Drivers of Financial Robot Continuance Usage Intentions: An Application of Self-efficacy Theory

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Abstract

As financial technology (FinTech) continues to improve, financial robots gradually become the direction for customers' investment and financial management references. This study develops an interactive model to illustrate how individuals use financial robots to achieve continuance intentions through self-efficacy. This study is conducted from the perspective of consumers. At present, most consumers obtain financial consulting services from financial robots and determine their investment directions based on data given. This study uses a self-efficacy model and the FinTech perspective to find the key factors for future investors to consider using financial robots. SPSS 21.0 and Smart PLS 3.0 are used in the analysis process. A total of 320 samples are obtained for the analysis in this study. Results show that financial and technological self-efficacy positively affect customers' continuance intention. This study will help consumers possess the ability to choose financial robots and improve their continuance intentions through financial literacy and task– technology fit (TTF).

Keywords: Financial self-efficacy, Technological self-efficacy, Financial literacy, Task-Technology Fit, Fintech continuance intention

1 Introduction

Financial technology (FinTech) has revised the financial operation process through technology investment. It helps companies, including banks, gain a competitive advantage mainly by reducing costs and improving efficiency [1]. FinTech is regarded as one of the most important innovations in the financial industry and is developing rapidly. FinTech promises to reshape the financial industry by reducing costs, improving the quality of financial services, and creating more diversified and stable financial markets for financial products [2]. Since the beginning of 2020, the world has been interacting with COVID-19, which has brought financial and psychological stress to industries and economies [3]. As a result, innovative technologies have proliferated to reduce challenges posed by government defenses against COVID-19, such as local and/or national lockdowns. FinTech applications have made significant strides to accelerate business and personal processes. FinTech offers important advantages over traditional technologies, such as enhancing business advantages and processing big data into meaningful data, which is cheaper and more secure than traditional technologies [4]. Furthermore, FinTech provides financial services while reducing traditional intermediaries [5] and obtaining the right financial message into the hands of consumers.

The COVID-19 pandemic has affected people all over the world [6]. People's increased self-protection and maintaining social distancing have direct effects on consumption and numerous industries. However, the turnaround resulted from the crisis in the financial industry has changed the relationship between finance and technology during this pandemic period. It has accelerated the development of FinTech and pushed financial development to a new level [7]. Financial robots under FinTech are the only financial management tools that have not been affected by the pandemic [8]. Financial robots provide consumers with precise investment directions through algorithms and artificial intelligence (AI). During the COVID-19 crisis, financial robots can support personal financial planning, wealth management, and investment at a low cost [9]. Although financial robots are a rapidly developing financial tool in recent years [7], limited research has been conducted on the personal psychology of the usage of financial robots in the past, resulting in the lack of awareness and understanding of many consumers on financial robots. In the past, finance and technology have been discussed separately with regard to consumers' continuance intentions to use in the financial industry. Ref [10] analyzed consumers' use of loan services through financial self-efficacy (FSE) and financial account ownership behavior. [11] explored the use intention of mobile payment through self-determination theory. Ref [12] examined the effect of consumers on the development of financial indicators of green technology through green technology innovation. Ref [13] used information and communication technology methods to understand consumers' continuance intention for financial services. To provide supplements for the lack of literature on financial services in the past and consider future development trends of FinTech, this study integrates two viewpoints, namely, the financial viewpoint and the technological development viewpoint.

By using financial robots in assessing personal wealth management and applying new technologies and financial

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management skills, Ref. [14] showed consistency with the concept of self-efficacy theory. Self-efficacy theory considers that individuals' behavior and motivation are influenced by one's self-confidence in one's own abilities [15-16]. Self-efficacy is regarded as one of the factors that directly or indirectly affect users' continuance intention in the financial service environment [12-13, 17]. Therefore, this study explores the continuance intention of financial robots through the perspective of self-efficacy. It applies the self-efficacy theory to consumers' continuance intention of financial robots. This study has two main contributions. First, it distinguishes FSE and technological self-efficacy to analyze the influences of different forms of self-efficacy on persistence intentions. Second, this study analyzes the intermediary factors of financial literacy and technology fit and confirms that the continuance intention of financial robots has valuable direct and indirect effects on banks' long-term FinTech services.

2 Literature Review and Hypotheses

2.1 Financial Robo-advisory Services

Financial robots are AI that can provide automated portfolio management services [1]. Such robots only require minimal human intervention in the personal financial consultation process [18]. Most wealth management robots obtain investor financial risk information through online questionnaires [19], which is in sharp contrast with traditional wealth management specialists. Financial professionals identify investor risk profiles through human-to-human interactions [8]. Financial management robots can simulate traditional financial professionals to provide financial services and customize and implement investment strategies without emotional factors in their financial advice [20]. When financial management robots perceive major market fluctuations, they can automatically maintain asset allocation goals for financial planning [21].

Financial robots provide advantages for consumers and bank managers [22]. Service providers can handle issues raised by relatively junior investors through financial robots to disintermediate and improve efficiency. Disintermediation helps service providers reduce costs and thus obtain lower administrative fees from consumers [17, 19]. As a result, using financial robo-advisory services is more beneficial than using more expensive traditional financial professionals. In addition, the automation of financial robots can provide high advisory services anytime, anywhere via mobile apps or the Web.

Financial robo-advisory services can contribute to a win-win situation for service providers and consumers. The financial industry will grow due to advances in FinTech. The main advantage and the importance of financial robots have been highlighted even more during the COVID-19 crisis. Furthermore, Ref. [23] argued that financial robots have seen more investment during the COVID-19 crisis, as financial robots are seen as another option for consumers to engage in investment management services. Financial robot advisory services can make investors be more interested in asking, mainly due to the good performance of financial robots in handling market volatility caused by the pandemic [24].

Ref. [25] predicted the economic, technological, and social development trends in the financial industry through financial robots, so that consumers can invest in advance. Ref. [26] predicted consumers' perceived risk, perceived usability, and continuance intention to use through financial robots. Therefore, financial robots not only help consumers formulate financial strategies but also reduce financial risks. Ref. [27] provided consumers with correct financial strategies through financial robot data analysis. Ref. [28] planned consumer financial risk assessments through financial robots and determined the practical value of financial robots.

2.2 Self-efficacy Theory

Ref. [15] proposed the concept of self-efficacy, indicating that self-efficacy represents the confidence one has in oneself when judging whether or one can complete a task. The three key factors presenting one's own performance are cognition, behavior, and environment. The interaction among these factors will change the behavior of individuals, and each has different evaluations and cognitions. Through the evaluation and cognition of self-efficacy, individuals will have cognition and self-awareness of the external environment [29]. Ref. [15] developed a set of views on self-efficacy. The idea behind self-efficacy is when an event have not happened yet, people will have a sort of pre-task expectation, hoping that they can deal with it properly, which is the expectation of their own ability. In addition when something progresses to a certain extent, people will expect certain results. On the basis of the difficulties encountered in tasks, an assessment of their own ability will help individuals' judgment under the influence of the two concepts [30]. Ref. [31] believed that self-efficacy is one's self-confidence that one can achieve continuous tasks, and that it has nothing to do with one's own ability but depends entirely on one's own assessment and self-confidence.

Self-efficacy is a structure derived from social cognitive theory [32]—a theory formed by behavior, cognition, and environment, in which all three assumptions interact in a dynamic manner, leading to the formation of self-efficacy. Self-efficacy represents the motivation, cognition, and behavior required to believe that one can accomplish and meet the needs of a particular situation.

Ref. [33] believed that self-efficacy is often regarded as the expected behavior brought about by personal expectations. The theory of expectations is influenced by two concepts, namely, behavioral and outcome expectations. Individuals will choose to perform tasks with relatively high expectations but avoid difficult tasks. Ref. [34] indicated that self-efficacy represents an individual's evaluation of being able to complete a certain task and reflects the individual's motivation rather than ability. The higher the self-efficacy is, the higher the motivation to complete the goal will be. Self-efficacy is a psychological concept that focuses on the ability and confidence to perform relevant behaviors in a given situation [16].

In the past, self-efficacy has been regarded as a driver that directly affects individuals' willingness to continue to use financial services [35]. Self-efficacy can be applied in different fields [36-38], such as electronic services and the use of Web information system (IS) [29-30]. Although previous studies have directly used self-efficacy in different fields, self-efficacy is a conceptual variable that is not easy to measure and must be measured in a specific field [39]. Ref. [40] suggested that self-efficacy must be transformed when applied to different domains.

Therefore, self-efficacy has greater predictive power in specific domains [41]. Then, in view of the wealth management characteristics that must be present in the field of FinTech, individuals must measure their own financial management and technology usage capabilities. Before conducting wealth management, individuals must understand the characteristics of financial products based on their own FSE. In mobile commerce, financial products can be searched and analyzed through technological self-efficacy to invest correctly. Therefore, individuals must have FSE and technological self-efficacy when conducting financial management and investment to correctly analyze and invest in financial products.

The social cognitive theory explores the role of cognitive thinking in motivating individuals and guiding their financial behavior [42], which is consistent with the concept of FSE. FSE refers to a measurement standard of an individual's confidence in using financial services and is based on a background in the financial sector. FSE is a concept of self-efficacy through inspection. Investors' cognition and behavior can accomplish tasks by believing in their own abilities because of FSE. Ref. [43] found that self-efficacy and financial literacy help predict the likelihood of getting a credit loan. Ref. [44] emphasized that self-efficacy significantly affects financial behavior, especially when adolescents are financially literate and have good financial behavior [45]. These findings are consistent with past research that investors need such financial confidence and literacy to drive financial products and services. Thus, in terms of financial services, high levels of self-efficacy may affect investors' financial literacy.

Task–technology fit (TTF) emphasizes the interaction among tasks, technology, and individuals [38]. According to Ref. [46], TTF refers to the degree to which technology helps individuals complete their task mix. Specifically, TTF focuses more on the relationship among task and technical characteristics, utilization, and influence of performance. TTF mainly includes the correlation between the task and the correct use of technology [47]. However, if the technology is not suitable for the task, then the corresponding system cannot be successfully implemented [47-48]. Ref. [49] believed that personal self-efficacy will be adapted to the tasks assigned by the company to meet the current task needs. When personal FSE is high, self-judgment and financial robots will be used to perform related tasks. Therefore, this study proposes the following hypotheses:

H1: FSE has a positive effect on financial literacy.

H2: FSE has a positive effect on TTF.

Ref. [50] pointed out that technological self-efficacy reduces individuals' anxiety about using technological innovation and enhances their personal ability. People with high technological self-efficacy are more likely to adapt to technological innovation than those with low technological self-efficacy [51].

Financial literacy is an individual's basic ability to manage money, which depends on personal responsibility and self-discipline. Ref. [51] believed that individuals must have a high degree of self-efficacy to make decisions under complex financial products. Wealth management is possible under the use of mobile commerce, consumers with high technological self-efficacy believe that they can download and operate wealth management applications [52]. Therefore, consumers can collect more financial information to improve their financial literacy through technological self-efficacy. Thus, personal self-efficacy contributes to the generation of financial literacy, which, in turn, leads to obtaining desired goals.

Ref. [53] believed that the success of an IS depends on whether its functions can meet users' task needs. Therefore, when individuals' self-efficacy is high, they can assign tasks better. Effectively supporting technology can increase processing efficiency. When individuals improve their technological self-efficacy, they can discover effective investment methods through task and technological characteristics. When using a financial robot, personal technological self-efficacy will produce a fit with the financial robot's investment advice and generate purchasing behavior for the investment portfolio [11]. Ref. [39] believed that task matching is adjusted when individuals' self-efficacy is high. Therefore, this study proposes the following hypotheses:

H3: Technological self-efficacy has a positive effect on financial literacy.

H4: Technological self-efficacy has a positive effect on TTF.

Ref. [54] believed that financial literacy is of great significance to every customer. In the past, many concepts related to financial literacy have focused on 1) financial literacy concepts, 2) financial literacy interactivity, 3) personal financial competence, and 4) financial decision-making skills [48-49]. Many studies have also suggested that consumers with higher financial literacy can make more proper financial decisions [55-56]. Ref. [57] claimed that when financial literacy is high, consumers can accept financial advice better from financial robots and then purchase financial products. Many studies have suggested that knowledge drives personal competence, and when personal financial literacy makes judgments based on the knowledge that individuals are exposed to, the willingness to use financial robots will increase when many financial decisions cannot be judged correctly [58]. Many previous works have proposed that TTF is a system that provides effective support that will increase usage and improve user performance [59]. Tasks and technology features affect TTF. The TTF model will affect users' personal performance and continuance intention [39, 53]. At present, many consumers in mobile commerce will operate and place orders on their mobile phones [60]. In TTF, consumers can observe that the use of financial robots in investments is only subject to the degree of fit between task and technological characteristics [54-55].

However, consumers, who have an understanding of the operating technology and features in the usage of financial robots can better generate continuance intentions for financial robots. Thus, this study proposes the following:

H5: Financial literacy has a positive effect on continuance intention.

H6: TTF has a positive effect on continuance intention.

3 Research Methodology

3.1 Research Model

This study aims to find out whether personal self-efficacy affects usage intention through financial literacy and task-technology fit. It uses financial self-efficacy, technological self-efficacy, financial literacy, task-technology fit and continuous intention to understand the direct and indirect relationships between variables. After reviewing the literature, this study developed a conceptual research model (Figure 1).

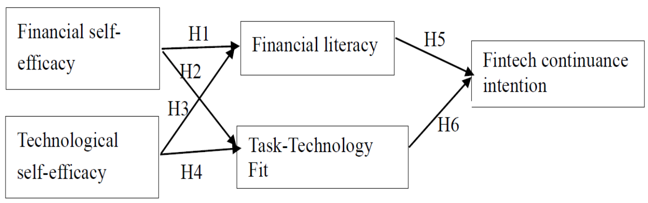

Figure 1. Research model

3.2 Data and Sample

The study aims to investigate the effect of personal usage of financial robots on consumers' continuance intentions. Therefore, this study measured the proposed variables based on the measurement items in the past literature that fit this context. After the management background experts revised the questionnaire items to ensure that the items could convey their meanings, a semantic revision was conducted, and the questionnaire items were verified by 50 consumers who have used financial robots and university professors with financial backgrounds. Finally, the accuracy and comprehension of the content of the questionnaire in this study were confirmed.

The main purpose of this study is to explore the continuance intention of financial robot users in terms of self-efficacy, financial literacy, and TTF. Given that financial robots are currently an investment service under FinTech, building a financial robot with continuance intention is crucial. Therefore, the population of this study was defined as consumers who have used financial robots. The questionnaire was distributed online; it allows easy exchange of opinions and is not limited by time and space. The online questionnaire platform, My survey, was selected as the tool for data collection. Table 1 shows the statistical analysis of basic data.

Table 1. Demographic analysis

Characteristics	N	%
Gender		
Male	127	39.70
Female	193	60.30
Age (years)		
21~ 30	124	38.75
31~40	164	51.25
41~50	25	7.81
> 51	7	2.19
Education		
Junior high school	13	4.06
High school	86	26.88
Bachelor or Master	202	63.12
Other	19	5.94
Month Income (dollars)		
<$1000	153	47.81
$1001~$2000	73	22.81
$2001~$3000	87	27.19
>$3000	7	2.19

3.3 Measurement

The purpose of the questionnaire was to collect information on the relationship among people's personal financial literacy, personal emotional response, and usage intention in terms of adopting and using financial robots. The first part of the questionnaire asked about basic personal information, and the second part asked about personal views on financial robots, including financial literacy and personal emotions, to understand personal willingness in using financial robots. To measure participants' responses on financial literacy, a five-point Likert scale was used, ranging from 1 (strongly disagree) to 5 (strongly agree). As proposed by [61-62], this scale was used to test financial literacy. Anxiety was proposed by [63], joy was proposed by [63]. FSE was proposed by [64], and Usage Intention was proposed by [65].

3.4 Nonresponse Bias

Nonresponse bias is when people who do not answer a questionnaire may create bias in the results of a study. This study's nonresponse approach follows the procedure suggested by [64, 66], who argued that late respondents are more likely to resemble non-respondents than earlier respondents. This study addresses this question by comparing the gender and age variables of early versus late respondents. The 101 respondents who completed the survey in the early stage were considered to be early respondents compared with the 219 who completed the survey in the latter stage. No significant difference was observed in gender, age, or education level among the subjects tested by the respondents' t-test in the early and late stages ($p > 0.05$). Therefore, the possibility of nonresponse bias was eliminated.

3.5 Common Method Bias

When all data are from the same source, questionnaires may have a common method bias, which may threaten the validity of the study. Given that our questionnaires were collected online, the sample is not limited to a certain region or group. Nonetheless, this study used Harman's one-factor test to identify any potential factors for common method bias. If a single dimension can explain more than 50% of the variance for all variables, it is considered a serious common method variance problem [67]. In this study, the principal component analysis method was used. The variables were divided into a total of five dimensions, and the cumulative total variance was 59.46%; the first dimension accounted for 31.95%, and common method variance was not a problem for this study.

4 Results

4.1 Construct Validity and Reliability

Ref. [68] believed that an analysis must be conducted through a two-stage method of structural equation model. In the first stage, Cronbach's alpha coefficient analysis, exploratory factor analysis, and confirmatory factor analysis were performed to investigate the reliability, convergent validity, and discriminant validity of each construct to develop a stable measurement model. In the second stage, structural model was used to test the hypotheses of this study. The reliability and validity analysis is shown in Table 2.

Confirmatory factor analysis was used to explore the composite reliability (CR) and average variance extracted (AVE) of latent variables to test the convergent and discriminant validity. According to the suggestion of [69], this study used individual item reliability, CR, and AVE to measure the convergent validity of observed and latent variables. CR refers to evaluating all measured variables of the latent variable on their reliability composition, and AVE refers to the calculation of each measurement of the latent variable on the mean-variance explanatory power of the latent variables. As shown in Table 2, the Cronbach's α values of all dimensions were between 0.859 and 0.910. The CR values were higher than the 0.7 thresholds with higher internal consistency reliability [70]. The values of rA were all above the acceptable range (> 0.7) [71]. The AVE value was higher than 0.50, indicating that the proposed framework has convergent validity.

Table 2. Construct reliability and validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
FL	0.906	0.913	0.930	0.726
FSE	0.872	0.877	0.913	0.723
FCI	0.962	0.962	0.975	0.929
TTF	0.956	0.956	0.968	0.883
TSE	0.920	0.928	0.941	0.763

Note. Financial literacy: FL; Financial; self-efficacy: FSE; Fintech continuance intention: FCI; Task-technology fit: TTF; Technological self-efficacy: TSE

The judgment area of validity has three steps. According to Table 3 to Table 5, Fornell and Larcker estimated that the square root of the diagonal AVE value between latent variables must be greater than the value of the correlation coefficient between dimensions [70]. Table 3 shows that the square root of the diagonal AVE value has a correlation coefficient greater than that of the following dimensions. Table 4 shows that the cross-loading amount is under the requirement of the single-dimension criterion, and each item can only belong to a specific dimension; thus, it will have a higher correlation with a certain dimension, and no correlations will exist with other dimensions. In this study, the cross-loads were all greater than 0.8 and could be separated from other dimensions.

Table 3. Fornell-Larcker criterion

	FL	FSE	FCI	TTF	TSE
FL	0.852				
FSE	0.482	0.850			
FCI	0.319	0.270	0.964		
TTF	0.516	0.552	0.413	0.940	
TSE	0.522	0.603	0.305	0.618	0.874

Note. FL: Financial literacy; Financial; FSE : self-efficacy; FCI: Fintech continuance intention; TTF: Task-technology fit; TSE: Technological self-efficacy

Table 4. Cross loadings

	FL	FSE	FCI	TTF	TSE
FCI1	0.294	0.246	**0.952**	0.403	0.276
FCI2	0.308	0.255	**0.969**	0.386	0.288
FCI3	0.322	0.277	**0.970**	0.403	0.316
FL1	**0.876**	0.412	0.261	0.491	0.454
FL2	**0.872**	0.377	0.305	0.452	0.469
FL3	**0.846**	0.373	0.240	0.397	0.423
FL4	**0.789**	0.382	0.227	0.369	0.378
FL5	**0.875**	0.497	0.316	0.477	0.486
FSE1	0.375	**0.813**	0.219	0.532	0.429
FSE2	0.447	**0.884**	0.221	0.521	0.561
FSE3	0.409	**0.848**	0.261	0.383	0.535
FSE4	0.407	**0.856**	0.220	0.420	0.528
TSE1	0.419	0.424	0.249	0.412	**0.733**
TSE2	0.503	0.572	0.202	0.538	**0.867**
TSE3	0.461	0.526	0.295	0.576	**0.933**
TSE4	0.437	0.524	0.280	0.579	**0.920**
TSE5	0.459	0.574	0.305	0.578	**0.900**
TTF1	0.494	0.504	0.399	**0.943**	0.559
TTF2	0.488	0.543	0.379	**0.957**	0.597
TTF3	0.463	0.483	0.386	**0.927**	0.575
TTF4	0.495	0.542	0.386	**0.931**	0.592

Note. FL: Financial literacy; Financial; FSE : self-efficacy; FCI: Fintech continuance intention; TTF: Task-technology fit; TSE: Technological self-efficacy

The summary of the above analysis results indicate that this study has convergent and discriminant validity. A high confidence exists among the dimensions in the reliability section. Therefore, the framework proposed in this study has reliability and validity.

HTMT is an average of the correlation among the indicators of different dimension, with a threshold value of 0.85 or less. [70]. The results show Table 5.

Table 5. Heterotrait-Monotrait ratio (HTMT)

	FL	FSE	FCI	TTF
Financial literacy	0.538			
Fintech continuance intention	0.339	0.295		
Task-technology fit	0.551	0.597	0.430	
Technological self-efficacy	0.570	0.672	0.325	0.657

Note. FL: Financial literacy; Financial; FCI: Fintech continuance intention; TTF: Task-technology fit; TSE: Technological self-efficacy

4.2 Path Analysis

After the measurement model has been validated, the next step is to confirm the hypothesized relationships between the underlying latent model in the structural model. Structural models were evaluated using Smart PLS 3.0. To determine the PLS estimation accuracy in the framework, computations were resampled 2000 times by bootstrapping to analyze the significance of the structural model. The results of the study are shown in Table 6. H1, FSE has a significantly positive effect on financial literacy, was accepted ($\beta = 0.263$; $t = 5.971$ $p < 0.05$). H2, FSE has a positive effect on TTF, was also accepted ($\beta = 0.281$; $t = 5.909$; $p < 0.05$). H3, technological self-efficacy has a positive effect on financial literacy, was verified ($\beta = 0.363$; $t = 6.925$; $p < 0.05$). H4 indicates that technological self-efficacy has a positive effect on TTF ($\beta = 0.449$; $t = 7.870$; $p < 0.05$), H5 indicates that financial literacy has a positive effect on continuance intention ($\beta = 0.145$; $t = 2.792$; $p < 0.05$), and H6 claims that TTF has a positive effect on continuance intention ($\beta = 0.338$; $t = 5.749$; $p < 0.05$).

Table 6. Path analysis

	β	Sample Mean	t-teat	Support
FL→ SCI	0.145	0.143	2.792	Yes
FSE→ FL	0.263	0.266	5.971	Yes
FSE→ TTF	0.281	0.283	5.909	Yes
TTF→ SCI	0.338	0.333	5.749	Yes
TSE→ FL	0.363	0.360	6.925	Yes
TSE→ TTF	0.449	0.446	7.870	Yes

Note. FL: Financial literacy; Financial; FSE : self-efficacy; FCI: Fintech continuance intention; TTF: Task-technology fit; TSE: Technological self-efficacy

Table 7. Mediation analysis results

	β	Sample Mean	t-teat	Support
FSE → FL→ FCI	0.038	0.038	2.58	Yes
TSE →FL→ FCI	0.053	0.052	2.41	Yes
FSE → TTF→FCI	0.095	0.093	4.61	Yes
TSE → TTF→FCI	0.152	0.149	4.15	Yes
FSE → FL→ FCI	0.038	0.038	2.58	Yes

Note. FL: Financial literacy; Financial; FSE : self-efficacy; FCI: Fintech continuance intention;TTF: Task-technology fit; TSE: Technological self-efficacy

Finally, the study performed mediation analysiss to see if financial self-efficacy and technological self-efficacy significantly mediates the relationship between Fintech continuance intention. The results are presented in Table 7.

5 Discussion and Conclusion

5.1 Discussion

The field of FinTech is currently the hottest research field. FinTech mainly focuses on specific technologies in practice, emphasizing on practical methods in the financial field, which will cause the lack of basic theory to ignore the ability of scientific and technological innovation. FinTech is the combination of finance and technology, and the basic equipment in technology promotes the development of finance. Therefore, in the next stage, how to achieve deep integration by jointly promoting the innovation of finance and technology is the main topic of this study.

The first part of this study showed that FSE has a positive effect on financial literacy and technology fit. FSE refers to individuals' level of confidence in using financial services, and it is based on financial background. A positive relationship exists between FSE and financial literacy. Investor perceptions and behaviors in the financial industry may affect a particular task or activity by believing in their own abilities. Given that FSE can have a positive change in financial literacy, individuals believe that they can achieve their goals through their financial knowledge, resources and financial cognition. In many financial industries, banks continue to invest a large amount of money in the market to attract consumers. Given the lack of self-efficacy of personal financial management, investors cannot make the correct judgement when investing. Financial management robots can help investors conduct investment analysis in a timely manner. Individuals can also give opinions according to their own preference for financial products when financial robots conduct investment analyses. Therefore, in the overall financial market, self-efficacy in personal financial management will enhance the improvement of financial literacy, and individuals will actively search for relevant financial knowledge to match the financial management robots. By testing the financial management robot and giving relevant special tasks, individuals can confirm that the financial knowledge they recognized is in line with the task requirements recognized by the financial robot. Therefore, personal FSE and TTF of financial robots should be improved to make correct judgments on investment and financial management.

The study clearly found that technological self-efficacy has a positive effect on financial literacy. Technological self-efficacy has the self-assessed ability to use technology. Generally, people with high technological self-efficacy believe that they can manage their finances through their own abilities and are thus more willing to trust their chosen financial tools to manage their personal finances. Through financial management robots, people with high technological self-efficacy can perceive that the financial advice provided by the robot is compatible with their financial literacy and will create higher performance. With the same belief in technological self-efficacy, individuals can also have better use of financial robots for wealth management. The higher technological self-efficacy is, suitable financial management methods and information will more likely be found for individuals through TTF, that is to say, one can feel the convenience and high efficiency brought by financial robots.

5.2 Conclusion

The study found that financial literacy and TTF have a positive effect on continuance intention. Financial technological self-efficacy is a cognitive belief that represents how well actual usage can help consumers' expectations of FinTech. Consumers have certain expectations for the services provided by financial robots, such as customized financial solutions, high-yield and low-risk financial products, accurate and detailed financial product descriptions, flexible deposit and withdrawal mechanisms, and convenient customer service. FinTech companies should be able to understand consumer needs through financial robots. When these needs are met, consumers will trust financial robots to help individuals improve their financial returns. Therefore, FinTech companies can understand personal financial literacy and then plan financial projects to improve usage intention.

The study also found that technology fit affects usage intention. When individuals use financial management robots, they will match the financial goals of the financial robots with their own before they can make investments. Therefore, individuals will use mobile banking and financial management robots to search for relevant financial information and compare the information of the financial management robot to choose a more favorable investment portfolio. Therefore, technology fit is considered to be the degree to which financial robots can assist consumers to complete their work and finally achieve consumers' continuance intention.

Finally, the study found that FSE and technological self-efficacy have a mediating effect on continuance intention. Investors with higher FSE and higher financial literacy are more likely to purchase financial products after using financial robots. When consumers have high financial literacy, they can confirm the correctness of financial products. When financial management robots make investment judgments, they can more accurately reflect psychological expectations. Investors immediately invest when their expectations are in line with the financial robot's advice. FinTech and financial performance can be improved through this sense of customer recognition. In the part of technological self-efficacy, investors will have more confidence in their personal abilities by using financial robots in their investment, and they will have investment intentions when they can match their own financial goals with the appropriate goals during the entire operation process. Specifically, FSE and technological self-efficacy need financial literacy and TTF to confirm personal investment goals, and the usage intention of financial robots will be improved.

In the personal financial management part of financial robots, the robots can provide consumers with relatively objective judgments because they analyze through AI machine learning, are not affected by personal emotions and subjective factors, and are can thus provide consumers with more rational suggestions. Financial management robot can be completed online, so people can open an account and conduct investments without leaving their home. Given many financial products, consumers cannot judge the investment of financial products. Financial management robots can judge consumers' financial goals and risk tolerance for financial investment planning. After consumers improve their FSE and financial literacy, compared with other financial services, consumers can accept financial robot services more. This study proposed an integrated model to illustrate the current continuance intention to use financial robots through the combination of technology and financial development.

5.3 Research Contributions and Findings

The main contributions of this study are as follows. First, this study combines the theory of self-efficacy with TTF to understand the continuance intensions of users and investors for financial robots. The literature on the use of financial robots in financial-related fields has been less discussed by scholars, and related theories can be extended to other financial products in the future. Past related research has not accurately explained how the use of financial robots is linked to continuance intentions through personal self-efficacy. Therefore, the results of this study can improve investors' understanding of related researches on financial robots.

Second, according to the characteristics of the financial industry, this study is divided into FSE and technological self-efficacy. The two skills of finance and technology are related to the use of financial robot technology and the level of personal financial management ability. This study highlights the importance of self-efficacy in finance and technology under different specific circumstances—an approach that enhances companies' understanding of investors' investment projects and can accurately understand investment needs.

This study emphasizes the importance of FSE and technological self-efficacy in the use of financial robots by investors in the financial industry. Through the analysis of the results of this study, self-efficacy can indeed have an effect on continuance intention through financial literacy and TTF. Therefore, in the financial field, investors can better understand the investment results through financial robot analysis. A good technological experience can improve investors' awareness of investment and wealth management products and meet investors' needs, thereby making investors' financial performance more significant.

Therefore, FinTech companies or financial institutions can conduct segmental analysis on investors. Financial robots can customize services for different investors and formulate many financial portfolios. Therefore, investors with higher FSE are more useful for financial management using financial robots. Investors are confident in financial robots.

In addition, the literature has found that the failure of financial management leads to social problems. Therefore, this study suggests that the government can establish a database of personal investment behavior to manage personal investment and financial records. Individuals can judge whether to invest in financial products according to the database, such that investors can understand financial management capabilities and establish self-efficacy.

Financial robots are the most important key factor in the development of FinTech. The application of technology has great importance for investment and financial management. Therefore, technological self-efficacy and TTF are relatively important in the prediction model. Generally, using mobile commerce and software is not difficult for multiple investors. Therefore, investing online through financial robots can increase investors' willingness to invest in financial products.

This study also confirms that financial literacy and TTF are important indicators that can accurately influence investors' continuance intention on financial robots. Given that the investment experience of investors in financial products in the past will affect financial performance, the financial robot will advise investors to invest more objectively and will not affect investment projects due to personal emotions. Through the objective judgment of financial robots and the improvement of personal FSE, the performance of financial products can be accurately improved.

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