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MANAGING CONSUMERS' ADOPTION OF ARTIFICIAL INTELLIGENCE-BASED FINANCIAL ROBO-ADVISORY SERVICES: A MODERATED MEDIATION MODEL

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ABSTRACT

Introduction/Main Objectives: This study investigates the determinants of willingness to use financial robo-advisory services. The study aims to identify the intertwined roles of perceived value, perceived risk, and perceived financial knowledge in consumers' acceptance of financial robo-advisory services. **Background Problem:** Fintech and AI-based applications have opened up new prospects for financial management, but studies into the adoption and implementation of robo-advisors are limited and scant. **Novelty:** The study offers novel insights by exploring the direct and indirect effects of perceived value and risk on consumer decisions around adopting robo-advisory services. The study also identifies other major drivers of robo-advisory service adoption and formulates a comprehensive model. **Research Methods:** A quantitative method using a deductive approach was applied, with PLS-SEM performed on a sample of 285 respondents from Bangladesh. The sample was gathered using a purposive sampling method. **Findings/Results:** Findings revealed that while relative advantage and perceived innovativeness positively affected perceived value and adoption intention, complexity negatively impacted perceived value and adoption intention. The findings also highlighted that attitude had a negative effect on perceived risk and intention to adopt robo-advisory services. The mediating impact of perceived value and risk in predicting the relationship between relative advantage, attitude and behavioral intention to adopt robo-advisory services was also identified. Moreover, the study revealed that perceived financial knowledge moderated the relationship between perceived value and behavioral intention. **Conclusion:** This study contributes to the existing body of literature by showing the intertwined roles of perceived value, perceived risk, and perceived financial knowledge in consumer acceptance of robo-advisory services. The study provides meaningful insights for financial institutions, and policymakers seeking to make robo-advisory services more reliable and acceptable to consumers through innovative service design and positioning.

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INTRODUCTION

A financial robo-advisor is a digitalized platform that offers investment management services using automated and artificial intelligence-based algorithms, with little or no human intervention (Gan et al., 2021). There has been considerable recent scholarly interest in financial robo-advisors due to the increasing demand for low-cost portfolio management systems in the financial sector. Industry sectors ranging from manufacturing and retail to service providers are all being transformed by robots and artificial intelligence (AI).

Long-held economic and labor norms are threatened by such a technological revolution, with the adoption of automated technologies growing at a 31% annual rate according to the International Federation of Robotics (2022). This growth rate would see half of all occupations currently performed by people replaced over the next two decades (Acemoglu and Restrepo, 2017). Similarly, financial technology, commonly known as fintech, is emerging as a critical component of strategy development for financial start-up companies and banks (Muthukannan et al., 2022).

Fintech encompasses more than just e-banking and the digitalization of the customer experience. Fundamentally, it emphasizes the creation and effective implementation of new technological instruments to fulfill customers' financial requirements as well as their desires (Budiarani et al., 2021; Ashrafi et al., 2022). Therefore, considering the context, artificial intelligence offers clear potential to accelerate the financial industry's transformation through enhanced value for customers and increased profits for businesses (Gupta et al., 2022). For instance, a chatbot named Erica helps the Bank of America's more than one million customers with simple financial inquiries (Rosman, 2018). Moreover, at various branches of the Bank of Tokyo, a tiny humanoid named Nao serves as a customer service representative alongside actual bank personnel (Rahman et al., 2021). Nevertheless, fintech's most disruptive innovation has been the use of artificial intelligence (AI) commonly referred to as "robo-advisors" to automate or assist in managing investments.

A significant advantage of robo-advisory services over conventional human advisors is the reduction in fees and availability of financial information at any time of day or night, 24/7 (Bajwa et al., 2022). Abrardi et al. (2022) suggest that these self-driving technologies will make financial advisory services more accessible to a larger consumer base. Hence, in order to stay ahead of the competition, financial institutions have started launching automated investment advisors. As per Statista (2022), it was expected that industry assets under robo-advisor management would total \$1.66 trillion in 2022. Increasing at a rate of over 14.19% annually, this market is forecast to reach \$3.22 trillion by 2027 (Statista, 2022). However, customer acceptance of financial robo-advisory services has thus far been limited, and commercialization could be slowed if consumers hold a negative attitude toward such novel services (Tiberius et al., 2022; Gupta et al., 2012). This innovative system, which replaces traditional financial management services, has attracted only a limited number of early users (Laukkanen and Pasanen, 2008). Ryu (2018) suggests that after the first wave of early adopters, firms have struggled to expose the service to a wider target group that may be reluctant to realize the benefits of using these technologies. Hence, to help maintain and attract present and future customers, managers need assistance with the successful implementation of robo-advisors.

Fintech and AI-based applications have opened up new prospects, but studies into the implementation of these robo-advisors are limited and scant. Most studies in this field have concentrated on technical or legal concerns, disregarding the consumer perspective (Tiberius et al., 2022; Bhatia et al., 2021; Glaser *et al.*, 2019; Khan and Hashim, 2021), even though this would assist in increasing the number who may utilize robo-advisory services. While studies on robo-advisory service designs are limited (Bhatia et al., 2021; Tiberius et al., 2022), the existing literature shows these systems need to be made more user-friendly for effective interaction with the users (Yeh et al., 2022). However, due to the potential for extensive robo-advisor development, there is a need for a comprehensive, systematic, and holistic model that can provide meaningful insights into the key drivers and motivations for adoption of robo-advisory services by a diverse customer base.

Previous studies in the field of robo-advisory services have adopted various models such as UTAUT, UTAUT2, the innovation resistance model, and TAM (technology acceptance model) to explain consumer behavior toward robo-advisory services. For instance, Yeh et al. (2022) and Gan et al. (2021) apply the UTAUT model to explore intentions to use robo-advisory services, while Figà-Talamanca et al. (2022) incorporate the TAM model to explain consumer acceptance of such novel technology. Manrai and Gupta (2022) and Susilo et al. (2022) extend the TAM model by adding constructs such as trust, perceived behavioral control, perceived risk, and subjective norms. Furthermore, Kwon et al. (2022) combine the innovation resistance model and TAM to explore the impact of factors such as social presence, customization, transparency, and perceived safety on adoption intentions. However, existing studies have ignored the direct role of perceived innovativeness and the mediating effects of perceived value and risk in determining adoption intentions toward robo-advisory services. One study conducted in Malaysia by Gan et al. (2021) explores perceived financial knowledge as an exogenous construct impacting consumers' behavioral intention to adopt financial robo-advisory services. However, no prior study has identified the moderating effect of perceived financial knowledge on the relationship between perception of value and adoption intention. To bridge this significant research gap, this study proposes a comprehensive framework incorporating the pivotal determinants of consumer acceptance of AI-based financial robo-advisors as part of the innovative endeavor.

The goal of this study set in Bangladesh is to examine how complexity, hedonic value, and relative advantage affect perceived value, which in turn affects consumer behavioral intentions toward adopting robo-advisory services. The study also intends to explore the direct impact of perceived innovativeness, perceived value, perceived risk, attitude, and the mediating impact of consumers' value and risk perceptions in determining their acceptance of financial robo-advisory services. The study also intends to explore the moderating effect of perceived financial knowledge in the association between perceived value and consumer inclinations toward adopting robo-advisory services. While the disruptive nature of robo-advisory services is clear, the proposed research model seeks to make predictions about drivers and barriers for consumer adoption of AI-based robo-advisory services.

The contributions of this study are as follows. Firstly, the study provides theoretical depth by proposing the direct and indirect effects of perceived value and risks on consumer decisions to adopt robo-advisory services. Consumers' risk and value perceptions are therefore proposed as mediators since the literature has thus far paid limited attention to their impact in the context of financial technology-based services (Nourallah et al., 2022; Kwon et al., 2022). Secondly, the study makes a contribution to the current literature on AI-based financial robo-advisory service acceptance by integrating perceived financial knowledge as a moderating component. Consumers' financial ability and knowledge vary, and the study framework suggests that perceived financial knowledge may play a moderating role in their decisions with regard to using such novel technology. Consumers who have better financial knowledge are more likely to prioritize their value perceptions, whereas customers with less financial knowledge are more likely to resist the idea of making investment decisions through AI-based robo-advisory services. Thirdly, the study integrates perceived innovativeness into the model. Existing studies have highlighted the influence of perceived innovativeness in determining users' behavioral intentions in various contexts (Jiang et al., 2022; Ashrafi and Easmin, 2023). However, no prior studies have addressed the effect of perceived innovativeness in the context of robo-advisory service adoption. Thus, this study contributes by examining the role of perceived innovativeness in determining adoption intentions with regard to the use of robo-advisory services. Furthermore, businesses need to better understand their customers' requirements and desires for the purpose of successfully introducing robo-advisory services in response to the transformation of the financial sector. Empirical evidence to support the use of robo-advisors is currently lacking. This study enhances the existing body of literature by evaluating the significance of major drivers of consumers' choice to use robo-advisory services and analyzing how the adoption process and consumer behavioral intentions are affected by perceptions of risk and value. Lastly, this study contributes by improving the existing knowledge regarding consumer attitudes toward robo-advisory services, supporting effective AI-driven innovation implementation that benefits companies and both existing and potential users.

The paper is structured as follows. After a brief introduction, the proposed conceptual framework is presented, followed by the development of hypotheses. Next, details on the data collection procedure and methodology are provided. The key findings are then presented, followed by a discussion section. The last section outlines the study's implications for theory and practice, as well as highlighting the study's limitations and future research directions.

REVIEW OF LITERATURE AND DEVELOPMENT OF RESEARCH FRAMEWORK

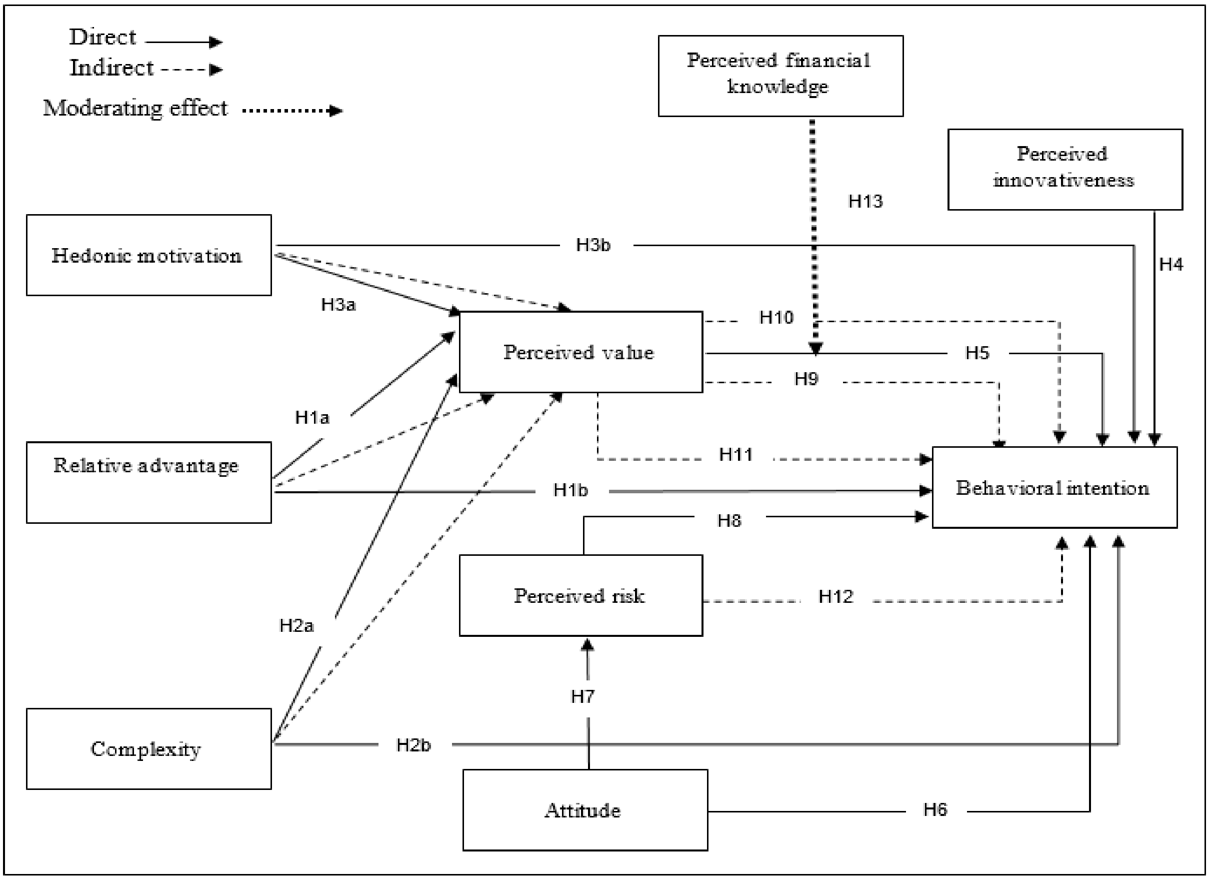
1. Understanding Robo-Advisory Services and Customers' Behavioral Adoption

Robo-advisory services are delivered in a digital environment and include interactive and dynamic user support components that employ IT (information technology) in an automated financial advisory process (Manrai and Gupta, 2022). Using this technology-based solution, the customer's profile is first evaluated via a simple introductory questionnaire that includes questions about risk appetite, goals, and return expectations. Next, the service begins to make precise recommendations regarding investment management, just like human financial advisors. However, such services provide investment-related suggestions using artificial intelligence. There are numerous advantages of robo-advisors over human advisors, including better access to financial services in terms of time, location and lower management costs. Robo-advisors also offer a more extensive range of investment alternatives based on quantitative and systematic assessments that are free from ulterior motives (Tiberius et al., 2022). As per Statista (2022), the number of users of robo-advisory services is anticipated to reach 543.167 million by 2027.

According to Belanche et al. (2019), such new services are being introduced by banks and financial institutions to gain a competitive edge and reach a larger audience.

Although this innovative investment alternative has been gaining attention, the literature on robo-advisor implementation is still limited. Thus far, research has focused predominantly on legal issues and risk management perspectives in relation to using robo-advisory services (Bhatia et al., 2021; Khan and Hashim, 2021; Glaser et al., 2019). As outlined by Muthukannan et al. (2022) and Bhatia et al. (2021), while lay people are skeptical of AI-driven platforms like robo-advisors, financial institutions are becoming increasingly enthusiastic about fintech and the prospect of launching robo-advisors. In other studies, Yeh et al. (2022) and Jung et al. (2018) report that improved robo-advisory service design (particularly in terms of form and usability) is necessary to encourage potential customers to accept and adopt this innovation. Compared to traditional human advisory services, robo-advisors are distinguished by their ability to provide customization (Tiberius et al., 2022). Talha et al. (2022) also suggest that advice related to information technology will improve consumers' learning and help them make better financial decisions. However, because robo-advisory services are new, not much is known about the key factors determining customers' behavioral intention toward using and accepting AI-based robo-advisory services.

Figure 1: Research framework



Source: Author's own illustration

To address this research gap, we explore a comprehensive research framework that includes hedonic motivation, relative advantage, and complexity as antecedents affecting perceived value and perceived innovativeness, which in turn influence behavioral intention to use robo-advisory services. Additionally, we propose that attitude influences perceived risk and so also has a direct impact on behavioral intention. This study further suggests that both perceived risk and value can act as exogenous and mediating variables, influencing consumers' behavioral intentions. Furthermore, perceived financial knowledge is proposed as a moderating variable in the relationship between perception of value and adoption intentions.

2 Rationalization of Research Framework Design

UTAUT2 is a theoretical framework widely used to predict and explain technology acceptance and usage behavior. It is an extension of the original UTAUT model and includes four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. Hedonic motivation is among the constructs added to the extended model (UTAUT2). While TAM's perceived ease of use and perceived usefulness are similar to the effort expectancy and performance expectancy constructs in UTAUT, there are important differences between the two models (Iskender et al., 2022). TAM focuses on the cognitive aspects of technology adoption and usage, whereas UTAUT takes a more holistic approach that includes social, cultural, and organizational factors that can influence adoption behavior. However, UTAUT2 has limitations as it does not fully capture the contextual factors that influence adoption behavior (Shachak et al., 2019), including the perceived value and risks of a particular technology in relation to existing alternatives. Therefore, researchers have attempted to integrate these consumption attributes into an adoption model. Additionally, the inclusion of hedonic motivation in UTAUT2 helps to account for the emotional and subjective aspects of customers' decision-making when it comes to using financial robo-advisory services. This is particularly relevant in the context of financial robo-advisory services as customers are likely to use such services not only for practical purposes, but also for the satisfaction of achieving their financial goals. The Diffusion of Innovation Theory, developed by Rogers (1995), is a framework used to understand how new technologies are adopted and diffused over time, and includes factors such as perceived relative advantage and complexity of a new technology. The theory explains the rate at which new ideas and products spread through a population or social system. Relative advantage and complexity are important in understanding customers' perceptions of the benefits and challenges associated with using financial robo-advisory services. These constructs can help researchers better understand customers' attitudes and beliefs about these services and how they compare to other options available to them.

In the case of financial robo-advisory services, consumers may already be familiar with technology-enabled financial services such as online banking or mobile payment services. Therefore, the degree to which robo-advisory services are perceived as compatible with existing financial behaviors and values may be relatively high. However, it may not be feasible or desirable for consumers to experiment with the service on a limited basis due to the significant financial consequences of investment decisions. Additionally, the benefits of using robo-advisory services may be less tangible or visible to others, as investment decisions are often made in private and not easily observable. While compatibility, trial ability, and observability are important constructs in the Diffusion of Innovation theory, their relevance and applicability to investigations of consumer intentions to adopt financial robo-advisory services may be limited and therefore are excluded from this study.

The Theory of Reasoned Action (TRA) and its extension, the Theory of Planned Behavior (TPB), are other models widely used in social psychology to explain human behavior. According to TRA and TPB, attitudes and subjective norms are key determinants of behavioral intentions, which in turn drive actual behavior (Ajzen, 1991; Fishbein, 1979). However, the presence of other situational factors can also influence behavior. In this study, we argue for perceived risk as a situational factor that influences the relationship between attitude and behavioral intention. We propose perceived risk as a mediator rather than an antecedent of attitude because a negative attitude toward robo-advisory services may give rise to perceived risk in many forms, including the risk of losing money, the risk of not achieving one's financial goals, or the risk of data breaches and cyber-attacks, ultimately reducing the intention to adopt such novel technologies. We propose that a consumer who has a positive attitude toward the service may still hesitate to use it if they perceive high levels of risk associated with it. Therefore, within the context of financial robo-advisory services, it is reasonable to argue that perceived risk can mediate the relationship between attitude and behavioral intention. Hence, perceived risk is included as a mediator in this study instead of an antecedent of attitude. Furthermore, perceived innovativeness is subjective and can change over time and across different contexts, and therefore may not be stable as a moderating variable. This could limit the reliability and validity of the findings, as its impact may vary depending on the specific context and time period in which the study is conducted. Therefore, perceived innovativeness is not included as a moderating variable in this study.

Additionally, although perceived value is a key factor determining intention to use robo-advisory services, we argue this relationship may differ for users with varying levels of financial knowledge. Therefore, by exploring how perceived financial knowledge moderates the relationship between consumers' value perceptions and adoption intentions, we can provide a more accurate understanding of the adoption behavior of robo-advisory services among different user groups. Hence, perceived financial knowledge is used as a moderating variable in this study. This study integrates components from both UTAUT2 and DOI to form a comprehensive model that takes into account both cognitive and emotional factors to better understand technology adoption behavior. Furthermore, we also integrate additional factors such as perceived value and risk into the adoption model to fully capture all contextual factors influencing adoption of financial robo-advisory services.

HYPOTHESES DEVELOPMENT

1. Relative Advantage

Relative advantage refers to the degree to which an innovation enhances efficiency, economic advantage, and status in comparison to previous innovations (Rogers, 1995). The terms "relative advantage" and "perceived usefulness" are often used interchangeably in scholarly work and treated as identical constructs (Moore and Benbasat, 1991). However, according to Wang et al. (2006), in situations where other technologies are readily available, it may be challenging to explain or anticipate the adoption of a novel technology if its relative advantage is treated as identical to its perceived usefulness. Consequently, Wang et al. (2008) reexamined the term "relative advantage" against perceived usefulness to identify fundamental distinctions between the two constructs. The utilitarian benefits to one's job performance are the main determinant of perceived usefulness, whereas other factors such as economic profitability, savings in time and effort, social prestige, reduction in discomfort, initial cost, and immediacy of reward also contribute to relative advantage, making the two constructs conceptually different. According to Kavota et al. (2020) and Rogers (1995), relative advantage is the extent to which the benefits of an innovation exceed those of its predecessor. Meyer-Waarden and Cloarec (2022) further suggest that people are more likely to adopt a new innovation if they think it will improve their lives. As such, in this study relative advantage relates to the extent to which people feel they will benefit from utilizing online platforms created for wealth and investment management compared to using traditional investment management systems.

When an individual makes the decision to adopt a novel technology, they make comparisons between multiple innovations and relative advantage plays a significant role in making such a decision. Hence, relative advantage is incorporated into the model. As previously stated, the "received" component of perceived value relates to the relative advantages users may derive from using fintech. As discussed by Venkatesh et al. (2003), adoption behavior is influenced by the desire for external benefits, which in turn is connected with the "received" component of perceived value. Previous research in the contexts of manufacturing, augmented reality, ride-sharing platforms, mobile banking and applications has shown that the relative advantage both positively and significantly impacts consumers' adoption intentions and value perceptions (Ashrafi and Easmin, 2023; Alam et al., 2022; Mehra et al., 2021; Lin et al., 2020). Consequently, in the context of robo-advisory services, it can be assumed that perceived value and adoption intent are affected by relative advantage. To put it simply, if adopting such technology provides individuals with a greater relative advantage, this will be viewed as valuable and enhance their intent to adopt robo-advisory services. Hence, we hypothesize that:

H1a: The perceived value of adopting robo-advisory services will be higher with the increase in relative advantage received by individuals.

H1b: Higher levels of relative advantage will increase an individual's intention to adopt robo-advisory services.

2. Complexity

Complexity refers to how hard it is for people to understand and use a technology (Rogers, 1995; Venkatesh et al., 2012), and innovation adoption rate is inversely associated with complexity. Although "complexity" and "ease of use" are frequently treated as similar terms in prior literature, there is a conceptual distinction between a person's appraisal of a task's complexity and their estimation of the amount of effort required to accomplish that task (Plouffe et al., 2001; Reynolds and Ruiz de Maya, 2013). We argue that complexity and perceived ease of use are distinct constructs because first, perceived ease of use is subjective and more intricate than complexity, which is an objective evaluation of the task elements and therefore conceptually a task (or task interface) design issue. Secondly, perceived ease of use of a task depends on a number of factors, including the task elements themselves, the task's presentation, and the individual's prior knowledge and experience with similar tasks (Nowlis et al., 2010). A study conducted by Reynolds and Ruiz de Maya (2013) in the context of website revisit intention confirms that complexity and perceived ease of use are not identical constructs. Many studies in the field of robo-advisory services have examined the effect of perceived ease of use on adoption intention (Atwal and Bryson, 2021; Gan et al., 2021; Manrai and Gupta, 2022). However, to date, no one has investigated the impact of complexity on perceived value leading to adoption intention to use robo-advisory services. Henceforth, complexity is incorporated in the model.

Prior studies have highlighted that the level of complexity related to the usage of technologies is a pivotal antecedent to the acceptance of novel technologies (Chin and Lin, 2015). According to Mehra et al. (2020), the less complicated a technology, the more likely it is to be accepted and adopted. In the current study, complexity indicates how difficult it is for consumers to use service-based systems. Robo-advisors are easy to navigate because consumers are only required to fill out standardized online surveys about their risk appetite and financial goals (Belanche et al., 2019). According to Gan et al. (2021), such novel technologies use computer algorithms to create, implement, and track investment plans, making it easier for users to make effective and unbiased decisions. In the development of technology acceptance theory, constructs related to the complexity of technologies are introduced to complement the impact of perceived ease of use on intention. Furthermore, no prior study has integrated the effect of complexity on perceived value to predict inclination toward adopting robo-advisory services.

Hence, this study seeks to fill the TAM theory gap regarding robo-advisory service adoption, and consequently we add technological complexity to the perceived value variables for intention to use robo-advisory services. Furthermore, the complexity of using such technology may prevent users from making better financial and investment-related decisions, which may in turn reduce their value perceptions and negatively influence their decision to adopt robo-advisory services (Ashrafi et al., 2021; Gan et al., 2021, Xie et al., 2021). Hence, the fintech-based platform's complexity is crucial in this regard and the following hypothesis is postulated:

H2a: A higher level of complexity will decrease an individual's perceived value in using robo-advisory services.

H2b: Higher levels of complexity will decrease an individual's intention to adopt robo-advisory services.

3. Hedonic Motivation

Diverse, enjoyable, and relaxing activities motivate people to engage in hedonistically pleasant pursuits (Venkatesh and Brown, 2001). Hedonic motivation refers to the way a person's pleasure and pain receptors influence their desire to take action (Gawior et al., 2022). Indeed, the Greek term "hedonic" means "marked by pleasure" (Higgins, 2006). As per Holbrook and Batra (1987), hedonic value is driven by pleasure and delight. When a user’s experience delivers enjoyment, fun, and excitement, it can meet their intrinsic needs (Al-Abdullatif and Alsubaie, 2022; Holbrook and Batra, 1987). Gawior et al. (2022) and Xie et al. (2021) demonstrate that the increased capacity for engaging in an exciting activity intrinsically drives people to become more involved with mobile technology and influences adoption behavior. Generally, hedonically motivated user engagement incentivizes consumption activity that is delightful and gratifying to people (Madhu et al., 2022). Hedonic motivation has also been empirically demonstrated to significantly predict users' value-driving systems (Turel et al., 2010). As a result, a greater level of hedonic engagement motivation may result in increased value perception, leading to the following hypotheses:

H3a: Higher levels of hedonic motivation result in higher perceived value in using robo-advisory services.

H3b: Higher levels of hedonic motivation increase customers' behavioral intention to use robo-advisory services.

4. Perceived Innovativeness

Perceived innovativeness refers to consumers' perceptions of a product's innovative qualities, including novelty and originality (Hwang et al., 2019). Perceived originality and creativity are key indicators of a product's innovativeness (Hwang and Hyun, 2016). Research on the factors that influence people's willingness to adopt a new technology has given considerable attention to the significance of perceived innovativeness. When consumers believe that new high-tech products are highly innovative, they perceive these products as superior to those currently available and gain confidence in using them (Hwang et al., 2019). According to Cranmer et al. (2022), the extent to which a product or service is seen to be creative and unique can be used as a competitive advantage.

Several empirical studies have demonstrated a strong association between perceived innovativeness, the purchasing process, and company performance. For example, according to Kleinschmidt and Cooper (1991), companies that produce products with a high level of innovation have a higher return on investment than those producing products with a moderate level of innovation. Another study by Faqih (2022) found that consumer impressions of a company's innovativeness play a major role in their adoption decisions and improve company performance. Moreover, prior studies have shown that consumers are more motivated to use a good or service if they perceive it as innovative and creative (Alam et al., 2022; Kim et al., 2022). Studies by Hwang et al. (2019) and Slade et al. (2015) in the respective contexts of drone food delivery services and remote mobile payment also report that perceived innovativeness positively impacts an individual's decision-making process. Therefore, in light of the prior literature, the following hypothesis is developed:

H4: A higher level of perceived innovativeness will lead to a higher willingness to adopt robo-advisory services.

5. Perceived Value

Commonly, consumer perceptions of value refer to their general evaluation of the utility of offers, which may be either products or services, based on their "given" and "received" components (Zeithaml, 1988). Furthermore, according to behavioral decision-making theory, consumers' decisions to engage in a particular behavior are largely shaped by their knowledge of the trade-off between the outcome's value and the work required to achieve it (Beach and Mitchell, 1978; Payne, 1982). The concept of perceived value suggests that individuals may hold varying levels of value perceptions for the same kinds of goods and services (Patma et al., 2021).

Fintech platforms' value will therefore change depending on the consumer, as various users have different perceptions. "Price value" was incorporated in the consumer setting by Venkatesh et al. (2012) for the purpose of expanding the UTAUT further. When it comes to adopting new technology, consumer perceptions regarding the balance between perceived benefits and associated monetary costs influence the price value (Venkatesh et al., 2012). However, this multidimensionality is overlooked whenever perceived value is observed from the perspective of benefits and costs. Furthermore, Jünger and Mietzner (2020) have shown that perceptions related to price do not affect fintech adoption behavior. As a result, a more thorough understanding of the influence of perceived value on individuals' adoption behavior across diverse settings is essential (Sweeney and Soutar, 2011). Perceived value can be monetary or non-monetary in nature (Zeithaml, 1988). The monetary dimension denotes the economic cost. However, the non-monetary component primarily indicates the effort, time, and other non-monetary characteristics expended onofferings throughout the consumption process (Zeithaml, 1988). Hence, in accordance with Zeithaml's (1988) concept, this study defines perceived value as how fintech users assess platforms' overall utility based on their views of what is "given" and what they "receive". The decision-making behavior of an individual, according to behavioral decision theory (Johnson and Payne, 1985), is largely shaped by the balance between the decision's utility and the efforts required to decide, and is comparable to perceived value. This concept represents users' judgments of the utility of various fintech-based platforms, which primarily depends on two components: what is "received" and "provided". Here, the value perceived by a user reflects the judgment of his selection method, which also influences their decision-making behavior (Kim et al., 2007).

Scholars are increasingly interested in assessing consumer value perceptions and the overall effects on behavior. A number of empirical studies confirm that perceived value influences customers' attitudes and behavior (Gordon et al., 2018; Ashrafi and Easmin, 2022; Roh et al., 2022). For example, Ashrafi et al. (2021) found that a customer's value perceptions of an offering's worth influence their intention to use services. An earlier study by Kim et al. (2007) combined two theories, i.e., consumer choice theory and decision-making theory, to come up with the value-based adoption model (VAM),which showed that perceived value explained customers' desire to accept the M-internet (Kim et al., 2007). Meanwhile, Roh et al. (2022) argue that value can be experienced when exchanging, consuming, or experiencing progress and this influences consumer behavior.

While some scholars suggest that perceived value can predict an individual's behavioral outcomes in the area of social marketing (Gordon et al., 2018), other scholars argue that utilitarian and hedonic values affect people's online purchasing intentions (Ashrafi et al., 2021; Chiu et al., 2014). Furthermore, the acceptance of an online wealth management platform is viewed as a type of consumption behavior with regard to financial services. As existing studies have shown that consumer value perceptions impact purchase intentions, it is anticipated that the perceived value of fintech platforms will impact people's adoption intentions. Therefore, we postulate:

H5: Customers' behavioral intention to use robo-advisory services will be higher as a result of an increase in their perceived value.

6. Attitude toward AI

Attitudes are the sets of beliefs individuals hold about other people, things, ideas, actions, and events that cause them to feel a certain way (Skitka et al., 2021). In the context of this study, attitude toward artificial intelligence (AI) is conceptualized as individuals' subjective evaluations of robo-advisory services. Previous studies have investigated the association between attitude and adoption intention toward novel technologies (Ashrafi et al., 2021; McLean et al., 2020; Siahaan et al., 2022). In this vein, recent studies on adoption of AI-based technologies suggest attitude is crucial for understanding individuals' adoption intentions (Ashrafi and Easmin, 2022; Dwivedi and Wang, 2022). For instance, in the airline industry, Feng et al. (2018) found that customers view artificial intelligence-based technology as a risk to their autonomy, leading to the formation of a negative attitude toward adopting such technology. Furthermore, Pan et al. (2019) report that reluctance and resistance to change among doctors had a considerable effect on their likelihood of using artificial intelligence in healthcare. Therefore, based on the literature, we hypothesize that:

H6: Negative attitudes toward AI decrease individuals' intention to adopt robo-advisory services.

The degree to which an individual embraces advances in artificial intelligence depends on the sector in which those advancements are implemented and the specific concerns arising from that implementation (Vu and Lim, 2022). According to Ashrafi and Easmin (2022), the risks associated with artificial intelligence (AI)-based technologies are often substantial. Individuals' feelings about algorithmic recommendations have been demonstrated to affect their attitudes to trying new technologies due to their perceptions of risk. For instance, Ashrafi and Easmin (2022) report that users' attitudes significantly influence their intention to adopt artificial intelligence-based voice assistants. Furthermore, despite the fact that the quality of healthcare services performed by AI is better than that provided by humans, Longoni et al. (2019) discovered that consumers demonstrated a negative attitude toward adopting such services. Because financial robo-advisors offer investment management services using automated and artificial intelligence-based algorithms with little or no human intervention, this may enhance perceptions of risk and negatively impact attitudes toward using such novel technology. Hence, the following hypothesis is postulated:

H7: Negative attitude toward AI increases an individual's level of perceived risk associated with using robo-advisory services.

7. Perceived Risk

Users' perceptions of risk are a major barrier to new technology adoption (Ashrafi et al., 2020). People will be reluctant to make an online transaction if they perceive there is any risk involved. A decision-making model established by Kim et al. (2008) found that customer perceptions of risk influence their readiness to make online purchases. Ashrafi et al. (2021) argue that the privacy and security issues associated with mobile-based financial transactions are exacerbated because mobile devices are constantly saving the personal information of users. Risk perception is also an essential factor in fintech adoption because financial products have inherent risks. Thakur and Srivastava (2014) found that perceived risk had a detrimental impact on willingness to accept mobile payments. This conclusion is also supported by findings reported by Ashrafi et al. (2022) in the context of ride-sharing services. In a different setting, de Luna et al. (2019) investigated the parameters associated with accessing various E-payment portals, finding perceived security to be influential in customers' inclinations toward using M-payment platforms. Individuals' intentions to use a fintech platform will therefore be hampered by the uncertainties of e-commerce as well as financial risk. As a result, perceived risk is regarded as an antecedent with a detrimental impact on consumers' willingness to use fintech-based portals.

H8: Adoption intention toward using robo-advisory services is negatively affected by perceived risk.

8. Mediating Role of Perceived Value

Research has shown that customers' value perceptions are heavily influenced by relative advantage (Xie et al., 2021), which is the degree to which a person benefits from the usage of the new technology (Venktatesh et al., 2012). Prior studies have demonstrated that relative advantage positively impacts perceived value (Xie et al., 2021; Kim et al., 2007), and higher perceived value leads to stronger adoption intentions toward contemporary technology-based services (Ashrafi et al., 2021). Hence, we hypothesize:

H9: Perceived value positively mediates the relationship between relative advantage and adoption intention toward using robo-advisory services.

Gan et al. (2021) point out that to use robo-advisory services, an individual needs to fill out a form where they specify their preferred risk level and financial goals, with this process making it easier for users to navigate the service platform. Robo-advisory services employ computer algorithms to make investment decisions, which can develop value for new investors interested in making effective investment decisions with minimum time and effort (Gan et al., 2021). Therefore, we argue that higher levels of complexity in the usage of such novel technology will reduce perceptions of value and reduce adoption intention. Thus, the following hypothesis is postulated:

H10: Perceived value negatively mediates the relationship between complexity and an individual’s intention toward using robo-advisory services.

Activities that are pleasant, thrilling, and rewarding satisfy an individual's hedonic motivation (Venkatesh and Brown, 2001), with hedonic value driven by personal (intrinsic) pleasure and enjoyment. Consumers' intrinsic needs are met when the experience is enjoyable and exciting (Holbrook and Batra, 1987), making hedonic motivation a major component driving value (Turel et al., 2010). Thus, a higher level of hedonic motivation should result in higher perceived value (Kim et al., 2013). Studies conducted by Shaw and Sergueeva (2019) and Kim et al. (2007) confirm that perceived value positively affects an individual's adoption intention. Hence, we hypothesize that perceived value will mediate the relationship between hedonic motivation and adoption intention toward robo-advisory services:

H11: Perceived value positively mediates the relationship between hedonic motivation and adoption intention toward using robo-advisory services.

9. Mediating Role of Perceived Risk

Perceived risk and attitude are pivotal dimensions in studies exploring consumer decision-making and adoption behavior (Ashrafi et al., 2021). Indeed, in the context of fintech, many studies have highlighted the association between attitude and perceived risk. An individual's attitude toward something refers to how strongly they like or dislike it, and attitude is considered a vital determinant of an individual’s adoption intention toward using novel technologies (Ashrafi and Easmin, 2022). A study conducted by Hu et al. (2019) highlights negative attitude as increasing an individual's perceived risk levels and decreasing their adoption intention toward novel technologies. Laksamana et al. (2022) also demonstrate an association between security risk and an individual's attitude risk, impacting their adoption intention to use fintech platforms. On the other side, prior studies have shown that a negative attitude toward novel technologies increases perceived risk, which acts as a precursor of individuals’ reluctance to adopt contemporary technology-based services (Ashrafi et al., 2021; Kim et al., 2008). We argue that a negative attitude toward robo-advisory platforms will increase the level of perceived risk, in turn reducing an individual's intention to adopt robo-advisory services. Therefore, based on the above-mentioned relationships, we hypothesize the following:

H12: Perceived risk negatively mediates the relationship between attitude and adoption intention toward robo-advisory services.

10. Moderating Impact of Perceived Financial Knowledge

Perceived financial knowledge is an individual's perception regarding their own financial literacy and understanding (Lusardi and Mitchell, 2017). Konana and Balasubramanian (2005) suggest that individuals fall under the knowledge illusion when they use various sources for gaining more knowledge. As Gan et al. (2021) argue, the resulting self-belief regarding their perceived knowledge depth may exceed their objective knowledge level. Prior studies have shown that perceived financial knowledge impacts an individual's investment-related decisions (Nguyen, 2022; Henager and Cude, 2016). However, findings relating to robo-advisory services are mixed. While Brenner and Meyll (2020) report that robo-advisor users have lower financial literacy levels, Todd and Seay (2020) found that individuals with less investment understanding were less likely to use robo-advisors since they don't see the value in them. In contrast, in another study robo-advisors were seen as more beneficial and valuable by those who considered themselves to have a high level of financial knowledge (Gan et al., 2021).

Thus, we argue that perceived financial knowledge is pivotal in strengthening the relationship between perceived value and adoption willingness regarding robo-advisory services (Fan and Chatterjee, 2020). People with a higher level of financial knowledge understand the financial market and want to achieve effective financial planning. Therefore, it can be deduced that people with more financial knowledge will have a higher perception of the value of robo-advisors in a volatile market environment than those with less financial knowledge (Aw et al., 2019). Thus, in the context of robo-advisory service adoption, we propose that having a higher level of perceived financial understanding will reinforce the association between perceived value and adoption intention with regard to using robo-advisory services:

H13: The relationship between perceived value and behavioral intention to use robo-advisors will be stronger for those with a higher level of perceived financial knowledge compared to those with a lower level of perceived financial knowledge.

METHOD

1. Data Collection

1.1. Explanation of the unit of analysis

The unit of analysis is the main parameter or entity being investigated in a study. The current study sought to investigate behavioral intention to adopt robo-advisory services. Therefore, the unit of analysis was individual respondents who were potential users of robo-advisory services.

1.2. Sampling method

A non-probability sampling technique called purposive sampling was used for the distribution of the questionnaires (Etikan et al., 2016). As such, questionnaire responses were only considered if the following conditions were met: the respondent (i) was at least 18 years old, and (ii) had prior experience with internet banking, as using robo-advisory services requires e-transactions. The second criterion was based on findings by Gan et al. (2021) that robo-advisory services are more popular among those with e-banking experience and investment portfolios than those who have never used them before.

1.3. Data collection method

The responses were collected using a Google form, and all participants were given the assurance that their responses would be kept confidential. We distributed the electronic questionnaire on social platforms, the websites of investment-related associations, and related discussion websites. Due to this digital dissemination, responses were received from different locations across Bangladesh's eight divisions. The data collection period was September to October 2021. The questionnaire was divided into three parts. In the first part, a short video was shown to respondents for the purpose of explaining the study's purpose and describing the UI (user interface) and functionality of robo-advisory platforms. Respondents were then asked to complete a questionnaire containing measures to assess the variables of interest (see Section 3). Finally, there were questions aimed at collecting demographic data from the participants.

1.4. Response Rate

Participants voluntarily filled out 496 questionnaires for this study. After the removal of incomplete questionnaires with missing values, a total of 285 responses remained, giving a 57.45% response rate.

2. Measurement of Variables

Previously validated scales from relevant literature were adapted to measure the variables. The three items for robo-advisory service adoption intention were adapted from studies by Venkatesh et al. (2003,2012). Relative advantage and complexity were measured using four items adapted from Moore and Benbasat (1991), Venkatesh et al. (2003), and Venkatesh et al. (2012). The three items measuring perceived innovativeness in robo-advisors were adapted from Fu and Elliott (2013), with a further three attitude-related items adapted from Hassanein and Head (2007). Hedonic motivation was measured using three items from Kim et al. (2010), and four items from Kim et al. (2008) and Pavlou (2003) were used to measure perceived risk. The four items for perceived value were drawn from Kim et al. (2007) and Sirdeshmukh (2002) and the four items used to measure perceived financial knowledge came from Park et al. (2010). All the above-mentioned items were tailored to match the robo-advisory service framework. We used a five-point Likert scale to rate all items, from 1=strongly disagree to 5=strongly agree. The questionnaire was piloted with 30 potential respondents, resulting in some minor modifications. The details are provided in Table 1.

3. Survey Administration

As mentioned above, the survey had three sections. In the first section, a brief explanation of robo-advisory services and the purpose of the study was provided. The second section contained the questionnaire designed to measure the exogenous and endogenous variables. The final section was included to extract the demographic information of the respondents.

All respondents' demographic data were analyzed using SPSS. The frequency distribution of these demographic data is shown in Table 1. There were 61% male and 39% female respondents, and most respondents (28%) were aged between 25 and 29. 55% of respondents held a bachelor's degree and 41% had a postgraduate degree.

Table 1. Descriptive statistics

Variable		Frequency	Percentage (%)
Gender	Male	173	61
	Female	112	39
	Total	285	100
Age	<25	15	5
	25-29	83	28
	30-34	70	24
	35-39	73	26
	40-44	21	9
	>45	23	8
	Total	285	100
Educational level	High school or college	9	1
	Bachelor's degree	156	55
	Master's degree	117	41
	PhD	8	3
	Total	285	100
Income (Monthly)	< 20000 BDT	21	7.5
	20000-30000 BDT	120	42
	31000-40000 BDT	91	32
	> 40000 BDT	53	18.5
	Total	285	100

Source: This table is based on author's analysis of collected data

DATA ANALYSIS

PLS-SEM (partial least squares structural equation modeling) was performed to examine the hypotheses proposed in this study. PLS-SEM was used due to the small sample size and lower residual distribution (Wang et al., 2019). Additionally, the PLS-SEM approach provides a few advantages when dealing with complicated models (Hair et al., 2011). SMART PLS 3.3.4 was used to conduct the data analysis as it provides better accuracy and ensures robust analysis (Risher and Hair Jr., 2017). The composite reliability, which measures the internal consistency of data, was evaluated (Hair et al., 2014). Next, the validity of the measurement model was examined using convergent and discriminant validity. Furthermore, the structural model was evaluated using the coefficient of determination and path coefficients.

1. Measurement Model

To ensure high internal consistency, we assessed the composite reliability. AVE (average variance extracted) and outer loadings were also evaluated to determine convergent validity. As demonstrated by the composite reliability results (see Table 2), all the variables met the minimum benchmark of 0.70, as suggested by Hair et al. (2014). Items that had outer loadings of more than 0.70 were maintained (Hair et al., 2014). Items with outer loadings ranging from 0.40 to 0.70 were deleted when the CR and AVE values were improved by deletion. However, the outer loading of one item related to perceived innovativeness fell below the required benchmark and was removed. Moreover, as per the results, all the variables' AVE and composite reliability values were above the appropriate thresholds of 0.50 and 0.70, respectively. Hence, the measurement model was found adequate in terms of reliability and validity.

Table 2. Construct validity and reliability

Construct	Items	Factor Loading	Average Variance Extracted (AVE)	Composite Reliability	Cronbach's Alpha
BITN	BITN1	0.751	0.832	0.952	0.933
	BITN2	0.834			
	BITN3	0.813			
CMPX	CMPX1	0.847	0.763	0.906	0.844
	CMPX2	0.763			
	CMPX3	0.789			
	CMPX4	0.816			
RLA	RLA1	0.876	0.73	0.89	0.815
	RLA2	0.842			
	RLA3	0.785			
	RLA4	0.747			
PINV	PINV1	0.759	0.752	0.901	0.836
	PINV2	0.863			
	PINV3	0.858			
ATT	ATT1	0.912	0.65	0.813	0.802
	ATT2	0.863			
	ATT3	0.837			
HDMV	HDMV1	0.788	0.788	0.917	0.865
	HDMV2	0.865			
	HDMV3	0.858			
PR	PR1	0.816	0.796	0.94	0.914
	PR2	0.858			
	PR3	0.787			
	PR4	0.748			
PV	PV1	0.751	0.705	0.905	0.861
	PV2	0.825			
	PV3	0.771			
	PV4	0.816			

Note: BITN, Behavioral intention; CMPX, Complexity; HDMV, Hedonic motivation; PV, Perceived value; PR, Perceived risk; RLA, Relative advantage; PINV, Perceived innovativeness; ATT, Attitude

Source: This table is based on author's analysis of collected data

To confirm that the variables in the proposed model are different from one another, discriminant validity was tested. It was assessed using the HTMT ratio (Heterotrait-monotrait ratio) and the Fornell-Larcker criterion. According to the Fornell-Larcker criterion, the AVE's square root should be larger than its highest connection with any variables suggested in the model (Fornell and Larcker, 1981). Table 3 reveals that the AVE's square root was indeed larger than the correlation values for all variables. Additionally, discriminant validity was tested using the Heterotrait-Monotrait (HTMT) measurement ratio. The HTMT values of all variables were less than 0.90, as shown in Table 4. An HTMT value of less than 0.90 establishes discriminant validity, as per Henseler et al. (2015).

Table 3. Discriminant Validity (Fornell-Larcker Criterion)

	BITN	CMPX	HDMV	PV	PR	RLA	PINV	ATT
BITN	0.912							
CMPX	0.669	0.873						
HDMV	0.614	0.436	0.888					
PV	0.647	0.438	0.576	0.840				
PR	0.778	0.673	0.579	0.566	0.892			
RLA	0.490	0.490	0.561	0.525	0.533	0.855		
PINV	0.731	0.529	0.531	0.555	0.617	0.358	0.867	
ATT	0.693	0.732	0.617	0.748	0.812	0.725	0.713	0.829

Note: BITN, Behavioral intention; CMPX, Complexity; HDMV, Hedonic motivation; PV, Perceived value; PR, Perceived risk; RLA, Relative advantage; PINV, Perceived innovativeness; ATT, Attitude

Source: This table is based on author's analysis of collected data

Table 4. Discriminant Validity (HTMT ratio)

	BITN	CMPX	HDMV	PV	PR	RLA	PINV	ATT
BITN								
CMPX	0.748							
HDMV	0.673	0.504						
PV	0.710	0.505	0.651					
PR	0.839	0.761	0.646	0.635				
RLA	0.558	0.592	0.667	0.624	0.614			
PINV	0.813	0.607	0.614	0.656	0.695	0.412		
ATT	0.713	0.680	0572	0.763	0.72	0.532	0.67	

Note: BITN, Behavioral intention; CMPX, Complexity; HDMV, Hedonic motivation; PV, Perceived value; PR, Perceived risk; RLA, Relative advantage; PINV, Perceived innovativeness; ATT, Attitude

Source: This table is based on author's analysis of collected data

2. Structural Model

The path coefficient values were used to evaluate the proposed hypotheses. Table 5 summarizes the findings. It demonstrates that the relative advantage of using financial Robo-advisors was positively linked to perceived value, supporting H1a (β_{1a}= 0.238, t=2.851, p=0.002). In the same way, the findings revealed a statistically significant relationship between relative advantage and willingness to use robo-advisory services (β_{1b}= 0.192, t=5.23, p=0.002), validating H1b. Complexity was found to be negatively associated with perceived value (β_{2a}=-0.159, t=2.420, p=0.008) and adoption intention (β_{2h}= -0.162, t=5.63, p=0.000). Thus, H2a and H2b were supported. Although, a positive significant association between hedonic motivation and perceived value (β_{3a}= 0.374, t=5.056, p=0.001) was observed, no significant relationship was found between hedonic motivation and adoption intention (β_{3b}= 0.257, t=1.78, p=0.152). Thus, H3a was supported while H3b was not. Perceived innovativeness showed a positive association with adoption intention (β_4= 0.347, t=6.423, p=0.000), validating H4. Perceived value also showed a positive significant relationship with intention to use robo-services (β_5= 0.41, t=5.41, p=0.001), supporting H5. Moreover, while negative attitude showed a significant impact on users' intention to use robo-advisory services (β_6= -0.191, t=4.12, p=0.001), a negative association between attitude and perceived risk was observed (β_7= -0.212, t=5.62, p=0.001). Thus, H7 was supported. Nevertheless, perceived risk showed a negative relationship with adoption intention (β_8= -0.324, t=8.55, p=0.001), supporting H8. Figure 2 depicts the empirical model, as well as the path coefficients and their level of significance.

2.1. Mediating Impact of Perceived Value and Risk

Next, the mediating impact of consumers' perceived value and risk were tested. Firstly, the study tested whether perceived value mediated the association between relative advantage (β_9= 0.086, t=3.961, p=0.002), complexity (β_{10}= -0.036, t=1.874, p=0.112), hedonic motivation (β_{11}= 0.084, t=1.64, p=0.162), and intention to use robo-advisory services, respectively. Thus, while H9 was supported, H10 and H11 were not. Furthermore, the results showed that perceived risk significantly mediated the path between attitude and behavioral intention to adopt robo-advisory services, supporting H12 (β_{12}= -0.124, t=4.544, p=0.012).

2.2. Moderating Impact of Perceived Financial Knowledge

The study tested whether perceived financial knowledge moderated the relationship between perceived value and intention to use robo-advisory services. The results revealed that an individual's perception of their own financial knowledge significantly moderated the association between perceived value and adoption intention. Therefore, H16 was supported (β_{13}= 0.11, t=5.365, p=0.011). In other words, the positive impact of consumers' perceived value on their intentions toward adopting robo-advisory services was significantly increased by perceived financial knowledge. For respondents who believed their financial knowledge was higher, perceived value had a stronger influence on their intention to adopt robo-advisory services. In other words, perceived value will have a more substantial effect on an individual's adoption intention if they believe their financial knowledge to be high compared to those who perceive their financial knowledge to be low.

Table 5. Path analysis results

Hypothesis	Path(s)	Coefficients (Beta)	t value	p value	Decision
H1a	RLA -> PV	0.238	2.851	0.002	Supported
H1b	RLA -> BITN	0.192	5.23	0.002	Supported
H2a	CMPX -> PV	-0.159	2.42	0.008	Supported
H2b	CMPX -> BITN	-0.162	5.63	0.003	Supported
H3a	HDMV -> PV	0.374	5.056	0.001	Supported
H3b	HDMV -> BITN	0.257	1.78	0.152	Not Supported
H4	PINV -> BITN	0.347	6.423	0.001	Supported
H5	PV -> BITN	0.41	5.41	0.001	Supported
H6	ATT-> BITN	-0.191	4.12	0.001	Supported
H7	ATT-> PR	-0.212	5.62	0.001	Supported
H8	PR -> BITN	-0.324	8.55	0.001	Supported

Note: BITN, Behavioral intention; CMPX, Complexity; HDMV, Hedonic motivation; PV, Perceived value; PR, Perceived risk; RLA, Relative advantage; PINV, Perceived innovativeness; ATT, Attitude

Source: This table is based on author's analysis of collected data

Table 6. Mediating effect of Perceived Value and Perceived Risk

Hypothesis	Path(s)	Coefficients (Beta)	t value	p value	Decision
H9	RLA -> PV -> BITN	0.086	3.961	0.001	Supported
H10	CMPX -> PV -> BITN	-0.036	1.874	0.112	Not Supported
H11	HDMV -> PV -> BITN	0.084	1.64	0.162	Not Supported
H12	ATT -> PR -> BITN	-0.124	4.544	0.012	Supported

Note: BITN, Behavioral intention; CMPX, Complexity; HDMV, Hedonic motivation; PV, Perceived value; PR, Perceived risk; RLA, Relative advantage; PINV, Perceived innovativeness; ATT, Attitude

Source: This table is based on author's analysis of collected data.

3. Coefficient of Determination

The coefficient of determination (R2) was used to assess the model's predictive accuracy. The results indicated that while hedonic motivation, complexity, and relative advantage accounted for 58% of the variance in perceived value, attitude accounted for 41% of the variance in perceived risk. Additionally, the model explained 72% of the variation in intention to use financial robo-advisory services.

DISCUSSION AND THEORETICAL IMPLICATIONS

The findings of this research show the factors associated with an individual's adoption intention toward robo-advisory services are relative advantage, complexity, attitude, perceived value, and perceived risk. Relative advantage was found to positively affect individuals' perception of value and adoption intention. Because robo-advisors can make financial choices without any emotional bias, this may influence customer preferences for the advisory platform. Relative advantage may therefore augment perceived value via enhanced perceived reliability. As a result, the intention to adopt robo-advisory services increases. This finding is theoretically consistent with previous studies on fintech, specifically Xie et al. (2021), Arias-Oliva et al. (2019), and Widodo et al. (2019), where relative advantage was the strongest predictor of perceived value and willingness to use fintech based applications. Furthermore, this is also consistent with Ruhr et al. (2019), who discovered that relative advantage had a substantial positive influence on adoption of decision support systems with a high level of automation.

However, complexity showed a negative relationship with adoption intention toward robo-advisory services and perceived value. Therefore, making robo-advisory services user-friendly, easy to navigate, and non-complex will enable people to make better financial and investment decisions, which will in turn, enhance their value perceptions and usage intentions. Conversely, if users perceive robo-services as complex and difficult to understand, this may reduce their intention to use such novel technology. These findings are in line with Gan et al. (2021), Xie et al. (2021), and Chang et al. (2016)

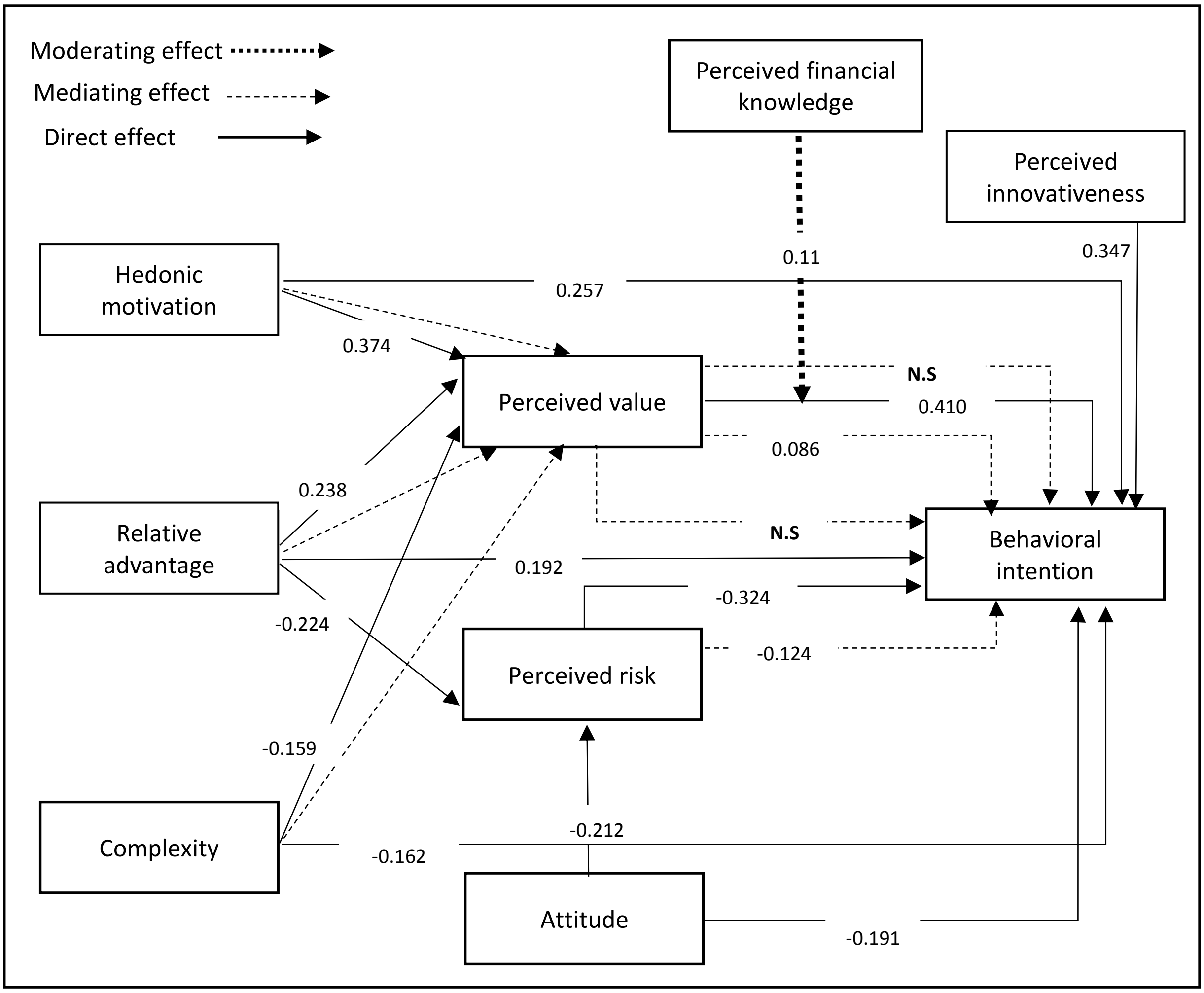
Table 7. Moderating impact of Perceived Financial Knowledge

Hypothesized path(s)	Beta Coefficient	T-statistics	P value	Decision
PV*PFNKL-> BITN	0.11	5.365	0.001	Supported

Note: PV, Perceived value; PFNKL, Perceived financial knowledge; BITN, Behavioral intention

Source: This table is based on author's analysis of collected data

Figure 2: Path analysis results



Source: Author's own illustration

While hedonic motivation exhibited a positive association with consumers' value perceptions, it did not significantly affect their adoption intentions. This finding is consistent with Kim et al. (2013) but contradicts Moorthy et al. (2018). Therefore, if people find the service pleasurable, engaging, and exciting, they may perceive higher value in it, but increased hedonic motivation does not necessarily indicate a higher probability of adopting robo-advisory services (Hohenberger et al., 2019). One explanation could be that because robo-advisory services incorporate financial risk, users may only find hedonic motivation important if it adds value to using such novel technologies.

Attitude showed a negative influence on both intention to use financial robo-advisory services and perceived risk. As an alternative to traditional human advisors for financial and asset management, robo-advisors may nevertheless be perceived as risky by consumers. Robo-advisory services use computer algorithms to provide people with investment advice, which may enhance risk perceptions. Hence, people's willingness to use financial robo-advisors may decrease as a result of their negative attitude. From a theoretical standpoint this finding supports previous findings suggesting that customers' negative attitudes toward automated financial advisory services negatively affect their adoption intention and perceived risk (Lourenco et al., 2020). Moreover, the results confirm Bruckes et al.'s (2019) claim that customers' propensity to utilize robo-advisory services is lower if they perceive a higher level of risk from using such novel technology. However, perceived innovativeness showed a positive impact on behavioral intention to use robo-advisory services, implying that if such novel technologies are seen as innovative by individuals, their inclination toward using such services will be enhanced. This result is consistent with findings from Hwang et al. (2019), where perceived innovativeness showed a significant impact on the adoption of drone-based food delivery services.

The study results also showed that perceived value partially mediated the relationship between relative advantage and adoption intention with regard to usage of robo-advisory services. This implies that relative advantage impacted perceived value, which in turn affected adoption intention. It can therefore be argued that in terms of fostering adoption intention, the importance of perceived value as generated through relative advantage cannot be ruled out. On the other hand, complexity and hedonic motivation did not mediate the path between perceived value and adoption intention. Thus, perceived value served to clarify the nature of the relationship between relative advantage, complexity, hedonic motivation, and adoption intention. These findings are consistent with Xie et al. (2021), where these factors affected decision-making via perceived value. Perceived risk, on the other hand, negatively mediated the relationship between attitude and adoption intention, which is consistent with prior studies showing risk to be negatively influenced by attitude, in turn affecting consumer decision-making (Laksamana et al., 2022; Hu et al., 2019). As another aspect, the current study showed the moderating impact of perceived financial knowledge on the association between customers' adoption intentions and value perceptions. Findings implied that people who have higher levels of financial knowledge will perceive higher value from using robo-advisory services than those who have a lower level of financial knowledge. These results are in line with prior studies where financial knowledge was revealed to moderate the relationship between factors such as financial attitude, emotional intelligence, firm growth, personality traits and investment decision-making (Ali et al., 2016; Hadi, 2017; Sadiq and Khan, 2019). Other studies by Todd and Seay (2020) and Fan and Chatterjee (2020) reveal similar results. However, the moderating effect of perceived financial knowledge was not examined in these studies. Hence, the current study's findings provide some insight into the connection between financial knowledge, perceived value, and customers' adoption intentions toward AI-driven financial robo-advisory services.

This study has contributed to the existing knowledge base by exploring the role of relative advantage, complexity, hedonic motivation, perceived innovativeness, and attitude in predicting customers' adoption of robo-advisory services. Furthermore, it extends understanding of how customers' motivation is enhanced and reduced through their perceptions of value and risk, respectively. The findings showing that perceived value is positively impacted by relative advantage and hedonic motivation and negatively impacted by complexity. While prior studies focus on perceived value and risk as antecedents of attitude, the empirical findings of this study provide a new understanding of how negative attitudes toward AI-based technologies impact perceived risk.

Prior studies have shown that perceived value and risk are essential factors in predicting consumers' behavioral decision-making. This study sheds further light on the role of value and risk in determining consumers' adoption intentions for robo-advisory services. It highlights the impact of risk, enhancing understanding of what factors contribute to consumers’ reluctance to use and adopt robo-advisory services. Consumer behavior assessment is a critical strategic challenge for the service industry, and this study builds theoretical depth by demonstrating that consumers’ acceptance behavior is not only subject to the direct impact of perceived value and risk, but also the indirect impact of relative advantage and attitude. The analysis of perceived value and perceived risk extends knowledge on the role of mediating variables in the context of financial robo-advisory services. Additionally, prior research on perceived financial knowledge as a moderating variable in the context of robo-advisory services is rare. This findings further strengthens understanding of the role of this variable in the association between consumers' perceived value and their inclination toward adopting robo-advisory services.

Finally, the proposed moderated mediation model developed in this study provides insight on the complex relationships between relative advantage, complexity, hedonic motivation, perceived innovativeness, attitude, perceived value, and risk and their combined effect on consumers' intention to adopt financial robo-advisory services. This study was undertaken to examine perceptions toward adopting robo-advisory services, and as detailed in the next section, the findings may help service providers, policymakers, and marketers manage their value and risk effectively and efficiently, as well as provide valuable insights for developing effective marketing and communication strategies for financial robo-advisory services.

PRACTICAL IMPLICATIONS

This study's results have wide-ranging implications for robo-advisory service providers, regulators, customers, and existing financial advisory organizations. According to the findings, relative advantage has a positive and significant impact on adoption of financial robo-advisors. Moreover, the benefits of using robo-advisory services are evident because the digital platform enables automated financial and investment planning with no or minimum human interaction at an affordable cost. Furthermore, views, opinions, and comments concerning the services provided by automated online robo-advisors play an important role in encouraging acceptance. The findings also highlight the significance of hedonic motivation and complexity for customers' adoption of robo-advisory services, providing meaningful insights for marketers and policymakers on how to design the process to make it more interesting, engaging, easy to use, and uncomplicated for users.

Because robo-advisory services do not require any human interaction, their uncomplicated navigation could improve consumer perceptions and willingness to adopt robo-advisors to build financial wealth management. When it comes to perceived innovativeness, knowing that robo-advisors are powered by AI algorithms and entirely unbiased could encourage people to use the technology. Nevertheless, users should investigate and evaluate the firms that provide AI-based robo-advisory services before using such automated services. Firms with strong reputations may foster a high level of confidence and reduce users' risk levels, thereby serving as a precursor to the development of more reliance on robo-advisory services.

The study's outcomes will assist service providers in comprehending the critical elements affecting adoption of AI-driven robo-advisory services in Bangladesh. Because the results show relative advantage is a critical component, customers of AI-driven financial robo-advisory services should be encouraged to discuss and promote their experiences on social media platforms through evaluations and ratings (Gan et al., 2021). Such exposure may inspire new consumers to adopt such services. Robo-advisory service providers can also implement awareness campaigns and ads to emphasize service providers' adherence to procedures that safeguard a customer's data privacy, resulting in decreased risk. Furthermore, companies can increase user perceptions of value if they tailor services on the basis of risk profiling, which may encourage people to use such AI-based financial advisory services. Additionally, the robo-advisory service sector can assist in enhancing potential customers' financial understanding and awareness of automated financial robo-advisors. Service providers can allay the concerns of investors by emphasizing the advantages of robo-advisors over conventional human advisors in terms of transparency, cost, neutrality, and unbiased advice. By concentrating on the factors discussed above, service providers will be able to expand their customer base and acquire a greater market share. Service providers can also focus on distinctive target markets by assessing their requirements, risk appetite, and preferences and tailoring their services to meet those needs.

The results of the study have significance for conventional financial advisory businesses since they will be impacted to some extent with the launch of robo-advisors. Therefore, it is also feasible for traditional advisory companies to consider providing robo-advisory services. To maintain relevance and viability, they may contemplate shifting to online automated financial advisory systems. There are also implications for regulators, who may decide to launch learning initiatives to raise awareness among consumers regarding robo-advisory services, boosting their understanding as well as their confidence.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH DIRECTION

This study investigated the antecedents of the adoption of financial robo-advisory services. The data collection period of the study was critical because participants were seeing a major shift toward digital and virtual activities during the collection period. The study included two mediating variables: consumers' perceived value and. However, the study has advanced existing knowledge by including perceived financial knowledge as a moderating variable in the model. The findings highlight relative advantage, complexity, perceived innovativeness, attitude, and perceived value and risk as significant predictors of consumers' intention to use financial robo-advisory services. However, in Bangladesh, robo-advisory services are still in their infancy. Hence, they have the potential to grow in popularity. The study's emphasis on only one nation, Bangladesh, is one of its limitations. Nevertheless, the antecedents explored in the study are relevant beyond borders since robo-advisors offer online services. Another drawback is that regulatory issues were overlooked in the context of this study, as were other factors, for instance extrinsic and intrinsic incentives that may influence intention to use robo-advisory services. There is thus a need for future research on robo-advisory service adoption to look at more than one nation and consider the above-mentioned factors to enhance the prediction value of the model. Finally, to understand more about how consumers use AI-driven financial robo-advisory services, researchers could conduct a larger-scale study in the future.

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