.06	0.05	–										
4. Marital status	-0.01	0.40	0.04	–									
5. Performance expectancy	0.03	0.08	0.01	0.15	***0.91***								
6. Effort expectancy	-0.03	0.04	0.05	0.07	0.18	***0.88***							
7. Social influence	0.00	0.04	0.02	0.08	0.65	0.12	***0.87***						
8. Facilitating conditions	0.08	0.05	-0.05	0.16	0.57	0.29	0.55	***0.91***					
9. Perceived security	0.09	0.03	-0.10	0.06	0.46	0.20	0.45	0.58	***0.91***				
10. Perceived privacy	0.09	0.01	-0.13	0.01	0.37	0.19	0.40	0.56	0.65	***0.92***			
11. Trust	0.02	0.06	-0.02	0.14	0.60	0.35	0.56	0.70	0.72	0.60	***0.89***		
12. Attitude	0.05	0.02	0.00	0.11	0.65	0.31	0.62	0.74	0.64	0.63	0.77	***0.92***	
13. Intention to use	0.02	0.06	0.00	0.13	0.64	0.32	0.62	0.70	0.58	0.55	0.73	0.75	***0.92***

Note: N = 638; boldface and italicized numbers denote the square root of the AVE of each construct

5.2. Hypothesis Testing

Figure 2 reports the results of our structural equation model. As shown in Figure 2, we found support for 13 of the 15 hypotheses, with nonsignificant results for the other two hypotheses. Table 3 summarizes both the hypothesized direct relationships and any mediating effects of attitude, facilitating conditions, and trust by decomposing the total effect of each parameter into direct and indirect effects. As shown and in line with UTAUT, the results suggest strong support for Hypotheses 1a, 1b, 1c, and 1d; these respectively indicate that the performance expectancy (b = 0.168, p < 0.001), effort expectancy (b = 0.053, p < 0.05), social influence (b = 0.128, p < 0.01), and facilitating conditions (b = 0.245, p < 0.001) enhance user attitudes toward adopting robo-advisors. There is also strong evidence for both Hypotheses 2a and 2b, thus suggesting that both attitude (b = 0.352, p < 0.001) and facilitating conditions (b = 0.242, p < 0.001) increase user intentions to adopt robo-advisors, respectively. Hypotheses 3a, 3b, and 3c propose that perceived security is positively associated with user trust in robo-advisors, facilitating conditions, and attitudes toward robo-advisors, respectively. As presented in Figure 2 and Table 3, the coefficient for perceived security on user trust is positive and statistically significant (b = 0.574, p < 0.001), thus providing strong support for Hypothesis 3a. However, there is no evidence for Hypothesis 3b, which predicts that perceived security is positively associated with facilitating conditions (b = 0.062, n.s.). There is also no evidence for Hypothesis 3c, which predicts that perceived security increases user attitudes toward robo-advisors (b = 0.041, n.s.). Therefore, both Hypotheses 3b and 3c are not supported. A plausible explanation for these peculiar findings is that it was not until recently that the majority of respondents began to pay attention to personal information security. While this seems plausible, the results of a recent survey conducted by the China Youth Daily demonstrated that this is not very likely. According to a survey by the China Youth Daily, 92% of respondents are very much worried about the security of their personal information and are therefore concerned about revealing their personal information. Chinese legislators and regulators have also adopted a specific new law on personal information protection and have increasingly implemented new rules or policies, respectively, to protect users' data security and personal information. Therefore, there is no reason to believe that Chinese consumers are not concerned about the security of their personal information. Given that perceived security is positively and significantly associated with trust, which in turn positively and significantly affects both attitude and facilitating conditions, it would seem plausible to expect that perceived security has no direct effect but an indirect effect on the facilitating conditions or attitudes via trust. It seems that there is no alternative explanation for the nonsignificant direct effects of perceived security on facilitating conditions or attitudes other than the plausibility of this argument supporting possible indirect effects of perceived security on facilitating conditions or attitudes through mediation of trust. We will assess and discuss the plausibility of this assumption of the two indirect effects in the following paragraphs.

Moreover, we test the respective contribution of perceived privacy to user trust, facilitating conditions, and attitudes toward robo-advisors. As indicated, there is strong evidence for Hypotheses 4a, 4b, and 4c, thus suggesting that perceived privacy is positively associated with user trust (b = 0.227, p < 0.001), facilitating conditions (b = 0.198, p < 0.001), and attitudes toward robo-advisors (b = 0.178, p < 0.001), respectively. We also examine Hypotheses 5a, 5b, and 5c by empirically testing the effects of user trust on facilitating conditions as well as both attitudes and intentions to adopt robo-advisors. The results in Figure 2 and Table 3 provide strong support for Hypotheses 5a, 5b, and 5c, thus indicating that user trust is positively and significantly associated with facilitating conditions (b = 0.535, p < 0.001), attitudes toward robo-advisors (b = 0.274, p < 0.001), and intentions to adopt robo-advisors (b = 0.282, p < 0.001), respectively.

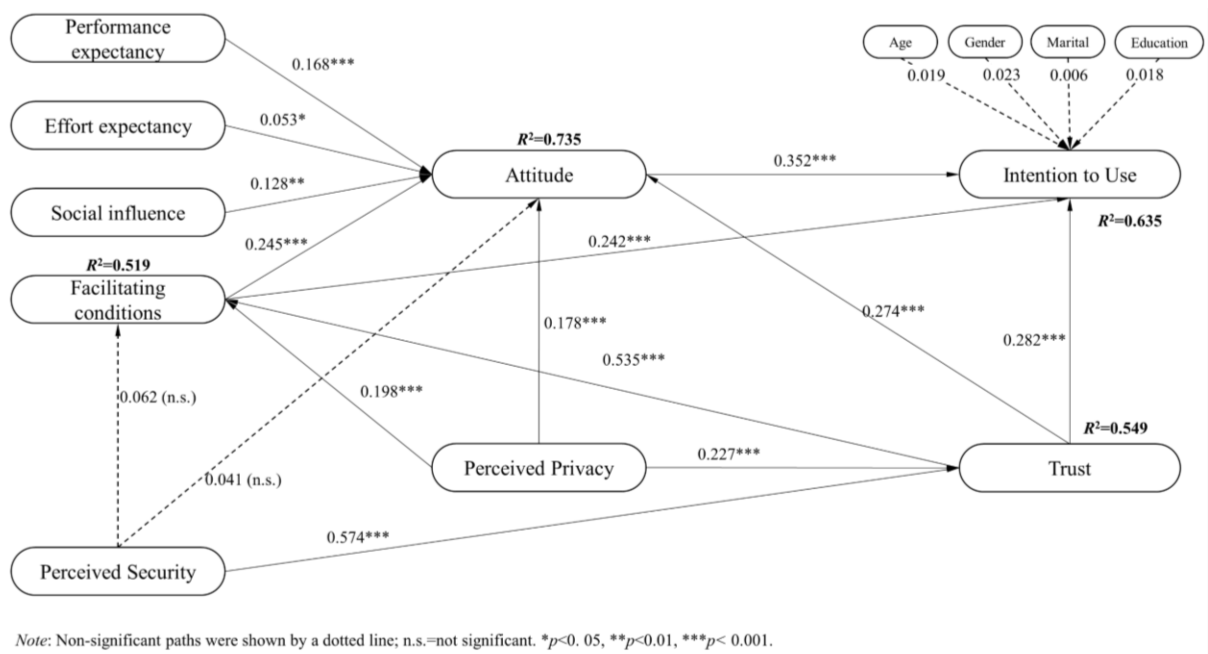

Figure 2: Estimated Results of the Structural Equation Analysis

Table 3: Results of Structural Model Assessment for Direct and Indirect Effects

Effects	Estimates	P-values
Direct effects		
H1a: Performance expectancy→Attitude	0.168	***
H1b: Effort expectancy→Attitude	0.053	*
H1c: Social influence→Attitude	0.128	**
H1b: Facilitating conditions→Attitude	0.245	***
H2a: Attitude→Intention to use	0.352	***
H2b: Facilitating conditions→Intention to use	0.242	***
H3a: Perceived security→Trust	0.574	***
H3b: Perceived security→Facilitating conditions	0.062	n.s.
H3c: Perceived security→Attitude	0.041	n.s.
H4a: Perceived privacy→Trust	0.227	***
H4b: Perceived privacy→Facilitating conditions	0.198	***
H4c: Perceived privacy→Attitude	0.178	***
H5a: Trust→Facilitating conditions	0.535	***

H5b: Trust→Attitude	0.274	***
H5c: Trust→Intention to use	0.282	***
Indirect effects		
Performance expectancy→Attitude→Intention to use	0.059	**
Effort expectancy→Attitude→Intention to use	0.019	*
Social influence→Attitude→Intention to use	0.045	**
Facilitating conditions→Attitude→Intention to use	0.086	***
Perceived security→Attitude→Intention to use	0.015	n.s.
Perceived privacy→Attitude→Intention to use	0.063	***
Trust→Attitude→Intention to use	0.097	***
Perceived security→Trust→Facilitating conditions	0.307	***
Perceived privacy→Trust→Facilitating conditions	0.122	***
Perceived security→Trust→Attitude	0.158	***
Perceived privacy→Trust→Attitude	0.062	***
Perceived security→Trust→Intention to use	0.162	***
Perceived privacy→Trust→Intention to use	0.064	**
Perceived security→Trust→Facilitating conditions→Attitude	0.075	***
Perceived privacy→Trust→Facilitating conditions→Attitude	0.030	**
Perceived security→Trust→Facilitating conditions→Intention to use	0.074	***
Perceived privacy→Trust→Facilitating conditions→Intention to use	0.029	**
Perceived security→Trust→Attitude→Intention to use	0.056	***
Perceived privacy→Trust→Attitude→Intention to use	0.022	**
Perceived security→Trust→Facilitating conditions→Attitude→Intention to use	0.027	***
Perceived privacy→Trust→Facilitating conditions→Attitude→Intention to use	0.011	**
Perceived security→Facilitating conditions→Attitude	0.015	n.s.
Perceived privacy→Facilitating conditions→Attitude	0.049	***
Perceived security→Facilitating conditions→Intention to use	0.015	n.s.
Perceived privacy→Facilitating conditions→Intention to use	0.048	**
Perceived security→Facilitating conditions→Attitude→Intention to use	0.005	n.s.
Perceived privacy→Facilitating conditions→Attitude→Intention to use	0.017	**
Trust→Facilitating conditions→Attitude	0.131	***
Trust→Facilitating conditions→Intention to use	0.129	***
Trust→Facilitating conditions→Attitude→Intention to use	0.046	***

Notes: $N = 638$; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; n.s. = not significant.

5.3. Post-hoc Analyses

Although it is beyond the scope of our study to examine the ideas of possible mediating effects in the model or discuss their implications in detail, we explore the potential indirect effects reported in Table 3 to provide a more comprehensive perspective on the phenomenon of interest. As indicated in Table 3, user attitudes play an important role in mediating the effects of performance expectancy (indirect effect: $b = 0.059$, $p < 0.01$), effort expectancy (indirect effect: $b = 0.019$, $p < 0.05$), social influence (indirect effect: $b = 0.045$, $p < 0.01$), and facilitating conditions (indirect effect: $b = 0.086$, $p < 0.001$) on user intentions to adopt robo-advisors. Similarly, the results in Table 3 suggest that attitude also plays an important role in mediating the effects of both perceived privacy (indirect effect: $b = 0.063$, $p < 0.001$) and trust (indirect effect: $b = 0.097$, $p < 0.001$) on user intentions to adopt robo-advisors. By contrast, as the coefficient for the direct effect of perceived security on attitude is positive but statistically insignificant ($b = 0.041$, $p < 0.001$), attitude does not serve as a mediator in the relationship between perceived security and user intentions to adopt robo-advisors (indirect effect: $b = 0.015$, n.s.). As indicated in Table 3, trust also plays a vital role in mediating the effects of perceived security and perceived privacy on consumers' attitudes (perceived security indirect effect: $b = 0.158$, $p < 0.001$; perceived privacy indirect effect: $b = 0.062$, $p < 0.001$) and intentions to adopt robo-advisors (perceived security indirect effect: $b = 0.162$, $p < 0.001$; perceived privacy indirect effect: $b = 0.064$, $p < 0.01$). In terms of the potential mediating role of trust, the results listed in Table 3 suggest that trust plays a crucial role in mediating the effects of both perceived security and perceived privacy on facilitating conditions (perceived security indirect effect: $b = 0.307$, $p < 0.001$; perceived privacy indirect effect: $b = 0.122$, $p < 0.01$), and user attitudes (perceived security indirect effect: $b = 0.075$, $p < 0.001$; perceived privacy indirect effect: $b = 0.030$, $p < 0.01$) and intentions to adopt robo-advisors (perceived security indirect effect: $b = 0.074$, $p < 0.001$; perceived privacy indirect effect: $b = 0.029$, $p < 0.01$) through the effects of facilitating conditions. These findings offer empirical evidence regarding the aforementioned plausibility of the argument supporting indirect effects of perceived security on facilitating conditions or attitudes via mediation of trust. These findings clarify why it is important to build trust between firms and users for user-perceived security to successfully produce positive effects on either the facilitating conditions or attitudes toward fintech services, such as robo-advisors. This significant evidence of the mediating role of trust illustrates that perceived security facilitates trust, which in turn influences successful realization of facilitating conditions or positive attitudes toward fintech services. The trust-building perceptions therefore offer a theoretical explanation for how perceived security influences facilitating conditions or user attitude by clearly underscoring the intermediary position of trust as an essential ingredient in the facilitating conditions or attitudes. Moreover, as noted in Table 3, we see that facilitating conditions play a decisive role in significantly mediating the effect of perceived privacy on user attitudes (indirect effect: $b = 0.049$, $p < 0.001$) and intentions to adopt robo-advisors (indirect effect: $b = 0.048$, $p < 0.01$), respectively. By contrast, as the coefficients for the indirect effects of perceived security on either user attitudes (indirect effect: $b = 0.015$, n.s.) or user intentions to adopt robo-advisors (indirect effect: $b = 0.015$, n.s.) via facilitating conditions are found to be positive but statistically insignificant, this indicates that facilitating conditions do not play a mediating role in the relationships between perceived security and user attitudes or intentions to adopt robo-advisors. Finally, we examine the possible mediating role of the facilitating conditions in the relationships between trust and either user attitudes or intentions to adopt robo-advisors. The results presented in Table 3 suggest that facilitating conditions play a positive and statistically significant mediating role in the relationships between trust and both attitude (trust indirect effect: $b = 0.131$, $p < 0.001$) and user intentions to adopt robo-advisors (trust indirect effect: $b = 0.129$, $p < 0.001$). More importantly, trust also exerts a positive and statistically significant effect on user intentions to adopt robo-advisors via user attitudes.

6. Discussion and Conclusion

6.1. Discussion

This study summarizes and compares the present findings with those of existing studies and theorizes them from our perspective. First, as hypothesized, the results partially confirm the effects of simultaneous consideration of UTAUT and TRA on robo-advisors. Several hypotheses were supported regarding the effects of perceived security, perceived privacy, and trust, which are psychological factors of the TRA, on UTAUT factors (H3, H4, and H5). Given that the attitudes toward fintech robo-advisors and intentions to use them are factors shared by both UTAUT and TRA, the simultaneous consideration hypotheses of the two theoretical models are H3b, H4b, and H5a. For the facilitating conditions, perceived security was insignificant, and the effects of perceived privacy and trust were each found to be significant (H4b and H5a, respectively). Since facilitating conditions are essential in connection with other theoretical models, the significance of consumers' privacy and trust is considered to be the contribution to those theories. A plausible reason for these findings is that the insignificance of perceived security can be interpreted as information that consumers entrust to the fintech service provider per se not helping to form positive attitudes or acting as prerequisites for activating a technological acceptance attitude (Chen et al., 2022). The manner in which consumer information is linked with other financial factors (e.g., current interest rates, stocks, and multiple indexes) can contribute to expanding this discussion, except for perceived security. In other words, there is a need for exploratory efforts to identify the potential factors specific to consumer information about fintech robo-advisors (Cheng et al., 2021). Second, the hypotheses about the effects of UTAUT and TRA were all supported. Although this finding is in line with existing literature on fintech robo-advisors from a technological point of view, the TRA in this study is a distinct approach owing to the psychological trust in digital technology (Shin, 2019). When consumers use fintech robo-advisors, our simultaneous consideration of factors represents the belief that the expected outcome is guaranteed against technological expectations and that the psychological binding to trust the technology plays a role. Examining the manner in which the results of our proposed research model vary when another psychological theory model is added, such as task-technology fit—which emphasizes whether trust in technology is appropriate for tasks—will further enrich the theory. Technically, gamification-related elements to the fintech robo-advisor may be another approach (Singh et al., 2020). Finally, trust as an indirect effect was verified to be statistically significant. These findings help validate the learnings from existing literature: trust is a positive conduit for prefactors, perceived security and privacy, facilitating conditions, attitudes, and intention to use fintech robo-advisors (Roh, Yang, et al., 2022). Therefore, through a post-hoc analysis, various mediating approaches to trust were verified in this study to enhance the understanding of how consumers sensitive to financial information accept and use the technological activation attributes.

6.2. Implications

Based on the two overarching theoretical lenses (i.e., UTAUT model and TRA), we aimed to identify the components influencing consumer intentions to use robo-advisors and the paths by which these factors affected this phenomenon. Before confirming our research framework, data were collected from Chinese consumers living in two regions of the Chinese mainland—Beijing and Shanghai—through a survey. Then, an empirical analysis was conducted using the partial least-squares structural equation modeling method. The examination verifies that most of our anticipations are in the expected direction, which adds theoretical contributions and informs us of useful practical implications as presented below.

To reiterate, as a theoretical basis, the UTAUT model was applied and extended considerably for researchers to predict the usage of information systems in various areas. As examples, the studies by Curtis et al. (2010), Verhoeven et al. (2010), and Welch et al. (2020) have applied the UTAUT to study "the adoption of social media," "computer use frequency," and "factors contributing to mobile learning adoption," respectively. All of these studies in e-commerce research showed meaningful results (Mou et al., 2019). Moreover, Hewitt et al. (2019), Wang and Wang (2010), and Chao (2019) extended the UTAUT model to explore "the acceptance of autonomous vehicles," "gender differences in mobile Internet acceptance," and "factors affecting students' behavioral intentions toward using mobile learning," respectively. In contrast to these studies, the present work additionally theoretically contributes through the fact that we applied and extended the framework of the model to adoption of robo-advisors in fintech; we also found that the UTAUT is useful in explaining the observations. In a similar vein as that discussed above, this study furthers the understanding of the TRA model by confirming the effects of users' perceived privacy on consumer attitudes to use fintech. This study enriches the literature on AI-enabled technologies by presenting fresh insights into the relationships between perceived privacy protection and customer fintech adoption. Specifically, this study feeds the theoretical model by elucidating the mediating role of trust in illustrating the TRA. To the best of our knowledge, this study is also a unique study exploring customer intentions to use fintech by bridging both theoretical models within the same research framework. In addition to these contributions, Park (2010) warned that the adoption of a fragmental approach observing a certain phenomenon is possibly at risk in that it may produce inexact results, and such an approach in the theoretical aspect (e.g., simple collection of empirical outcomes based on a single theory) is not an exception. By contrast, this study takes a holistic approach by employing multiple theories in a single empiric to draw an overall picture. This is another highlight of this study from the theoretical aspect.

For practical implications, our study offers a couple of useful suggestions for managers by presenting the conditions under which consumers adopt AI-enabled technologies. First, nobody can deny that most consumers are generally unfamiliar with AI-enabled technologies such as fintech, so managers should try to develop relevant technological innovations from the consumers' perspectives. In cases where firms neglect to cautiously consider when consumers accept and use technologies and their perceived privacy, firms may face difficulty in achieving consumers' adoption and subsequent enhancement of firm performance because the consumers will turn away from such services and look elsewhere. Second, our empirical results reveal that when services are associated with new technologies, consumer attitudes and their eventual use of the services are significantly influenced by trust. Consumers have a propensity to wish to remain anonymous and protect their privacy and tend to trust services, which do not harm demand. However, the reality is somewhat different, and as AI evolves, it often increases the ability to use personal information in ways that can intrude on privacy interests. Therefore, managers are also advised that safeguards should simultaneously be designed carefully to escalate mutual trust between firm services and consumers through data collection by means of AI.

6.3. Limitations and Future Research Directions

Despite the theoretical contributions and practical implications provided herein, this work has some limitations. First, our research context is restricted to Chinese consumers. As globalization intensifies, the consumers' buying attitudes and purchase behaviors converge considerably, even in various geographical markets. However, consumers in different countries still exhibit unique characteristics, so there is clearly a need to conduct extra empirical tests of the same research framework in idiosyncratic economies. Second, we collected survey data from large cities in China, specifically Beijing and Shanghai. However, the attributes of consumers in small- and medium-sized cities or nonurban regions of China may differ, thus indicating that such comparisons could represent an interesting future research avenue. Further, consumers' intentions to use AI-enabled technologies are possibly incongruent between gender and/or among industrial sectors. We believe that future researchers can conduct further comparative studies. Third, although we dealt with the effects of trust, privacy, and security of AI-enabled innovations, we do not know the positive and negative sides of the effects of e-commerce. Fourth, we empirically simultaneously considered two theories in fintech, which is one of the crucial emerging technologies. Although this is a valuable endeavor, we believe that it will extend our understanding if other researchers examine other burgeoning AI technologies, such as big data analytics and blockchain in e-commence. Finally, this study used a survey method to collect data, and we believe that data obtained from surveys often have typical shortcomings in that the respondents perceptually answer questionnaires. However, the lack of available qualitative data from in-depth interviews does allow us to triangulate our survey findings. Future researchers may employ a triangulation method to improve the research quality and make research results more credible using data collected from different sources, for example, both quantitative and qualitative data from semistructured interviews with robo-advisor users and archival data from any corporate documents, annual reports, and press releases.

Acknowledgments

This work was supported by Sookmyung Women's University Research Grants. This work was also partially supported by Hankuk University of Foreign Studies Research Funds.

REFERENCES

Al-Okaily, M., Lutfi, A., Alsaad, A., Taamneh, A., & Alsyouf, A. (2020). The determinants of digital payment systems' acceptance under cultural orientation differences: The case of uncertainty avoidance. *Technology in Society*, *63*, 101367. https://doi.org/https://doi.org/10.1016/j.techsoc.2020.101367

Albarracin, D., & Ajzen, I. (2007). Predicting and changing behavior: A reasoned action approach. In I. Ajzen, D. Albarracin, & R. Hornik (Eds.), *Prediction and change of health behavior: Applying the reasoned action approach* (pp. 3-21). Lawrence Erlbaum Associates Publishers.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*(3), 396-402.

Balapour, A., Nikkhah, H. R., & Sabherwal, R. (2020). Mobile application security: Role of perceived privacy as the predictor of security perceptions. *International Journal of Information Management*, *52*, 102063.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, *119*(7), 1411-1430.

Bernstein, D. A., Penner, L. A., Clarke-Stewart, A., Roy, E. J., & Wickens, C. D. (2000). *Psychology*. Houghton Mifflin Company.

Brown, S. A., Venkatesh, V., & Hoehle, H. (2015). Technology adoption decisions in the household: A seven ‐ model comparison. *Journal of the Association for Information Science and Technology*, *66*(9), 1933-1949.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2007). The role of security, privacy, usability and reputation in the development of online banking. *Online Information Review*, *31*(5), 583-603.

Chang, S.-J., Witteloostuijn, A. v., & Eden, L. (2020). From the editors: Common method variance in international business research. *Journal of International Business Studies*, *41*(2), 174-184.

Chao, C.-M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in Psychology*, *10*, 1652.

Chen, Y., Chiu, J., & Chung, H. (2022). Givers or receivers? Return and volatility spillovers between Fintech and the traditional financial industry. *Finance Research Letters*, *46*, 102458.

Cheng, X., Bao, Y., Zarifis, A., Gong, W., & Mou, J. (2021). Exploring consumers' response to text-based chatbots in e-commerce: The moderating role of task complexity and chatbot disclosure. *Internet Research*, *32*(2), 496-517.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Eesearch*, *295*(2), 295-336.

Curtis, L., Edwards, C., Fraser, K. L., Gudelsky, S., Holmquist, J., Thornton, K., & Sweetser, K. D. (2010). Adoption of social media for public relations by nonprofit organizations. *Public relations review*, *36*(1), 90-92.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-339.

de Matos, C. A., Curth, M., & dos Santos Garcia, A. (2020). Customer loyalty in the online context: Understanding trust in different parties. *Journal of Electronic Commerce Research*, *21*(4), 237-251.

Deloitte. (2017). *Hands off guard up: Robo-advising platforms carry new risks*. Deloitte. Retrieved from: https://www2.deloitte.com/content/dam/Deloitte/us/Documents/risk/us-robo-adviser-platform-risks-asset-wealth-management-firms.pdf

Doswell, W. M., Braxter, B. J., Cha, E., & Kim, K. H. (2011). Testing the theory of reasoned action in explaining sexual behavior among African American young teen girls. *Journal of Pediatric Nursing*, *26*(6), e45-e54.

Erjavec, J., & Manfreda, A. (2022). Online shopping adoption during COVID-19 and social isolation: Extending the UTAUT model with herd behavior. *Journal of Retailing and Consumer Services*, *65*, 102867.

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

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. Psychology Press.

Fornell, C., & Cha, J. (1994). Partial least squares. In R. P. Bagozzis (Ed.). Blackwell.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Geebren, A., Jabbar, A., & Luo, M. (2021). Examining the role of consumer satisfaction within mobile eco-systems: Evidence from mobile banking services. *Computers in Human Behavior*, *114*, 106584.

Gefen, D. (2002). Nurturing clients' trust to encourage engagement success during the customization of ERP systems. *Omega*, *30*(4), 287-299. https://doi.org/https://doi.org/10.1016/S0305-0483(02)00032-4

Geisser, S. (1975). The predictive sample reuse method with applications. *Journal of the American statistical Association*, *70*(350), 320-328.

Goh, C. (2020). *Robo-advisers catching on in China, industry looks poised for growth*. S&P Global. Retrieved from: https://www.spglobal.com/marketintelligence/en/news-insights/research/robo-advisers-catching-on-in-china-industry-looks-poised-for-growth#:~:text=Roughly%2038%25%20of%20adult%20internet,interest%20in%20using%20robo%2Dadvisers

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135.

Hewitt, C., Politis, I., Amanatidis, T., & Sarkar, A. (2019). Assessing public perception of self-driving cars: The autonomous vehicle acceptance model. *Proceedings of the 24th international conference on intelligent user interfaces*.

Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International Journal of Medical Informatics*, *101*, 75-84.

Huarng, K.-H., & Yu, T. H.-K. (2022). Causal complexity analysis for fintech adoption at the country level. *Journal of Business Research*, *153*, 228-234.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal*, *20*(2), 195-204.

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

Iman, N. (2018). Is mobile payment still relevant in the fintech era? *Electronic Commerce Research and Applications*, *30*, 72-82.

Jeong, J., & Roh, T. (2017). The intention of using wearable devices: Based on modified technology acceptance model. *Journal of Digital Convergence*, *15*(4), 205-212.

Johnson, R. E., Rosen, C. C., & Djurdjevic, E. (2011). Assessing the impact of common method variance on higher order multidimensional constructs. *Journal of Applied Psychology*, *96*(4), 744-761.

Jonker, N. (2019). What drives the adoption of crypto-payments by online retailers? *Electronic Commerce Research and Applications*, *35*, 100848.

Jünger, M., & Mietzner, M. (2020). Banking goes digital: The adoption of FinTech services by German households. *Finance Research Letters*, *34*, 101260.

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

Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Computers in Human Behavior*, *70*, 460-474.

Kim, D., Park, K., Park, Y., & Ahn, J.-H. (2019). Willingness to provide personal information: Perspective of privacy calculus in IoT services. *Computers in Human Behavior*, *92*, 273-281.

Kim, K. H., & Yun, H. (2007). Cying for me, cying for us: Relational dialectics in a Korean social network site. *Journal of Computer-Mediated Communication*, *13*(1), 298-318. https://doi.org/10.1111/j.1083-6101.2007.00397.x

Kim, Y., Wang, Q., & Roh, T. (2021). Do information and service quality affect perceived privacy protection, satisfaction, and loyalty? Evidence from a Chinese O2O-based mobile shopping application. *Telematics and Informatics*, *56*, 101483.

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. Guilford Press.

KPMG. (2022). *Pulse of Fintech H2 2021*. KPMG. Retrieved from: https://home.kpmg/xx/en/home/insights/2022/01/pulse-of-fintech-h2-21-aspac.html

Kwon, W.-S., Woo, H., Sadachar, A., & Huang, X. (2021). External pressure or internal culture? An innovation diffusion theory account of small retail businesses' social media use. *Journal of Retailing and Consumer Services*, *62*, 102616.

Lee, J. M., & Kim, H. J. (2020). Determinants of adoption and continuance intentions toward Internet-only banks. *International Journal of Bank Marketing*, *38*(4), 843-865.

Miyazaki, A. D., & Fernandez, A. N. A. (2001). Consumer perceptions of privacy and security risks for online shopping. *Journal of Consumer Affairs*, *35*(1), 27-44. http://www.jstor.org/stable/23860070

Mombeuil, C. (2020). An exploratory investigation of factors affecting and best predicting the renewed adoption of mobile wallets. *Journal of Retailing and Consumer Services*, *55*, 102127.

Mou, J., Cui, Y., & Kurcz, K. (2019). Bibliometric and visualized analysis of research on major e-commerce journals using Citespace. *Journal of electronic commerce research*, *20*(4), 219-237.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, *64*(1), 12–40.

Park, B. I., & Xiao, S. (2020). Is exploring dynamic capabilities important for the performance of emerging market firms? The moderating effects of entrepreneurial orientation and environmental dynamism. *International Studies of Management & Organization*, *50*(1), 57-73.

Park, B. I., & Xiao, S. S. (2021). Doing good by combating bad in the digital world: Institutional pressures, anti-corruption practices, and competitive implications of MNE foreign subsidiaries. *Journal of Business Research*, *137*, 194-205.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903.

Richter, N. F., Cepeda-Carrion, G., Roldán Salgueiro, J. L., & Ringle, C. M. (2016). European management research using partial least squares structural equation modeling (PLS-SEM). *European Management Journal*, *34*(6), *589-597.*

Rios, R., Fernandez-Gago, C., & Lopez, J. (2018). Modelling privacy-aware trust negotiations. *Computers & Security*, *77*, 773-789. https://doi.org/https://doi.org/10.1016/j.cose.2017.09.015

Roh, T., Seok, J., & Kim, Y. (2022). Unveiling ways to reach organic purchase: Green perceived value, perceived knowledge, attitude, subjective norm, and trust. *Journal of Retailing and Consumer Services*, *67*, 102988.

Roh, T., Yang, Y. S., Xiao, S., & Park, B. I. (2022). What makes consumers trust and adopt fintech? An empirical investigation in China. *Electronic Commerce Research*, *forthcoming*.

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

Senyo, P. K., & Osabutey, E. L. (2020). Unearthing antecedents to financial inclusion through FinTech innovations. *Technovation*, *98*, 102155.

Shanmuganathan, M. (2020). Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions. *Journal of Behavioral and Experimental Finance*, *27*, 100297.

Shin, D.-H. (2017). Conceptualizing and measuring quality of experience of the internet of things: Exploring how quality is perceived by users. *Information & management*, *54*(8), 998-1011.

Shin, D. D. (2019). Blockchain: The emerging technology of digital trust. *Telematics and Informatics*, *45*, 101278.

Shin, D. H. (2010). The effects of trust, security and privacy in social networking: A security-based approach to understand the pattern of adoption. *Interacting with Computers*, *22*(5), 428-438. https://doi.org/10.1016/j.intcom.2010.05.001

Shin, D. H. (2011). Understanding e-book users: Uses and gratification expectancy model. *New Media & Society*, *13*(2), 260-278. https://doi.org/10.1177/1461444810372163

Shin, D. H. (2013). User experience in social commerce: In friends we trust. *Behaviour & Information Technology*, *32*(1), 52-67. https://doi.org/10.1080/0144929X.2012.692167

Singh, S., Sahni, M. M., & Kovid, R. K. (2020). What drives FinTech adoption? A multi-method evaluation using an adapted technology acceptance model. *Management Decision*, *58*(8), 1675-1697.

Singh, S., Sahni, M. M., & Kovid, R. K. (2021). Exploring trust and responsiveness as antecedents for intention to use FinTech services. *International Journal of Economics and Business Research*, *21*(2), 254-268.

Smith, H. J., Dinev, T., & Xu, H. (2011). Information privacy research: An interdisciplinary review. *MIS Quarterly*, *35*(4), 989-1015.

Statista. (2022). *Robo-advisors - Worldwide*. Statista. Retrieved from: https://www.statista.com/outlook/dmo/fintech/digital-investment/robo-advisors/worldwide#users

Stone, M. (1974). Cross‐validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, *36*(2), 111-133.

Tokic, D. (2018). BlackRock robo‐advisor 4.0: When artificial intelligence replaces human discretion. *Strategic Change*, *27*(4), 285-290.

Tripathy, A. K., & Jain, A. (2020). FinTech adoption: strategy for customer retention. *Strategic Direction*, *36*(12).

Venaik, S., Midgley, D. F., & Devinney, T. M. (2005). Dual paths to performance: The impact of global pressures on MNC subsidiary conduct and performance. *Journal of International Business Studies*, *36*(6), 655-675.

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

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

Verhoeven, J. C., Heerwegh, D., & De Wit, K. (2010). Information and communication technologies in the life of university freshmen: An analysis of change. *Computers & Education*, *55*(1), 53-66.

Vijayasarathy, L. R. (2004). Predicting consumer intentions to use on-line shopping: The case for an augmented technology acceptance model. *Information & Management*, *41*(6), 747-762.

Wang, H.-Y., & Wang, S.-H. (2010). User acceptance of mobile internet based on the unified theory of acceptance and use of technology: Investigating the determinants and gender differences. *Social Behavior and Personality: An International Journal*, *38*(3), 415-426.

Wang, Z., Zhengzhi Gordon, G., Hou, F., Li, B., & Zhou, W. (2019). What determines customers' continuance intention of FinTech? Evidence from YuEbao. *Industrial Management & Data Systems*, *119*(8), 1625-1637.

Warshaw, P. R., & Davis, F. D. (1985). Disentangling behavioral intention and behavioral expectation. *Journal of Experimental Social Psychology*, *21*(3), 213-228.

Welch, R., Alade, T., & Nichol, L. (2020). Using the unified theory of acceptance and use of technology (UTAUT) model to determine factors affecting mobile learning adoption in the workplace: A study of the science museum group. *IADIS International Journal on Computer Science and Information Systems*, *15*(1), 85-98.

Xiao, S. S., Lew, Y. K., & Park, B. I. (2021). International new product development performance, entrepreneurial capability, and network in high-tech ventures. *Journal of Business Research*, *124*, 38-46.

Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: Implications for designing mobile shopping services. *Journal of Consumer Marketing*, *27*(3), 262-270.

Yu, C.-S. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research*, *13*(2), 104-121.

Zott, C., & Amit, R. (2008). The fit between product market strategy and business model: implications for firm performance. *Strategic Management Journal*, *29*(1), 1-26.