Scholar Publishing Group
International Journal of Business Management and Economics and Trade
https://doi.org/10.38007/IJBMET.2026.070118
ISSN 2790-0959 Vol. 7, Issue 1:157-166

Trust-Based Acceptance of AI Financial Advisory Chatbots: A Conceptual Study of Service Quality, Perceived Risk, and Continuance Intention

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Keywords: Artificial intelligence, financial management, FinTech, robo-advisor, AI chatbot, service quality, trust, perceived risk, technology acceptance model, continuance intention

Abstract: Artificial intelligence is changing the banking sector by automating customer service, customised recommendations for all types of financial products, risk assessment of credit and other areas, early warning of fraud, etc. Although artificial intelligence (AI) financial chatbots and robo-advisory services have sped up the pace of service and lowered operating costs, they will be ineffective if customers do not trust them; they do not believe that their risks are well-managed; there is a lack of transparency in management, and a sense of alignment among the parties is missing. The above theory can help us understand why people have been using AI-driven financial advisory chatbots in the era of digital finance for a long time. According to the Technology Acceptance Model, based on the concepts of electronic service quality, trust frameworks and research on AI adoption, it has been proposed that AI service engagement and financial data quality affect perceived utility, perceived usability, perceived risk, trust and continuance behaviour. The choice of financial services contains one's personal data, investment risk, etc., and may not be convenient for one's own interests or the normal development of business. The first three reasons for this paper are as follows. First, it expands the scope of research on the quality of AI chatbot service from commercial and public service sectors to financial administration and the environment of FinTech services. Second, there is the concept of risk and openness in the Trust-Centered Technology Acceptance Model. Thirdly, it provides some helpful ideas for banks, securities companies, FinTech enterprises and platform operators on how to build stable, transparent and convenient AI financial service platforms. Empirical studies using a survey-based structural equation model will be conducted in the next paper of this journal to verify the new model.

1. Introduction

Electronic finance has grown from the start of internet banking and mobile payment services to build an intelligent ecosystem that can handle users' information, make decisions using computation, assess risks, operate autonomously, etc. Therefore, the purpose of the AI-based fiscal advice agent is not only to answer general questions. They are now serving as the connection points for various financial operations, including account check-ins, savings advice and wealth management education, asset portfolio monitoring, credit risk warnings, insurance recommendations, complaint handling, regulatory alerts, etc. The administrative utility of such platforms is also expanding; that is to say, the conversational records can help banks better understand what their customers need, reduce redundant operating costs, improve the uniformity of services, and strengthen the construction of customer relationships.

However, the environment of the financial services will not be that of a typical e-commerce or standard digital-service environment. When people speak with AI chatbots about investments, loans and credit, insurance, wealth management, etc., they are unsure of the money-related results and concerned about the privacy of their personal information. A fast reply is not to be used if the advice is vague, biased, inappropriate or difficult to verify. In finance, consumers do not only need to know that a platform is efficient but also whether it is responsible, transparent and trustworthy. If the client cannot understand the reason for the AI-generated result or is concerned that their private data will be leaked by the system, they will choose not to use the service even though it is technologically advanced.

In the past, studies on technology acceptance found that people are more likely to use new technologies if they believe they are useful and convenient. According to experiments on online trust, people are willing to speak online only if they can feel both trust and perceive a low risk. Research on the application of artificial intelligence has found that people's trust in algorithmic systems is based on how accurate, transparent, reliable and responsive they are. Therefore, there are many new risks for banks as a result of changes in technology for digital finance in actual practice. Nevertheless, an elegant theoretical system that connects the quality of AI services with the quality of financial data, risk perception, trust and the intention to keep using AI-powered financial advisory systems still needs to be built.

Therefore, in this paper, based on the elements of finance, management and AI service quality, a concept of the adoption of AI-based financial advisory chatbots will be established. First of all, why are the customers still using the AI-powered financial advisory chatbot many times in the digital finance ecosystem? To address the problem above, this paper will employ the Technology Acceptance Model (TAM), electronic service quality, trust theory and literature on FinTech adoption. The six basic elements of this paper are AI service interactivity, quality of financial information, perceived usefulness, perceived ease of use, perceived risk and trust, and continuance intention.

This paper provides some support for the development of law and administration. First, the object of study for chatbots can be changed to the reliable and secure nature of the fiscal and administrative system. It also explains how to make continuous interaction with artificial intelligence for people convenient and safe by means of utility and simplicity of use, accurate data, etc. Finally, it will offer some practical support for the construction of AI consultation platforms in banks to protect the legitimate rights and interests of customers and strengthen manual supervision and operation.

2. Literature Review

2.1. AI in Digital Finance and Management Transformation

Now, many places in the banking and other parts of society have introduced artificial intelligence. In banking, asset management, insurance and retail lending, etc., many people are now using artificial intelligence technology to handle large volumes of data, identify risks in loans and fraud, customise financial products, etc. At the level of strategy, new tools need to be introduced that can make banks more active managers of their clients instead of being passive service providers. AI conversational agents can be used to address problems in the development of the economy, point out some specific issues for expert advisors, and provide all-around guidance through various means.

The start of Robo-advisors is also a change. The advisor function of the robot helps people better know about their own assets, sets a reasonable level of risk for the portfolio according to algorithms, and so on. Often, the client portal is in the form of conversation or semi-interaction; people post their tax goals and get personalised advice. The new AI-driven advisory model will have lower operating costs and make more people able to access financial planning services than the old way. Nevertheless, such technologies may also have problems of appropriateness, bias, over-reliance, information security and accountability when people are led to believe that they have reached a conclusion through a computer.

Therefore, there are not only technical problems but also problems in management and regulation for the application of AI-driven financial consultation chatbots. The system administrator needs to know how the AI framework will present the recommended results, how to handle unclear replies, when a person needs to step in, and what the algorithm's output for the bank will be. Thus, it may not meet people's demands for happiness and order.

2.2. Service Quality in AI Financial Interfaces

The five attributes of service quality are reliability, responsiveness, assurance, empathy and tangibles. The main directions of the Digital Service Environment are efficiency, system availability, privacy, fulfilment and fast response. The quality of AI chatbot service is considered to be a conversational extension of electronic service quality. Consumers want to know if the chatbot understands the questions, can provide relevant and timely answers, keeps track of the previous conversation, and solves problems without making them repeat themselves.

Data integrity must also be guaranteed for the good operation of financial chatbots. The economy's data should be accurate, timely, all-encompassing, suitable for the background of the client, etc. A general introduction to the investment tools will be insufficient if it fails to consider risks, the time span of funds, the proportion of debt, income stability, legal reporting requirements, etc. The conversational AI will be given account and credit information, and it needs to specify whether the tax guidance is general or customised. Given the seriousness of the fiscal results, Data Excellence will directly affect people's sense of risk and certainty.

The other is the problem of AI platform participation. Interactivity refers to how much a framework can respond to the goals of a person, raise related questions in response, change according to environmental changes, and guide the person to the next step. To make the virtual agent more interactive can be helpful and simple to use; however, if it is too attractive and lacking in openness, people may develop a false sense of security. Therefore, the good of life and reason should serve as substitutes for it.

2.3. TAM, Trust, and Perceived Risk in Financial AI Adoption

The Technology Acceptance Model is based on the idea that people are more willing to use a new system if they believe it will be more convenient and efficient. Under the framework of AI-driven financial advice, perceived usefulness is one's belief that the conversational agent can help a person make money-related decisions, save time, compare various options and identify risks efficiently in the course of life. Perceived ease of use is the degree to which people believe that the chatbot is easy to use, understandable and operate.

Due to the nature of money services, Credibility is required. The public may not be familiar with the complex fiscal suggestions, and they will have to disclose private and financial information. Confidence in AI monetary consulting chatbots is the sense of trust people have in the platform, how accurate the data is, how safe the information is, and how reliable the operating organization is. If people believe in the software, they will be more likely to follow the advice given by the software and use it continuously. Low confidence is a higher sense of danger and a reduced will to fight.

Perceived risk is the perception by consumers that there will be harm or loss. Risk in this paper refers to financial risk, information risk, operational risk and liability risk. The AI platform will inform the user of the specific risks that are about to occur in a simple language, and some options will be available to turn off the algorithm or auto-completion, etc. Therefore, the sense of risk should be regarded as one of the problems to be solved by ethical engineering and structural supervision.

2.4. Research Gap

Research on AI chatbots, robo-advisors and FinTech integration has expanded greatly, but the three main problems have not been solved. First, most studies have focused on the reasons for the application of artificial intelligence in finance rather than why it is still being utilised. Second, many studies have only examined trust, but in reality, trust in financial AI is also affected by interaction experience and the quality of financial data. Thirdly, there is a relatively small number of short frameworks that combine service quality, perceived risk, trust and managerial performance in one. The framework of trust-based acceptance for AI financial advisory chatbots is put forward in this paper to address the above problems.

3. Conceptual Framework and Hypothesis Development

The construction basis proposes that the degree of use in AI service and the quality of financial data are the reasons for consumers' opinions. Interactivity is the direction of communication, and the quality of information is the substance of fiscal advice. The two have affected people's sense of purpose and desire to act. They will also affect people's sense of risk and trust because they are using the system and viewing the data provided by the system. Confidence will likely affect the continuous use of the product and regulate how much of its utility, ease of use, danger, service quality, etc., will be experienced over time.

The system will be more effective for the public if it can sense people's needs and offer appropriate service. It can help people feel that it is convenient to operate. For example, instead of having to visit many pages to find a financing repayment option, an artificial intelligence chatbot could ask some questions to guide us to choose one. To improve the value of the financial data, it needs to be more precise and current. In addition, because it can assure us of reliability, we are less uncertain.

Perceived Usefulness and Convenience will Increase People's Sense of Confidence. A good framework that can help people manage their money properly is considered effective. A Platform that is simple to understand can also give people a sense of purpose. Perceived danger will reduce people's confidence and voluntary participation. In the monetary industry, even a good platform will be ignored if the client thinks it is too risky. Ultimately, confidence is the strongest direct sign of continuous participation because consumers will not repeatedly use an AI system for their finances if they do not believe it is capable, secure and responsible.

Table 1. Core constructs and operational meanings

Construct	Operational meaning in AI financial advisory platforms	Expected role in the model
AI service interactivity	The chatbot understands user intent, maintains dialogue context, asks follow-up questions, and guides the next action.	Antecedent of usefulness, ease of use, trust, and risk reduction
Financial information quality	Accuracy, completeness, timeliness, and suitability of information related to products, fees, risk, and procedures.	Antecedent of usefulness, trust, and perceived risk
Perceived usefulness	The extent to which users believe the chatbot improves financial understanding and service-task completion.	Mediator and predictor of trust and continuance intention
Perceived ease of use	The extent to which users believe the chatbot is clear, simple, controllable, and not mentally burdensome.	Mediator and predictor of trust and continuance intention
Perceived risk	Expected financial, privacy, performance, and responsibility-related losses from using AI financial advice.	Negative predictor of trust and continuance intention
Trust	Belief that the chatbot and operating institution are competent, secure, transparent, and accountable.	Central mediator and direct predictor of continuance intention
Continuance intention	User intention to keep using the AI financial advisory chatbot in future financial-service interactions.	Outcome variable

Table 2. Proposed research hypotheses

Hypothesis	Path	Expected direction
H1	AI service interactivity -> perceived usefulness	Positive
H2	AI service interactivity -> perceived ease of use	Positive
H3	Financial information quality -> perceived usefulness	Positive
H4	Financial information quality -> perceived risk	Negative
H5	Perceived usefulness -> trust	Positive
H6	Perceived ease of use -> trust	Positive
H7	Perceived risk -> trust	Negative
H8	Perceived risk -> continuance intention	Negative
H9	Trust -> continuance intention	Positive
H10	Trust mediates the effects of service quality factors on continuance intention	Mediating effect

4. Proposed Research Design and Methodology

This article is designed as a conceptual study, but the model can be tested empirically using a survey-based structural equation modeling approach. The target population would be users who have experience with AI chatbots, robo-advisors, or intelligent customer-response systems in digital banking, investment, insurance, or consumer-finance platforms. A suitable sample could include mobile banking users, online brokerage users, FinTech platform users, and customers who have used AI-based financial guidance at least once during the previous six months.

The measurement elements can be obtained from the validated framework of the studies on Technology Acceptance, Digital Service Quality, Online Trust, Perceived Risk and Information System Continuance. A Likert scale will be used to rate the components; for example, 1 = strongly disagree, 5 = strongly agree. Before collecting a large amount of data, a small-scale study will be conducted to have the subjects learn about the different types of customer-service chatbots and financial-advice chatbots. Given that some people may be unfamiliar with the language of financial services, too many technical terms should not be used in the survey.

There will be some evaluation at various stages. First, descriptive statistics will be used to explore the social and economic conditions of the sample, background in banking services, etc. Then, with the help of Cronbach's α, total reliability, mean variance extraction and plus discriminant validity standards, consistency and authenticity should be checked. Thirdly, in order to confirm the structure of the model, confirmatory factor analysis will be employed. Fourthly, Structural Equation Modelling will be used to test the above hypotheses. Finally, mediation analysis can be carried out to determine if the confidence function is a mediator of the effect of AI performance on persistent behaviour intention. Given sufficient data, the size of the multi-group comparison can be divided into those with high and low financial literacy or high and low digital skills.

Systematic methodological bias should be avoided; that is to say, the same person will provide data for both precursor and consequence indicators. Operational safeguards are confidential, have specific wording for the items, are separated from the explanation and the dependent variable, and different scale anchors should be used when possible. Both kinds of quantitative analysis are Harman's single-factor test and common factor decomposition. The standard of ethical research still needs to be met for the investigation of money-laundering. Let the participants know that they will not be required to provide their account information, income records or investment credentials in this study.

5. Discussion

Based on the above architecture, it can be concluded that the application of AI-powered financial consultation robots will likely not only depend on technological feasibility but also on other reasons. Financial institutions have introduced chatbots to reduce operating expenses, and at the same time, there are various opinions among customers regarding the quality of the AI service. They will ask if the chatbot knows their specific situations, whether the data is accurate, whether the advice is reasonable, and if the organisation will take responsibility for mistakes by the automated guide. Therefore, the first executive hurdle is not only mechanisation but also accountable mechanisation.

A serious problem is that the service interaction will be a guided problem-solving process rather than an ordinary conversation. A conversational agent that uses friendly rhetoric but cannot remember previous conversations or distinguish between general advice and personalised consultation may make people lose heart. On the other hand, an agent can also make reasonable requests, present many options, resolve uncertainty, and have a human operator step in. It is particularly necessary for older clients, new financiers and those who are not very knowledgeable about money.

Another is the problem of information management. The quality of the financial data is based on the combination of client information, service repositories, hazard warnings, statutory laws and live account details. If the chatbot's response does not consider the current service situation, prices and costs, qualifications, etc., the advice provided may be outdated or incomplete. Therefore, the administrator of the financial system should develop a rule to periodically check the results of artificial intelligence, update service data and log cases where the agent refers the client to a live consultant.

The other is that trust is miscalibrated. The goal is to develop reasonable self-confidence in the use of artificial intelligence, not blindly rely on it. Consumers need to know what the AI framework can and cannot do. For instance, although a virtual conversational agent can introduce the various savings plans, it needs to be specified that it will not provide personalised financial advice under certain circumstances when the answer is general information. There will be some errors in the previous assumptions, and this will affect everyone.

Money Management: Data on the content of AI chatbot conversations can be used for management. Frequent questions from the client may indicate that the explanation of the product is unclear, the operation is too complicated, there are defects in the system, etc. Based on the analysis of the dialogue, the supervisor can revise the commodity structure, consumer education, problem prevention and support-path distribution, etc. Therefore, the AI-driven financial counselling chatbot should be included in the general management information system and not used alone at first.

6. Theoretical and Practical Implications

6.1. Theoretical Implications

This study offers several theoretical implications. First, it extends technology acceptance research by integrating perceived risk and trust into the adoption of AI financial advisory chatbots. Although TAM explains usefulness and ease of use, financial AI adoption requires additional attention to risk and institutional trust. Second, the study connects electronic service quality with AI conversational service design. Interactivity and information quality are treated as separate but complementary drivers of user perception. Third, the proposed model highlights continuance intention rather than one-time adoption intention. This distinction is important because financial service value emerges through repeated interaction and long-term relationship management.

6.2. Practical Implications

For banks and FinTech firms, the findings imply that chatbot success should not be measured only by cost reduction, call-center replacement, or number of automated conversations. Managers should also track resolution quality, user trust, human-transfer rates, complaint reduction, and the clarity of financial explanations. Performance indicators should combine operational metrics with user-centered metrics.

For AI system designers, the study emphasizes explainable and controllable interaction. Users should be able to see why a recommendation is provided, what data were used, what assumptions were made, and what alternatives exist. When uncertainty is high, the system should admit uncertainty rather than producing overconfident answers. A visible human-adviser transfer function is also essential in high-risk financial situations.

For regulators and policy makers, the model shows why financial AI should be evaluated through both innovation and consumer protection. AI chatbots can improve access to financial information, but they can also increase risks if users misunderstand algorithmic outputs. Clear disclosure rules, audit trails, data-protection standards, and accountability mechanisms are necessary for sustainable adoption.

7. Conclusion

Based on theory, this paper has provided some reasons for the current demand from clients for artificial intelligence financial advisory robots. Based on the Theory of TAM (Technology Acceptance Model), research on service excellence, trust, perceived risk and FinTech integration has found that the operations of artificial intelligence and standards for monetary data will affect people's sense of usefulness, ease of use, risk, reliability, etc., and thus impact their willingness to continue using. First of all, the main hypothesis is that confidence is the basic mental link that connects excellent AI fiscal services with repeated use.

This paper has certain defects. The above propositions are theoretical suggestions that need to be verified experimentally. Later, gather questionnaire data from the clients of internet banking, automated advisory services, insurance, asset platforms, etc. Investigators may also divide the various groups of consumers by age, financial literacy, digital literacy, economic status, etc. Empirical studies can also examine how different types of clarifications, the revelation of ambiguities and choices in humanisation, etc., affect confidence and the sense of danger.

There are still some deficiencies in the present research, but it has provided some references for future research and development of artificial intelligence in finance platforms. With the deepening application of artificial intelligence in the management of financial institutions, it is necessary to build some practical and intuitive functions for users; these should be transparent and secure.

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