

Consumer Attitudes towards AI-based Financial Advice: Insights for Decision Support Systems (DSS) and Technology Integration

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Abstract

As financial technology (fintech) rapidly transforms the financial services landscape, the integration of artificial intelligence (AI) in providing financial advice becomes a focal point. This study delves into the intricate dynamics of AI-based financial advice adoption, focusing on technology integration, decision support systems, and the mediating role of perceived utility. The primary purpose of this research is to unravel the complex relationships between technology integration, Decision Support System (DSS), perceived utility, and their collective influence on consumer attitudes toward AI-based financial advice and technology adoption. Adopting a cross-sectional design, we target the Chinese population and utilize an online questionnaire for data collection. A sample size of 259 participants is determined using the rule of thumb technique, with random sampling ensuring representativeness. Data analysis will be conducted using the AMOS software, allowing for an in-depth examination of the relationships between variables. The study findings demonstrate how integrating technology enhances customers' perceptions and acceptance of it, especially when it comes to data security and compatibility. The study also demonstrates how customer attitudes and the uptake of AI-driven financial aid are significantly impacted by DSS aspects like decision transparency and predictive analytics precision. The study is unique because of its cross-cultural approach and perceived value as a mediating component. While this study focuses on the Chinese population, the researchers acknowledge the importance of cultural differences in shaping user perceptions and behaviors. While the findings may offer valuable insights into the Chinese context, caution is advised in generalizing the results to other cultural contexts.

Keywords: Technology Integration, Decision Support System (DSS), Consumer Attitude toward AI-based Financial Advice, Technology Adoption.

1 Introduction

AI is a big factor in financial technology, especially guidance which provides solutions to many revolutionizing financial decision-making in the increasingly complex financial world by providing specialized insights and ideas (Shanmuganathan, 2020). This study explores the complex dynamics of AI-based financial advice adoption, concentrating on technological integration, decision support systems, and perceived value. Technology affects the financial sector, with AI driving innovation (Bouteraa et al., 2024). Advanced technology enhances financial services' efficiency and accuracy but creates new difficulties. The introduction of these technologies raises concerns about how consumers perceive AI systems while making key financial decisions and the dynamics that impact their perceptions (Manser

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Payne & O'Brien, 2024). This study analyzes the complicated interaction between technology, decision support systems, and AI-driven financial advice customers' perceived value. Academics, politicians, business players, and technological engineers must comprehend how financial advice uses and accepts AI. Consumer attitudes and adoption trends can help create, deploy, and manage AI-driven financial systems (Dikmen & Burns, 2022). This cross-cultural study examines how Chinese culture affects AI-based financial advising perceptions and behaviors. Previous study shows a global movement toward AI-driven financial consultancy. This highlights the importance of user adoption viewpoints and choices. Technology matters because data security and interoperability impact customer acceptance and confidence, according to (Michaela Denise Gonzales & Hargreaves, 2022). Its dependability and usability depend on how well AI-powered financial advice interfaces with users' devices and is secure (Lei et al., 2022). More research is needed to determine how technology integration affects consumer impressions. Financial advice based on AI must use DSS.

Consumer trust and satisfaction increase with accurate predictive analytics and transparent decision-making (Conde et al., 2024). DSS components' effects on customer opinions and AI-driven financial advising system acceptability need further study. Empirical research is complicated by perceived value mediating technological integration, DSS, and user attitudes. According to the Technology Acceptance Model, perceived utility affects adoption (Yao et al., 2023). Using earlier research, it examines how customers' subjective assessments of integrated technologies impact the complex ecosystem of AI-based financial advice services (Hyun Baek & Kim, 2023). Research has increased banking and technology adoption knowledge. According to (Litterscheidt & Streich, 2020), technology integration, decision support systems, and other variables impact AI-based financial advising user acceptance. Security and interoperability influence user attitudes, studies show. Good data security boosts AI-powered financial system user confidence. Compatibility and device integration increase user experience. This study shows technological integration boosts consumer satisfaction. Clear predictive analytics is emphasized in DSS research (Kim et al., 2020). A good DSS improves financial advice accuracy and client satisfaction (Nikseresht et al., 2024). Kempeneer, (2021) recommends decision transparency for AI-driven financial system client confidence. It allows analysis of how DSS characteristics affect user perceptions and uptake.

Previous research has been crucial, but its shortcomings suggest further investigation in the current work. Technology integration and decision support systems are important in the literature, but little is known about how they affect customer attitudes and technology adoption (Santiago et al., 2024). Technological integration, DSS, perceived value, and user behaviors are examined to bridge the knowledge gap. Discover what makes AI-based financial advising popular (Kwon & Lee, 2024). More research is needed on perceived usefulness as a mediator. Previous research has focused on direct links between technical components and user opinions, ignoring user-subjective technology utility evaluations (Nikseresht et al., 2024). This research improves comprehension by integrating perceived utility as a mediator. The cognitive mechanisms underpinning AI-powered financial advice acceptance are shown. Researchers found a paucity of cross-cultural considerations and AI-based financial advice (Zhu et al., 2023).

This study examines how technological integration, DSS perceived usefulness, and customer perceptions of AI-based financial advice and technology adoption are interconnected. The research investigates several elements to understand the intricate links in the ever-changing financial technology adoption environment. Data security and compatibility are assessed to determine how technology integration affects AI-based financial advice product user impressions. The study examines how decision

transparency and predictive analytics accuracy affect customer perceptions and financial technology adoption. The study uses perceived utility as a mediator to evaluate how cognitive processes affect AI-powered financial advice user perceptions and decisions. This cross-cultural study evaluates Chinese user attitudes and adoption trends by culture. This contextualization makes the study more relevant and informative to worldwide audiences. Academic understanding and financial technologies are enhanced with this research. This study addresses a key knowledge gap by examining how decision support systems and technology integration affect consumer sentiments and technology adoption. Previous research has explored these aspects separately, but this study's holistic approach illuminates AI-driven financial advice's complex linkages. Including assessed mediator effectiveness broadens the investigation. To discover cognitive elements that promote integrated technology adoption, this study studies consumers' subjective value assessments. This better knowledge improves theoretical models, making financial technology usage assessment more inclusive. The cross-cultural study of China shows how culture affects financial technology adoption. This makes the results relevant outside China and contributes to the global financial technology discussion. Lawmakers, technology developers, and business stakeholders can apply the study's findings to various cultures. Financial technology solutions can become more effective and inclusive. The findings impact regulatory bodies, financial institutions, and technology firms developing AI-based financial advice systems. The study may help financial services organizations leverage current technology to enhance user confidence, satisfaction, and adoption.

2 Literature Review

Technology Integration and Consumer Attitude Toward AI-based Financial Advice

Technology integration influences how clients see AI-based financial advice, particularly data security and interoperability. Financial services need trustworthy data security. Data security greatly impacts consumers' financial information safety and privacy (Shiva et al., 2023). As AI-based financial advising platforms grow, customers' decision-making depends on data privacy. Manser Payne and O'Brien, (2024) discovered that increased security and encryption reduce these issues and increase client trust in AI-driven financial advice. The seamless integration of AI-based financial systems with current technology influences user experiences and perceptions. Compatibility, as described in comprehensive research (Sedrati et al., 2023), is the smooth integration of AI systems with current client devices and interfaces. Financial advising systems appear user-friendly and accessible when they link to customers' devices and interfaces. This influences consumer usability impression. Sunder et al., (2024) discovered that clients trust AI financial advisory solutions that operate with their gadgets. It improves system usability and accessibility. Thus, technology compatibility is crucial to clients' positive opinions of AI-driven financial advising. AI-based financial advising benefits from modern automation. The Technology Adoption Model (TAM) indicates that perceived usefulness substantially influences customer adoption of technology (Aldammagh et al., 2021). Financial advice with AI enhances customer usability. Financial consultancy platforms benefit from predictive analytics algorithms' individualized investment suggestions based on large datasets. Lei et al., (2022) found that consumers who valued AI-based financial advice used it more. Technology integration impacts customer impressions by affecting ease of use. Users find AI-based financial guidance products with intuitive interfaces straightforward to use. Customers employ technology based on perceived simplicity of use, according to Gazit et al., (2023). AI-based financial advisory services' usability influences user uptake. This perception is improved by easy technology integration, including compatibility issues.

H1: Technology integration has a significant and positive impact on consumer attitude toward AI-based financial advice.

Technology Integration and Technology Adoption

Technology adoption in modern digital contexts is difficult and crucial owing to its integration, especially in data protection and compatibility. Yukhymenko-Lescroart et al., (2021) found that customers prioritize data security while adopting new technologies, especially in cybersecurity-focused environments. Technology infrastructures with strong data security standards reassure users and generate confidence. Chatterjee et al., (2023) observed that data security greatly impacts customers' views on technology's dependability and privacy, which affects their technology usage decisions. Technology adoption is sped up by compatibility as well. Compatibility as a new idea's fit with potential adopters' attitudes, experiences, and wants (Ngoc Su et al., 2023). For consumer technological advances, compatibility is crucial. Innovative technologies are seamlessly integrated into existing systems and gadgets to simplify usage and fit into daily routines. Siyal et al., (2023) say, that compatibility strongly affects customers' perceived ease of adopting new technologies. This shows how important compatibility is for adoption. Customer technology adoption risk and uncertainty depend on data security and compatibility. Technology adoption increases with reduced security concerns and system incompatibility (Aldammagh et al., 2021). Privacy, security, and unwanted access are reduced via data-protection technology integration. Reduces risks and boosts tech adoption. Compatibility makes new technology simpler to integrate with users' tools and habits, reducing risks and improving comfort. Cavalcanti et al., (2022) revealed that customers choose secure, compatible technology. The study demonstrated a favorable association between data security and compatibility and clients' technology adoption. Prioritizing technology integration, especially data security and compatibility may improve technology adoption by addressing user concerns and improving the user experience.

H2: Technology integration has a significant and positive impact on technology adoption.

Decision Support Systems and Consumer Attitude Toward AI-based Financial Advice

DSS integration influences customers' perceptions of AI-based financial advising platforms' utility and usability, which impacts technology uptake. Decision Support Systems using predictive analytics increase financial advice reliability. Christiansen et al., (2022) say predictive analytics in DSS helps financial platforms examine huge datasets and generate better forecasts and suggestions. AI-powered financial advice is valued more because customers seek data-driven, accurate financial advice. Consumer attitudes are altered by open decision-making in these systems. Goodell et al., (2023) describe decision transparency as a system's communication of its decision-making processes. AI-based financial advice with transparent decision-making boosts trust. According to (Battistini et al., 2023), customers who understand decision-making are more inclined to accept AI-driven financial advice. Decision openness boosts financial advising service value, affecting consumer trust. A Decision Support System emphasizes customer mindset. Comprehensibility and clarity boost consumers' perceptions of DSS decision-making simplicity. The Technology Acceptability Model states that user perception of ease of use strongly influences technology acceptance (Maulik et al., 2022). DSSs that encourage open decision-making and predictive analytics simplify AI-based financial advising. Jayasiri et al., (2023) say transparent decision support systems assist buyers pick user-friendly tech. Consumer impressions of AI-based financial advice are also crucial, as are accurate predictive analytics and transparent decision assistance. Azmi et al., (2023) found that perceived efficacy predicts technology attitudes and intentions. The AI system's financial

guidance benefits from precise predictive analytics and transparent decision-making. As financial advice becomes more useful, customers' technological views change, making them more open to AI-powered financial guidance.

H3: The decision support system has a significant and positive impact on consumer attitude toward AI-based financial advice.

Decision Support Systems and Technology Adoption

Technology deployment and DSS efficiency—especially decision transparency and predictive analytics—are linked. DSS predictive analytics accuracy strongly affects user and stakeholder satisfaction. Conde et al., (2024) discovered that DSS predictive analytics with accurate information increases consumer acceptance of technology. DSS's ability to analyze data, predict results, and provide accurate recommendations affects user trust and adoption. Technology adoption is influenced by Decision Transparency, a DSS essential. Transparency in decision-making shows how alternatives and suggestions are created. Pour et al., (2023) found decision-making clarity increases tech adoption. Transparent DSS decision procedures increase user confidence and usability, spreading technology adoption. DSS users rate their usefulness by transparency and predictive analytics accuracy. Effective predictive analytics and transparent decision-making are desired by DSS users. Perceived usefulness increases consumers' tech adoption (Siconolfi, 2022). DSS's accurate predictive analytics and clear decision help boost usability, which drives new technology adoption. Usable technology is acknowledged more (Schetgen et al., 2021). Users see advanced decision support systems with precise forecasts and clear decision-making procedures as simple and beneficial.

H4: Decision support system has a significant and positive impact on technology adoption.

Perceived Utility as a Mediator

Perceived utility mediates consumer attitudes toward AI-based financial advice and technology integration, notably data security and compatibility, demonstrating the complex processes that impact consumers' adoption and views of modern financial technology solutions. Client trust and AI-based financial advising technology integration require data protection. Li et al., (2023) say customers' technological opinions are shaped by financial data security. Technology compatibility means AI systems can work with consumer devices. According to (Sutcliffe et al., 2023), compatibility has a significant influence on clients' judgments of the utility of AI-based financial advice systems. Compatibility simplifies and improves various platforms. This complex connection is mediated by usefulness. Customers independently evaluate the technology's financial potential. Customer view of AI-driven financial advice depends on data security, interoperability, and usefulness. Consumers trust the technology's data security and interoperability for safety and convenience. According to (Putri et al., 2023), perceived usefulness affects consumers' ease of use ratings, which influence consumer attitudes. User views of fully integrated and protected AI-driven financial advising systems affect usability and client perceptions. User acceptance models describe technology adoption via technological integration, usefulness, and simplicity (Tian et al., 2023). Customers analyze AI-based financial advice for data security and interoperability. AI-based financial advice is used more by clients who like it (Uzir et al., 2023). Therefore, perceived usefulness, which impacts technical efficacy, strongly influences consumer uptake and attitudes.

H5: Perceived utility mediates the relationship between technology integration and consumer attitude toward AI-based financial advice.

Due to complex interconnections, data security, compatibility, and perceived value affect customer attitudes and decisions when embracing modern technology. Technical integration and customer trust in digital platforms necessitate data security. Zhong, (2024) stresses data security for privacy and secrecy. For smooth integration, (Wang et al., 2020) recommended technological compatibility with current systems and user interfaces. Perceived utility affects user adoption decisions across technological integration aspects. Value depends on whether a tech solution fits user demands. Consumers trust technology more when data is secure. Ryu & Park, (2020) discovered data security affects tech usability. Compatibility improves technology's usability by integrating with users' devices and interfaces. Compatibility increases utility. Technologies' perceived usefulness affects their perceived ease of use, which is crucial to their acceptability, and usable technology is acknowledged more. Safe data processing and system integration make the technology valuable (Voinescu et al., 2020). Security, interoperability, and acceptability improve usability. Effectiveness influences consumer technology uptake. Compatibility and data security boost integrated technology perceptions. The acceptance model asserts that perceived usefulness affects user behavior.

H6: Perceived utility mediates the relationship between technology integration and technology adoption.

Perceived utility mediates the relationship between DSS components such as predictive analytics accuracy and decision transparency, which affects consumer attitudes toward AI-based financial advice. The intricate relationship between DSS features and customer attitudes is mediated by perceived utility or users' subjective assessment of the technology's ability to help them work (Spoladore et al., 2024). According to the TAM, usefulness strongly influences customers' technology attitudes and actions (Mukred et al., 2024). DSS predictive analytics affects AI-powered financial advice client happiness. Tanguay-Sela et al., (2022) found that precise estimates boost AI-generated financial advice and consumer confidence. DSS decision-making transparency affects customer impression of AI-powered financial advice. Decision openness facilitates system value evaluation by describing how choices are made. Transparent decision-making increases AI-based financial advice trust (Zhu et al., 2023). Predictive analytics accuracy and selection-making transparency impact monetary recommendation provider value and purchaser belief. Consumer technology uptake relies upon perceived utility and ease. Correct estimations and obvious decision-making decide users' perceptions of AI-powered financial advice's usefulness and accessibility (Guidotti, 2021). The Unified Theory of Acceptance and Use of Technology (UTAUT) supports perceived utility's mediation of customer behavior and generation use (Zhani et al., 2022). This concept emphasizes the need to observe how DSS elements affect customers' perspectives of AI-based economic advice's usefulness and value.

H7: Perceived utility mediates the relationship between the decision support system and consumer attitude toward AI-based financial advice.

Customers' adoption of breakthrough technology depends on several variables. The subjective judgment of a technology's capacity to help users achieve goals and tasks is called perceived utility (Garmendia-Lemus et al., 2024). DSS evaluation and technology acceptance depend on it (Tonle et al., 2024). Users prefer accurate insights and estimations from DSS (Baffo et al., 2023). Understanding DSS's decision-making methods changes value appraisal. Educating clients about system options boosts system value. Transparent decision-making boosts client technology confidence (Sherman et al., 2020). Correct

predictive analytics and transparent decision-making impact customers' technology adoption and value judgments. The mediating role of perceived utility on customers' technical ease is crucial to technology adoption. Simple technology is more likely to be adopted, suggests (Seong & Hong, 2022). Users grade DSS's efficacy and simplicity based on accurate forecasts and straightforward decision-making. Consumers' perception of the system's decision-making utility affects uptake and usability. Unified Theory of Acceptance and Use of Technology says perceived utility mediates. This idea states that behavioral intentions strongly impact technology usage (Choudhury et al., 2022). Hence, perceived usefulness mediates DSS features and technology adoption. Figure 1 has been developed based on the above literature discussed.

H8: Perceived utility mediates the relationship between the decision support system and technology adoption.

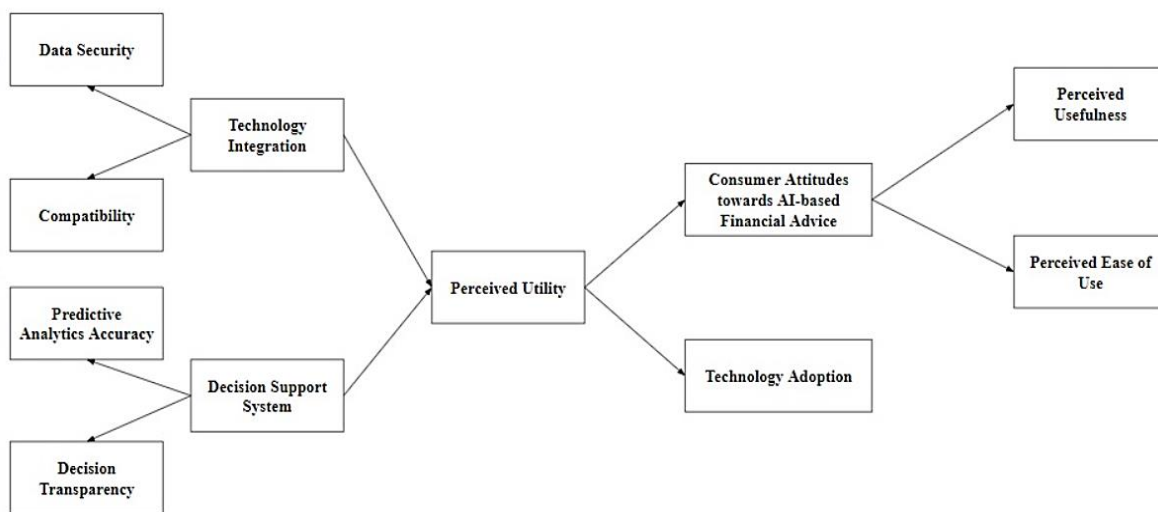


Figure 1: Study Model

3 Methodology

The study was quantitative and cross-sectional. This study strategy can collect data at a certain time, revealing key factors' relationships. This technique is ideal for studying how technology integration, decision support system components, and perceived utility impact AI-powered financial advice and acceptance. Financially active Chinese clients were investigated. China has several AI-powered financial suggestion talents due to its substantial use of digital financial technologies. We studied how cultural differences affect perceptions and adoption patterns in China's fast-changing financial technology environment by concentrating on its people. This study used the rule of thumb to select its sample size, as in quantitative research. Hair et al., (2019) employed structural equation modeling, which required a 200-person sample for statistical analysis. The foregoing requirements balanced research resource efficiency and statistical power. Excellent analysis is possible while decreasing participant and resource burden. The study participants numbered 259. Before choosing this measurement, the rule of thumb was carefully evaluated to accurately represent the desired population. The sample size of 259 exceeded the rule of thumb, making results more credible. This number of participants allowed a detailed investigation of technical integration, decision support system components, perceived utility, consumer attitudes

toward AI-based financial advice, and technology adoption in China. Participants from the population were randomly sampled. Random selection ensured that all population members had an equal chance of being studied. This strategy decreased preconceptions and supported the claim that the sample accurately represented the population. This method increased the study's external validity, making its findings more applicable to more Chinese financial services clients. This study collected data via an online questionnaire. This method collected data efficiently from a geographically distributed Chinese population. Standardized online questionnaires were delivered. This standardized data collecting and helped them respond consistently. The online survey simplified data entry, reducing errors, and improving data quality. Using AMOS for data analysis. AMOS, a structural equation modeling component, helped analyze the complicated variable interactions in the suggested theoretical model. This technique allowed us to comprehensively analyze the dynamic links between decision support system features, perceived technology usefulness, client technology attitudes, and AI-driven financial advice. AMOS improved the study's validity, reliability, and knowledge of research concerns by allowing full statistical analysis.

4 Results

Table 1 shows Cronbach's alpha scores for numerous study variables, indicating measurement scale internal consistency and reliability. Six items in the variable "Technology Integration," have a high Cronbach's alpha of 0.926, indicating great internal consistency and a robust measure of technology integration. The six-item "Decision Support System" variable has a high Cronbach's alpha of 0.916, indicating great reliability in measuring decision support system use. Five-item "Perceived Utility," with a Cronbach's alpha of 0.817, shows strong internal consistency in evaluating perceived utility, albeit significantly lower than the previous variables. "Consumer Attitude toward AI-based Financial Advice", a six-item scale, with a Cronbach's alpha of 0.907, indicating its reliability. Finally, the four-item "Technology Adoption" variable has a Cronbach's alpha of 0.837, showing good internal consistency. High to adequate Cronbach's alpha values across variables show that the study's scales are reliable for assessing the desired constructs.

Table 1: Cronbach's Alpha

Variable	No. of Items	Cronbach's Alpha
Technology Integration	6	0.926
Decision Support System	6	0.916
Perceived Utility	5	0.817
Consumer Attitude Toward AI-based Financial Advice	6	0.907
Technology Adoption	4	0.837

Table 2 shows the skewness and kurtosis values for the study's primary variables' normality assessment. Skewness indicates distribution asymmetry, while kurtosis measures tail heaviness. Positive skewness numbers imply a right-skewed distribution, while negative values indicate a left-skewed distribution. Compared to a normal distribution, kurtosis values above or below 3 suggest heavier or lighter tails. The variable "Technology Integration" has -1.709 skewness and 4.047 kurtosis. This implies a left-skewed distribution with a heavy tail, suggesting technology integration outliers at the lower end. With negative skewness (-1.372) and kurtosis (2.991), the "Decision Support System" has a left-skewed distribution with a less heavy tail than Technology Integration. Considering "Perceived Utility", the negative skewness of -1.692 and kurtosis of 3.642 indicate a left-skewed distribution with a somewhat strong tail Negative skewness (-1.324) and kurtosis (2.616) indicate a left-skewed distribution with a

light tail for "Consumer Attitude toward AI-based Financial Advice". Finally, the "Technology Adoption" variable has negative skewness (-1.487) and high kurtosis (4.195), indicating a left-skewed distribution with a heavier tail and possible outliers on the lower end.

Table 2: Normality Assessment

Variable	Skewness	Kurtosis
Technology Integration	-1.709	4.047
Decision Support System	-1.372	2.991
Perceived Utility	-1.692	3.642
Consumer Attitude Toward AI-based Financial Advice	-1.324	2.616
Technology Adoption	-1.487	4.195

The outer loading analysis for items within each variable is shown in Table 3 and Figure 2, revealing the strength of the association between the assessed constructs and their indicators. In a structural equation model, outer loading is the correlation between each item and its latent variable. All six "Technology Integration" components (TI1–TI6) have positive outside loadings from 0.655 to 0.749. The items have a relatively significant association with the latent variable Technology Integration, suggesting that each item contributes meaningfully to its assessment. In the "Decision Support System" variable, DSS1, DSS2, DSS4, DSS5, and DSS6 have outer loadings of 0.566 to 0.825. DSS6 has a poorer link with the construct than other items, which have a significant association with the latent variable. For "Perceived Utility," all five elements (PU1–PU5) have outside loadings from 0.602 to 0.849. These scores indicate a strong relationship between the items and the latent variable, confirming the scale's Perceived Utility measurement accuracy. "Consumer Attitude toward AI-based Financial Advice" had positive outer loadings for all six items (ATAIFS1–ATAIFS6), ranging from 0.654 to 0.786. These data show a good correlation between the measured items and the latent variable, confirming the scale's capacity to capture consumer sentiments toward AI-based financial advice. Finally, for "Technology Adoption," items TA1, TA2, and TA3 had outer loadings from 0.589 to 0.761, showing a significant latent variable relationship. TA4 has a lower loading of 0.589, suggesting a weaker link with the concept.

Table 3: Outer Loading

Variable	Items	Outer Loading
Technology Integration	TI1	0.662
	TI2	0.655
	TI3	0.73
	TI4	0.665
	TI5	0.749
	TI6	0.689
Decision Support System	DSS1	0.729
	DSS2	0.683
	DSS3	0.825
	DSS4	0.714
	DSS5	0.789
	DSS6	0.566
Perceived Utility	PU1	0.849
	PU2	0.602
	PU3	0.67
	PU4	0.721
	PU5	0.76
Consumer Attitude Toward AI-based Financial Advice	ATAIFS1	0.786
	ATAIFS2	0.765
	ATAIFS3	0.722
	ATAIFS4	0.708
	ATAIFS5	0.673
	ATAIFS6	0.654
Technology Adoption	TA1	0.62
	TA2	0.707
	TA3	0.761
	TA4	0.589

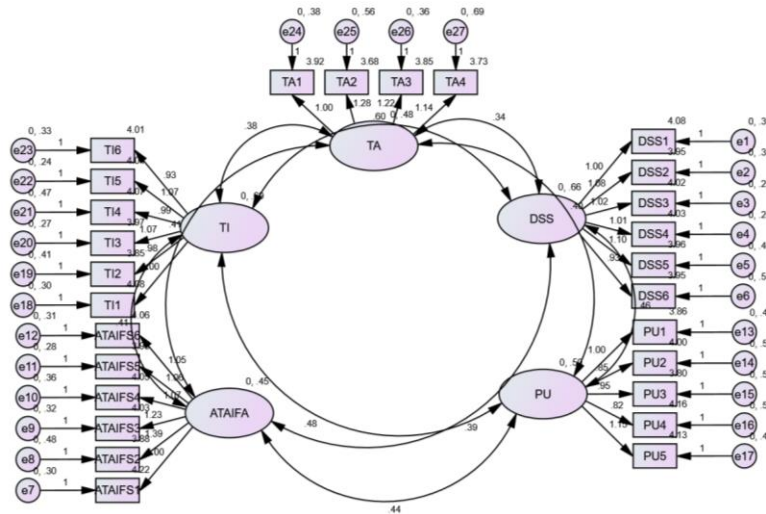


Figure 2: Measurement Model

Table 4 evaluates the measurement model's fitness indices across model fit factors. How well the model matches the data depends on these indexes. Fitness indexes include Absolute Fit, Incremental Fit, and Parsimonious Fit. Absolute Fit has an RMSEA of 0.073. The RMSEA score is acceptable, indicating that the model fits the data well. This index measures the difference between the model-implied and observed covariance matrices, and 0.073 indicates a good match at the required level. The Comparative Fit Index (CFI) for Incremental Fit is 0.818. The CFI is satisfactory despite being somewhat below 0.90. CFI values of 0.818 indicate an acceptable incremental fit for the supplied model over a null model. The Parsimonious Fit Chisq/df ratio is 2.536. The Chisq/df ratio measures parsimony, or how well the model fits the data compared to degrees of freedom. The model meets the required parsimonious fit with a value of 2.536.

Table 4: Fitness Index Assessment for Measurement Model

Name of Category	Name of Index	Index Value	Comment
Absolute Fit	RMSEA	0.073	The required level is achieved.
Incremental Fit	CFI	0.818	The required level is achieved.
Parsimonious Fit	Chisq/df	2.536	The required level is achieved.

The regression route coefficients and statistical values for the model relationships are shown in Table 5 and Figure 3. These coefficients show the intensity and direction of the independent-dependent variable correlations, while the T value and P value indicate their significance. A positive link exists between "Technology Integration" (TI) and "Consumer Attitude toward AI-based Financial Advice" (ATAIFS), with a Beta value of 0.186. The T value of 3.798 and P value of 0.0001 indicate a statistically significant association. Thus, Technology Integration positively affects Consumer Attitudes toward AI-based Financial Advice, rejecting the null hypothesis of no association. The path from "Technology Integration" to "Technology Adoption" (TA) has a Beta of 0.240, T of 4.728, and P of 0.0001. A positive and statistically significant association exists between Technology Integration and Technology Adoption, supporting its inclusion in the model. The association between "Decision Support System" (DSS) and "Consumer Attitude toward AI-based Financial Advice" (ATAIFS) has a Beta of 0.325, T of 5.915, and P of 0.0001. This shows a strong and favorable association, validating the Decision Support System to

Consumer Attitude toward AI-based Financial Advice relationship. Finally, the path from "Decision Support System" to "Technology Adoption" (TA) has Beta = 0.143, T = 2.521, and P = 0.012. Though positive, the lower T value and higher P value show a weaker and marginally meaningful association from Decision Support System to Technology Adoption than the preceding pathways. However, the criteria allow it.

Table 5: Regression Path Coefficients

Variable	Beta value	T value	P value	Decision
TI -> ATAIFS	0.186	3.798	0.0001	Accepted
TI -> TA	0.240	4.728	0.0001	Accepted
DSS-> ATAIFS	0.325	5.915	0.0001	Accepted
DSS -> TA	0.143	2.521	0.012	Accepted

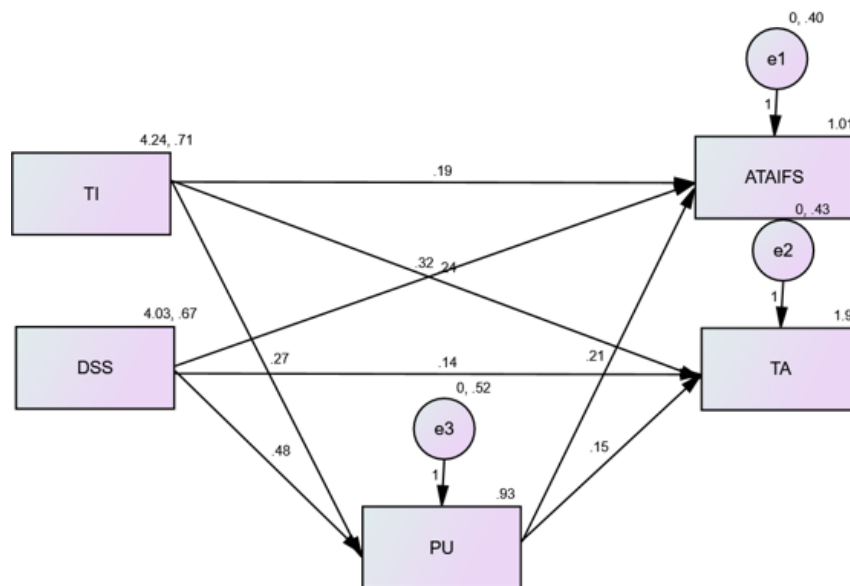


Figure 3: Structural Model

In Table 6, the mediator variable "Perceived Utility" (PU) mediates the indirect effects of the independent variables ("Technology Integration" and "Decision Support System") on the dependent variables ("Consumer Attitude toward AI-based Financial Advice" and "Technology Adoption"). The Beta, T, and P values reveal the strength and relevance of these mediated interactions. The path from "Technology Integration" (TI) to "Perceived Utility" (PU) to "Consumer Attitude toward AI-based Financial Advice" (ATAIFS) has a Beta of 0.109, T of 4.643, and P of 0.0001. The indirect effect is positive and statistically significant, validating the mediation hypothesis that Perceived Utility mediates Technology Integration and Consumer Attitude toward AI-based Financial Advice. For the path from "Technology Integration" to "Perceived Utility" to "Technology Adoption" (TA), Beta is 0.206, T is 3.165, and P is 0.0001. This supports the mediation hypothesis that Perceived Utility mediates Technology Integration and Technology Adoption with a positive and statistically significant indirect effect. From "Decision Support System" (DSS) to "Perceived Utility" to "Consumer Attitude toward AI-based Financial Advice," the Beta is 0.334, T is 2.898, and P is 0.001. This shows a positive and statistically significant indirect effect, validating the mediation hypothesis that Perceived Utility mediates

Decision Support System and Consumer Attitude toward AI-based Financial Advice. Finally, for the path "Decision Support System" to "Perceived Utility" to "Technology Adoption," Beta is 0.303, T is 2.654, and P is 0.0001. This shows a positive and statistically significant indirect effect, confirming the mediation hypothesis that Perceived Utility mediates Decision Support System and Technology Adoption.

Table 6: Mediation Analysis

Variable	Beta value	T value	P value	Decision
TI -> PU -> ATAIFS	0.109	4.643	0.0001	Accepted
TI -> PU -> TA	0.206	3.165	0.0001	Accepted
DSS -> PU -> ATAIFS	0.334	2.898	0.001	Accepted
DSS -> PU -> TA	0.303	2.654	0.0001	Accepted

5 Discussion

H1 states that technological integration negatively affects customer attitudes toward AI-powered financial advice. The current study supports employing technology to improve financial consumer attitudes. According to (Shiva et al., 2023), good data security and interoperability increase client trust and confidence in AI-powered financial advising services, boosting perceptions. Technology integration, including interoperability and data security, makes AI-powered financial advice trustworthy and easy to understand. Manser Payne & O'Brien, (2024) recommend device and interface compatibility to improve user experience. According to (Aldammagh et al., 2021), the TAM determines technological acceptability by perceived utility and ease of use. H1 technology boosts consumer perceptions by improving these two traits. Academic research on user-centric design and functionality shows that technology integration enhances customer sentiment. Lei et al., (2022) say readily integrated technology is more beneficial. Financial advice demands trust and usability. Modern technology can help customers make educated financial decisions feel safe and profit from the system. Consumer attitudes and technology integration are favorably connected, supporting technical improvement acceptance research. Gazit et al., (2023) say clients choose useful, easy-to-use solutions. Technology integration, notably data security and compatibility, improves customer impressions of AI-driven financial advice's usability and efficacy.

Technology integration has a significant and positive impact on technology adoption, according to H2. This study complements previous studies on technology's role in customers' adoption of advanced technologies. Technology integration, including data security and compatibility, affects consumers' system value and use (Ngoc Su et al., 2023). Technology integration boosts acceptance and use, according to (Siyal et al., 2023). The TAM states that customers accept and embrace technology based on its perceived value and simplicity. Technology, data safety, and interoperability increase AI-powered financial advice platforms in H2. The findings confirm (Mukred et al., 2024), who found that users accept technology if it enhances their decision-making. The study emphasizes confidence in new technology adoption and shows that technical integration increases adoption. Effective data security boosts user confidence and technology adoption, according to (Aldammagh et al., 2021). Confidence determines financial services clients' acceptance of innovative financial management solutions. The findings support previous financial technology adoption research showing that user-centric design and functionality are essential. Cavalcanti et al., (2022) observed that seamless device and interface integration improves user experience and adoption.

Empirical and theoretical evidence support Hypothesis 3 (H3), that the DSS improves client opinions of AI-based financial advice. The data supports studies suggesting DSS components including predictive analytics accuracy and decision transparency improve financial consumer perspectives. Goodell et al., (2023) say a solid DSS boosts client trust by improving financial advice reliability and accuracy. Effective DSS components improve consumers' interest in AI-based financial advice in H3. Li et al., (2023) revealed that customers choose trustworthy and useful technology. Transparent decision-making literature demonstrates the positive relationship between decision support systems and consumer perceptions. Jayasiri et al., (2023) propose that decision transparency improves user attitudes by building trust and confidence. Good DSS, especially decision transparency, helps clients understand and trust AI financial advice in H3. Predictive analytics research emphasizes user views. Battistini et al., (2023) say accurate predictive analytics increases AI system suggestions and insights, boosting user sentiment.

H4 says decision-help tools boost tech adoption. Empirical and theoretical data support this. This study shows how DSS components like decision transparency and predictive analytics accuracy affect customers' technology adoption. Sharma & Yetton, (2003) discovered that a good DSS enhances decision-making dependability and quality, which boosts user opinions and adoption. Effective DSS components in the H4 framework boost AI-based financial advising platforms' perceived value, affecting adoption. Previous research (Pour et al., 2023) revealed similar results. In the study, consumer adoption of trustworthy and useful decision-making tools was higher. Decision assistance systems increase technology acceptance owing to research on clear decision-making procedures. Siconolfi, (2022) emphasizes decision transparency helps in gaining consumer trust, confidence, and technology adoption. H4 believes that clients trust and comprehend AI-driven financial advising systems' decision-making processes when DSS components like decision transparency work. Thus, technology adoption improves. This study supports prior predictive analytics research by showing that it affects user perceptions and technology uptake. Galanti et al., (2023) discovered that effective predictive analytics improves AI systems' suggestions and insights, changing users' technology usage intentions. Regarding H4, precise predictive analytics in the DSS improves technology adoption, supporting previous research on advanced analytics' impacts on user behaviors and perceptions.

The relationship between technology integration and consumer attitude toward AI-based financial advice (H5) and technology adoption (H6) is mediated by perceived usefulness. There is a compelling theoretical and literary justification for mediation. Consumer attitudes and adoption decisions are influenced by perceived utility or customers' subjective evaluations of a technology's usefulness. According to Hypotheses 5 and 6, the perceived value of AI-driven financial guidance systems is increased by technical integration, especially in the areas of data security and compatibility. Wang et al., (2020) discovered that when people perceive technology as helpful for their work, they would embrace it. The notion that perceived utility acts as a mediator between the two is supported by the study on utility perceptions and user attitudes (Ogundipe et al., 2023). Technology utility has a significant influence on consumers' attitudes and intentions toward using technology, according to (Voinescu et al., 2020). Technology provides customers with a perceived advantage that enhances their perceptions of AI-based financial advice, according to Hypothesis 5. This study confirms earlier research on perceived usefulness as a technology adoption driver. The perceived utility was discovered (Zhong, 2024) to mediate extrinsic influences on technological adoption. The adoption of AI-based financial guidance systems is influenced by the perceived value of completely integrated technology, according to hypothesis 6. This connects acceptability and technological integration.

The relationship between the DSS, client attitudes regarding AI-based financial advice, and technological adoption is mediated by perceived usefulness, according to Hypotheses 7 and 8. Both theoretical and empirical evidence favor mediation. It emphasizes how consumer attitudes and the uptake of DSS components are impacted by perceived usefulness. The results are consistent with the UTAUT (Zhani et al., 2022). This demonstrates how intentions to embrace technology are influenced by perceived utility. Hypotheses 7 and 8 state that the perceived value of AI-driven financial advising platforms is influenced by the effectiveness of DSS components. These include the accuracy of predictive analytics and the clarity of decision-making. This study confirms the findings of (Spoladore et al., 2024), who discovered that when consumers believe technology would help them make better decisions, they will be more likely to accept it and is supported by the study that highlights explicit decision-making processes and the positive correlation between perceived usefulness and DSS (Mukred et al., 2024). Consumer perceived utility, according to (Tanguay-Sela et al., 2022), fosters client acceptance, confidence, and trust. DSS elements assist users in understanding and putting their faith in the decision-making processes of AI-based financial advising systems. This boosts tech uptake and customer perceptions. This study validates past findings that perceived utility affects technology adoption. Perceived usefulness mitigates extrinsic impacts on technology adoption, according to (Sherman et al., 2020). Hypothesis 8 indicates that DSS components' perceived utility increases customers' adoption of AI-based financial advice services. This influence mediates technical acceptability-decision support system impacts.

6 Conclusion

In conclusion, this study has explored the intricate relationships between technology integration, decision support systems (DSS), perceived utility, consumer attitudes toward AI-based financial advice, and technology adoption within the context of the rapidly evolving landscape of financial technology. Through a quantitative research approach and structural equation modeling analysis, the study has provided valuable insights into the factors influencing consumer behaviors and perceptions in adopting AI-driven financial advisory services. The findings of this study have supported the hypotheses posited, highlighting the significant and positive impacts of technology integration and DSS components on both consumer attitudes and technology adoption. Specifically, technology integration, comprising robust data security measures and seamless compatibility, has been shown to foster positive consumer attitudes toward AI-based financial advice and increase the likelihood of technology adoption. Similarly, the effective functioning of DSS components, including predictive analytics accuracy and decision transparency, has been found to positively influence both consumer attitudes and technology adoption decisions. Moreover, the study has identified perceived utility as a critical mediating factor in these relationships. Perceived utility, representing users' subjective assessment of the technology's usefulness, has been shown to play a pivotal role in shaping consumer attitudes toward AI-based financial advice and influencing technology adoption decisions. The mediation analyses have underscored the importance of perceived utility in bridging the gap between technology integration, DSS components, and consumer behaviors, highlighting its significance in understanding user acceptance and adoption of advanced financial technologies.

The findings of this study have important implications for both academia and industry. From an academic perspective, the study contributes to the existing body of literature on technology adoption and acceptance theories by highlighting the nuanced interplay between technology integration, DSS components, perceived utility, consumer attitudes, and technology adoption. The empirical evidence presented in this study offers valuable insights into the factors influencing consumer behaviors in the

rapidly evolving landscape of financial technology, providing a foundation for future research in this area. From a practical standpoint, the findings of this study have implications for financial institutions, technology developers, and policymakers involved in the development and implementation of AI-based financial advisory services. By understanding the factors that influence consumer attitudes and adoption decisions, stakeholders can design and deploy more effective and user-centric financial technology solutions. Strategies aimed at enhancing technology integration, optimizing DSS components, and promoting perceived utility can help build trust, confidence, and adoption of AI-driven financial advisory services among consumers. Overall, this study contributes to a deeper understanding of the complex dynamics that shape consumer behaviors and perceptions in the realm of AI-based financial advice and technology adoption. By elucidating the roles of technology integration, DSS components, and perceived utility, the study provides valuable insights that can inform the development and implementation of innovative financial technology solutions, ultimately advancing the digital transformation of the financial services industry.

7 Implications

The findings of this study offer practical implications that can guide stakeholders involved in the development and implementation of AI-based financial advisory services. Firstly, financial institutions and technology developers can prioritize the integration of robust data security measures and compatibility features into these services. By ensuring seamless integration, firms can enhance user trust and confidence in the technology, ultimately fostering positive consumer attitudes and increasing the likelihood of technology adoption. Additionally, stakeholders can focus on optimizing Decision Support Systems (DSS) components, such as predictive analytics accuracy and decision transparency. By providing more accurate and transparent financial advice, firms can enhance user satisfaction and drive technology adoption. Moreover, promoting perceived utility among users is crucial. Strategies aimed at emphasizing the usefulness and value of the technology, such as tailored communication strategies and user training programs, can enhance user perceptions and attitudes, ultimately increasing the likelihood of technology adoption. These practical implications can guide stakeholders in developing user-centric financial technology solutions that meet the needs and expectations of consumers.

From a theoretical perspective, this study contributes to the advancement of technology acceptance theories by highlighting the complex interplay between various factors influencing user behaviors. By extending previous research and examining the mediating role of perceived utility in the relationships between technology integration, DSS components, consumer attitudes, and technology adoption, this study offers insights into the underlying processes that shape user perceptions and behaviors. This contributes to a deeper understanding of technology adoption dynamics and enriches existing theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Furthermore, the focus on the Chinese population provides insights into the cultural nuances and specific factors influencing consumer attitudes and adoption decisions within this context. This contributes to cross-cultural research on technology adoption and highlights the importance of considering cultural factors in the design and implementation of AI-driven financial advisory services in diverse global markets. Additionally, the study provides a foundation for future research in the field of financial technology, offering insights into the factors influencing technology adoption in the rapidly evolving landscape of AI-driven financial advisory services. Future studies may build upon these findings to explore additional factors influencing technology adoption, such as regulatory environments, user demographics, and market dynamics. In summary, the practical and

theoretical implications of this study extend beyond AI-based financial advisory services, offering valuable insights that can inform the development and implementation of innovative financial technology solutions. By prioritizing technology integration, optimizing DSS components, and promoting perceived utility among users, stakeholders can enhance user trust, confidence, and adoption of AI-driven financial technology, ultimately advancing the digital transformation of the financial services industry.

8 Limitations and Future Directions

While this study contributes valuable insights into the factors influencing consumer attitudes and adoption decisions in the realm of AI-driven financial advisory services, several limitations should be acknowledged. Firstly, the study's focus on a single population, namely China, may limit the generalizability of the findings to other cultural contexts. Future research could explore the cross-cultural variations in consumer attitudes and adoption behaviors to provide a more comprehensive understanding of the phenomenon. Moreover, the study primarily focuses on the impact of technology integration and decision support systems on consumer attitudes and adoption decisions, overlooking other potential influencing factors. Future research could delve deeper into algorithmic biases and transparency, exploring their implications for user trust and acceptance. Additionally, providing more insight into specific contextual factors such as regulatory changes, economic conditions, and societal events that may influence user beliefs and behaviors would enrich the discussion. Furthermore, while the study suggests future research on moderating factors, clarity on the specific factors and their empirical investigation methods would enhance the discussion. Identifying concrete research questions or hypotheses to address the gaps mentioned in the limitations would provide clearer guidance for future research endeavors. Moreover, discussing the potential ethical implications of AI-driven financial advice in more detail and suggesting ways to address them in future research would add depth to the discussion. In terms of methodological considerations, future research could explore mixed-methods approaches and longitudinal investigations to overcome the limitations of cross-sectional data and provide a more comprehensive understanding of the dynamics at play. Moreover, explaining how emerging technologies such as quantum computation and blockchain relate to AI-driven financial advice and why they are important for investigation would provide a better context for future research endeavors. By addressing these limitations and exploring these future directions, researchers can further advance our understanding of the complexities surrounding AI-driven financial advisory services and contribute to the development of more effective and ethical financial technology solutions.

9 Conflict of Interest

No potential conflict of interest was reported by the author.

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