Application of Generative AI in Investment Information Analysis: Effects on Investment Decision Quality and Investor Confidence

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Abstract

This study aims to examine the impact of generative AI investment information on investment decision quality and investor confidence, while also testing the mediating role of decision quality in this process. With the rapid development of artificial intelligence in the financial sector, generative AI tools can provide real-time, structured, and personalized investment information, potentially influencing investors' decision-making behavior and psychological confidence. However, empirical research on how AI information improves investment decision quality and subsequently affects investor confidence remains limited. Focusing on investors as the research population, this study collected data through a questionnaire survey. The empirical results indicate that generative AI investment information has a significant positive effect on investment decision quality. In turn, decision quality significantly positively affects investor confidence. At the same time, generative AI investment information also exerts a direct impact on investor confidence and produces an indirect effect through decision quality, highlighting the key mediating role of decision quality between AI information and confidence. Overall, the model demonstrates good fit, and the research hypotheses are supported. Based on the findings, this study provides practical recommendations. Overall, the research not only confirms the value of generative AI investment information in behavioral finance but also offers operationalized scales and application guidelines, contributing significant theoretical and practical insights for fintech development, improved investment decision-making, and the construction of investor psychological confidence.

Keywords: Generative AI, Investment Information, Investment Decision Quality, Investor Confidence

Introduction

In recent years, with the rapid advancement of artificial intelligence (AI) technology—particularly the rise of generative AI—information processing and decision-support systems have undergone structural transformations. Generative AI possesses capabilities in language comprehension, content generation, and cross-domain knowledge integration, making it more than a traditional data analysis tool. It is gradually evolving into a critical decision-support system capable of participating in reasoning and providing actionable recommendations. From ChatGPT and Claude to various AI investment assistants, these tools are increasingly applied in financial market analysis, investment strategy recommendations, and risk assessment, reshaping the way investors access and interpret information.

In investment decision-making, information quality has long been considered a key determinant of outcomes. According to traditional financial theory, rational investors make decisions based on sufficient and accurate information to achieve an optimal balance between risk and return. In practice, however, investment behavior is often influenced by information asymmetry, cognitive limitations, and psychological biases, such as overconfidence, confirmation bias, and herding behavior, leading to decision quality that deviates from rational expectations. Especially in the era of information explosion, investors face not a lack of information but an overload of data and insufficient interpretive ability.

The emergence of generative AI offers a potential solution. Using natural language processing and deep learning models, generative AI can rapidly integrate large volumes of structured and unstructured data, transforming complex financial information into easily digestible analysis reports and even offering specific investment recommendations. For example, AI can analyze company financial statements, news sentiment, and macroeconomic indicators in real time, generating investment summaries that lower the barriers for investors to interpret information. For retail investors lacking professional expertise, these tools have the potential to enhance decision efficiency and reduce information-processing costs.

However, the involvement of generative AI also raises concerns about its impact on investor psychology and behavior. As investors increasingly rely on AI-generated analysis and recommendations, their decision confidence may rise—but whether this confidence is built on higher-quality decision-making remains uncertain. On one hand, AI can help investors make more rational judgments by providing structured information and multiple perspectives. On the other hand, overreliance on AI may lead to automation bias, where investors place excessive trust in AI recommendations and overlook potential risks. Additionally, investor confidence plays a critical role in investment behavior. Appropriate confidence helps investors execute decisions and take risks, while excessive confidence can result in overtrading and poor judgment. Therefore, it is worth exploring whether generative AI, while enhancing confidence, might indirectly amplify behavioral biases and affect investment performance.

From a practical perspective, In terms of industry-specific applications, using investment analysis in the construction industry as an example, investors must closely monitor a diverse array of unstructured information, including raw material price quotes, public infrastructure policies, and real estate economic cycles. Generative AI demonstrates exceptional capabilities in cross-domain data aggregation and natural language processing, enabling it to rapidly transform fragmented market news and financial data into logical investment insights. This profound level of informational support not only allows investors to more precisely evaluate the potential risks and profitability of construction firms—thereby enhancing overall investment decision quality—but it also effectively mitigates the uncertainties of subjective judgment by providing a solid foundation of data analysis, which in turn further bolsters their investor confidence.

Although existing literature has begun examining AI applications in finance, most studies focus on algorithmic performance, investment return forecasting, or quantitative trading strategies. Research specifically addressing the emerging field of generative AI is still relatively scarce. In the investment decision-making process, generative AI is no longer just an information provider; it increasingly serves as an interface influencing cognitive judgment, yet its potential impact mechanisms remain unclear. Most prior studies emphasize objective performance metrics while overlooking subjective measures of decision quality. Traditional investment research often evaluates outcomes using return rates or risk-adjusted performance, which are heavily influenced by market fluctuations and do not directly reflect the quality of the decision-making process. Investment decision quality should encompass aspects such as completeness of information gathering, logical coherence of analysis, and thoroughness of risk assessment—areas where generative AI can play a key role. However, empirical research on how AI affects decision quality is still limited.

Studies on investor confidence mostly focus on personality traits or market experience, with less attention given to the influence of technological tools. As generative AI becomes more widespread, investors may gain confidence due to access to more complete information, but they may also develop overreliance on AI due to its perceived authority and anthropomorphic characteristics. Whether this confidence increase is rooted in improved information quality or psychological attachment to AI remains empirically unverified. Moreover, the integration of the Technology Acceptance Model (TAM) and behavioral finance theory remains insufficient. Prior studies typically treat AI as a tool and explore how perceived usefulness and ease of use affect adoption intentions, with limited attention to actual decision-making behavior and psychological states. Meanwhile, behavioral finance research has identified various investment biases but rarely incorporates emerging technologies as moderating or intervening variables. Therefore, it is necessary to establish an integrated research framework connecting technology use, cognitive processes, and decision outcomes.

Based on this background, this study seeks to explore, from an integrated perspective of behavioral finance and technology acceptance, how generative AI applications in investment information analysis influence investment decision quality and investor confidence, while clarifying potential positive and negative effects. This research not only addresses gaps in the existing literature but also provides practical guidance for investors and financial institutions adopting AI tools.

Literature Review

Generative AI Investment Information

Lee et al. (2024) argue that generative AI is not merely a data processing tool; it can transform dispersed market information—such as financial statements, news, and macroeconomic data—into meaningful investment knowledge. Mo and Ouyang (2025) note in the field of financial economics that generative AI represents an intelligent system capable of simulating human reasoning and generating economic and financial interpretations. Yang and Lee (2024), from a service-dominant logic perspective, define generative AI as an intelligent system that co-creates value in financial services through interaction with users. Bonelli and Liu (2024), in their research on robo-advisors, highlight that AI—including generative AI—serves as a system providing investment decision support through real-time data analysis and predictive modeling. Huang et al. (2024), in studies on virtual investment advisors, point out that the application of generative AI in finance primarily lies in using algorithmic models to transform user data and market information into personalized investment strategies.

Based on these studies, this research defines generative AI investment information as: information produced by a generative AI system that integrates multi-source financial data, performs semantic understanding and inferential analysis, and dynamically generates investment decision-oriented guidance according to user needs.

Investment Decision Quality

Khoufi (2021) suggests that investment decision quality refers to an investor's ability to allocate resources effectively based on reliable, relevant, and timely information. High-quality information can reduce information asymmetry, thereby enhancing decision efficiency and accuracy. Biddle et al. (2009) operationalize investment decision quality as investment efficiency, defining it in terms of whether corporate decisions avoid over- or under-investment—that is, whether resource allocation is optimized. Cooremans (2012) argues that investment decisions are influenced by multiple factors beyond financial returns, defining investment decision quality as the ability to make the overall optimal choice under multiple evaluation criteria, such as risk, strategy, and organizational factors. Lathifunnisa and Dyarini (2024) note that investment decision quality can be measured through investment efficiency and is shaped by the quality of financial reporting and governance mechanisms. Howard (1988) defines decision quality as the ability to make decisions under uncertainty based on complete information, rational reasoning, and clear preferences.

Based on the above literature, this study defines investment decision quality as an investor's ability, under uncertain conditions, to integrate high-quality information with sound analysis, consider multiple evaluation factors, allocate resources effectively, and avoid over- or under-investment.

Investor Confidence

Cupák et al. (2022) define investor confidence as an investor's subjective belief in their own financial knowledge and investment abilities, which in turn influences their participation in risky asset investments. Gottesman and Morey (2024) suggest that investor confidence can be measured by the gap between self-assessed and actual knowledge, noting that overconfidence can affect investment behavior and decision outcomes. Hoffmann and Post (2016) describe investor confidence as a psychological mechanism that influences how investors interpret information and update their beliefs, thereby affecting trading behavior. Meier (2018) defines investor confidence as market participants' overall belief in their own abilities and market opportunities, which shapes trading activity and risk preferences. Kubilay et al. (2022) identify investor confidence as a critical psychological factor influencing whether investors allocate resources to risky assets, interacting with financial knowledge (Zhao and Zhao, 2024).

Based on the above literature, this study defines investor confidence as the subjective degree of certainty investors have in their own investment abilities and market judgment. This belief influences how they interpret information, assume risk, and make investment decisions, and it may lead to over- or under-confidence depending on the gap between perceived and actual abilities.

The Impact of Generative AI Investment Information on Investment Decision Quality

Chen et al. (2025), in their systematic literature review, indicate that generative AI can integrate multi-source financial information and produce structured analyses, thereby enhancing the informational foundation for investment decisions and improving decision quality. Lee et al. (2024) note that generative AI, through semantic analysis and model-based reasoning, can deepen the accuracy and insight of financial analyses, leading to higher decision quality. Liu and Wang (2024) highlight that generative AI, when applied in intelligent investment advisory systems, provides real-time investment recommendations and risk assessments, improving the decision-making process and consequently enhancing decision quality. Awwad et al. (2026) find that the impact of generative AI on financial performance is mediated by governance quality and institutional environment, suggesting that generative AI investment information can improve decision quality. Yao et al. (2025) further demonstrate that generative AI can enhance financial risk prediction accuracy and interpretability through data augmentation and feature extraction, reinforcing its positive effect on decision quality. Based on the above literature, this study proposes the following hypothesis:

H1: Generative AI investment information has a significant positive effect on investment decision quality.

The Impact of Investment Decision Quality on Investor Confidence

Hoffmann and Post (2016) note that investors' confidence adjusts according to the outcomes of their investment decisions, with good decision results reinforcing confidence and poor results weakening it. Cupák et al. (2022) find that higher financial knowledge and stronger investment decision-making capabilities significantly enhance investor confidence, which in turn influences investment behavior. Ahmad et al. (2024) suggest that behavioral biases affect investment decision quality through risk perception, and decision quality subsequently impacts both investment behavior and confidence. Kurniasari et al. (2024) argue that improving investment decision quality—such as by reducing cognitive biases—enables more rational investment behavior, stabilizes emotional responses, and builds steady investor confidence, ultimately improving decision outcomes. Gottesman and Morey (2024) highlight that investors often develop overconfidence due to poor decisions and market experience, that is, low investment decision quality, which then affects subsequent decisions. Based on the above literature, this study proposes the following hypothesis:

H2: Investment decision quality has a significant positive effect on investor confidence.

The Impact of Generative AI Investment Information on Investor Confidence

Zarifis and Cheng (2024) suggest that investors' trust in AI recommendations primarily stems from the accuracy, transparency, and quality of human–AI interaction in investment information, which in turn influences subsequent investor confidence. Luo et al. (2025) note that investors' perceptions of the decision quality provided by generative AI are key determinants of its usage; when investors perceive AI analyses as accurate, they are more likely to rely on AI recommendations over time, thereby enhancing confidence. Lee et al. (2024) argue that generative AI, through text analysis, data generation, and market forecasting, improves the processing of financial information, giving investors greater assurance and significantly boosting decision confidence. Ali and Aysan (2026) highlight that generative AI can provide personalized financial advice and risk analysis, enhancing user experience and decision support, reducing anxiety, and increasing confidence in decisions. Awwad et al. (2026) caution that if generative AI lacks proper governance and transparency, it may introduce risks and uncertainty, causing investors to doubt its recommendations and reducing confidence. Based on the above literature, this study proposes the following hypotheses:

H3: Generative AI investment information has a significant positive effect on investor confidence.

H4: Investment decision quality mediates the relationship between generative AI investment information and investor confidence.

Research Method

Research Variables and Construct Definitions

Generative AI Investment Information

This study measures generative AI investment information by referencing the evaluation scale developed by Ali et al. (2025). The following measurement constructs are proposed:

a. Task–Technology Fit: Refers to the extent to which investors perceive that the information and analyses provided by generative AI meet their investment decision-making needs (e.g., stock selection, risk assessment, asset allocation).

b. Perceived Usefulness: Refers to the extent to which investors believe that generative AI investment information can improve the quality and performance of their investment decisions.

c. System Compatibility: Refers to the degree to which generative AI investment tools align with investors' existing investment habits, analytical methods, and usage preferences.

The survey items for generative AI investment information in this study are presented in the table below:

Table 1. Survey Items for Generative AI Investment Information

Construct	Items
Task–Technology Fit	1. When using generative AI for investment analysis, the information provided effectively supports me in completing investment decision tasks.
	2. The investment recommendations provided by generative AI align with my actual decision -making needs.
	3. The information generated by generative AI is highly consistent with my work content during investment analysis.
	4. In investment scenarios, generative AI provides analyses that suit my decision -making needs.

Construct	Items
Perceived Usefulness	1. Using investment information provided by generative AI helps improve my investment decision quality.
	2. Generative AI assists me in making more efficient investment decisions.
	3. Using generative AI enhances my investment performance.
	4. The information provided by generative AI is practically helpful for my investment decisions.
System Compatibility	1. Using generative AI for investment analysis is compatible with my existing investment methods.
	2. The investment information provided by generative AI aligns with my investment habits.
	3. I believe generative AI can integrate into my current investment decision -making processes.
	4. Using generative AI does not change my original investment logic but rather serves as a supportive tool.

Investment Decision Quality

This study measures investment decision quality by referencing the perspective of Maluleke (2024) in behavioral finance research. Two measurement constructs are proposed:

a. Overconfidence: Refers to an individual's tendency to overestimate their own knowledge, judgment ability, and prediction accuracy.

b. Judgment Bias: Refers to systematic errors in decision-making caused by cognitive shortcuts or psychological biases during the decision process.

The survey items for investment decision quality in this study are presented in the table below:

Table 2. Survey Items for Investment Decision Quality

Construct	Items
Overconfidence	1. When using generative AI investment information, I do not overestimate my own investment judgment ability.
	2. Even with past successful experiences, I carefully evaluate investment decisions.
	3. When referencing generative AI recommendations, I do not blindly trust my intuitive judgment.
Judgment Bias	1. When using generative AI for investment, I check whether my judgments might be biased.
	2. When my opinions differ from AI recommendations, I re -evaluate my own judgments.
	3. I actively correct cognitive biases that could affect my investment decisions.

Investor Confidence

This study measures investor confidence by referencing Wright and Jenkins-Guarnieri (2024), who define it as an investor's confidence in their own judgment and decision-making abilities in volatile or uncertain market conditions. A single construct is used for measurement.

The survey items for investor confidence in this study are presented in the table below:

Table 3. Survey Items for Investor Confidence

Construct	Items
Investor Confidence	1. Even during significant market declines, I remain confident in investment decisions made with AI assistance.
	2. Even in volatile markets, I believe my AI-assisted investment judgments are superior to others'.
	3. Even when facing short-term losses, I maintain confidence in my investment abilities when using AI assistance.

Research Subjects

This study targeted investors in southern Taiwan who use generative AI for investment purposes. Physical questionnaires were distributed, with a total of 600 questionnaires issued. After excluding invalid or incomplete responses, 514 valid questionnaires were collected, resulting in an effective response rate of 86%. The questionnaire consisted of sections on demographic information, generative AI investment information, investment decision quality, and investor confidence. All items were measured using a 5-point Likert scale.

The demographic profile of the sample is as follows:

1. Gender: 238 males; 276 females.
2. Age: under 30 years old: 238; 30–50 years old: 196; over 50 years old: 80.
3. Marital Status: unmarried: 362; married: 152.
4. Education Level: high school or below: 31; university: 341; graduate degree or above: 142.

Methodology and Model

For assessing model fit in AMOS, evaluation can be performed from two perspectives: overall model fit (external quality of the model) and internal quality of the model. Specifically, common indicators for overall model fit include:

1. Chi-Square Ratio (χ^2/df): Measures the discrepancy between the observed model and expected values; a ratio less than 3 is considered optimal.
2. Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI): Values closer to 1 indicate better model fit.
3. Root Mean Square Residual (RMR): Reflects the square root of the average residual variance/covariance; values below 0.05 indicate a better fit.
4. Incremental Fit Index (IFI): Values above 0.9 suggest excellent model fit.

Common indicators for evaluating internal model quality in AMOS include:

1. Square Multiple Correlation (SMC): Equivalent to the R^2 value between each observed variable and its latent variable; values should exceed 0.5.
2. Composite Reliability (ρ): Equivalent to the Cronbach's α of observed indicators for a latent variable; values should exceed 0.6.
3. Average Variance Extracted (AVE): Calculated as the sum of the R^2 values of observed variables for a latent variable divided by the number of observed variables, representing the percentage of the latent construct explained by its indicators; values above 0.5 are considered desirable.

Empirical Results Analysis

Factor Analysis

The results of the factor analysis are presented in Table 4. For the generative AI investment information scale, three factors were extracted: the first factor is Task–Technology Fit (eigenvalue = 3.483, α = 0.90); the second factor is Perceived Usefulness (eigenvalue = 2.571, α = 0.88); and the third factor is System Compatibility (eigenvalue = 1.951, α = 0.87). These three factors together explain 80.236% of the total variance.

For the investment decision quality scale, two factors were extracted: the first factor is Overconfidence (eigenvalue = 2.746, α = 0.92), and the second factor is Judgment Bias (eigenvalue = 2.281, α = 0.90). These two factors together account for 82.633% of the total variance.

For the investor confidence scale, a single factor was extracted (eigenvalue = 3.657, α = 0.93), explaining 87.947% of the total variance.

Table 4. Factor Analysis Results

Variable	Factor	Eigenvalue	A	Cumulative Variance Explained (%)
Generative AI Investment Information	Task–Technology Fit	3.483	0.90	80.236
	Perceived Usefulness	2.571	0.88	
	System Compatibility	1.951	0.87	
Investment Decision Quality	Overconfidence	2.746	0.92	82.633
	Judgment Bias	2.281	0.90	
Investor Confidence	Investor Confidence	3.657	0.93	87.947

Correlation Analysis

As shown in Table 5, generative AI investment information, investment decision quality, and investor confidence are significantly correlated. These results suggest the potential for linear overlap among the research constructs. Moreover, the significant correlations among the constructs align with and support the hypotheses proposed in this study.

Table 5. Pearson Correlation Analysis

Research Construct	α	Generative AI Investment Information	Investment Decision Quality	Investor Confidence
Generative AI Investment Information	0.88			
Investment Decision Quality	0.91	0.25**		
Investor Confidence	0.93	0.23**	0.31**	

Note: **p < 0.01

Assessment of Model Fit

This study employed the maximum likelihood estimation method, and all analyses successfully converged. Overall, as shown in Table 6, all model fit indices meet the recommended criteria, indicating that the model demonstrates good external quality.

Table 6. Structural Model Fit Results

	Evaluation Indicator	Criterion	Result
Overall Fit	*p* -value	*p* –value>0.05	0.000
	$\chi 2$/d.f.	< 3	2.163
	GFI	> 0.9	0.977
	AGFI	> 0.9	0.936
	CFI	> 0.9	0.945
	RMR	<0.05, <0.025 optimal	0.017
	RMSEA	0.05–0.08 acceptable, < 0.05 optimal	0.026
	NFI	> 0.9	0.962
	IFI	> 0.9	0.931

Assessment of Path Relationships

If the constructs Task–Technology Fit, Overconfidence, and Investor Confidence are selected as the reference indicators (fixed at 1) for their respective latent variables, the causal path estimates among other constructs and variables, as shown in Table 7, are all significant. Specifically, Perceived Usefulness = 1.14 exhibits stronger explanatory power than Task–Technology Fit, while Judgment Bias = 1.04 shows stronger explanatory power than Overconfidence. The results of hypothesis testing are presented in Table 8.

Table 7. Structural Model Path Estimates

Factor Construct / Evaluation Standard		Estimate
Generative AI Investment Information	Task–Technology Fit (α1)	1.00
	Perceived Usefulness (α2)	1.06
	System Compatibility (α3)	1.04
Investment Decision Quality	Overconfidence (β1)	1.00
	Judgment Bias (β2)	1.03
Investor Confidence	Investor Confidence (σ1)	1.00
Generative AI Investment Information→Investment Decision Quality		0.851***
Investment Decision Quality→Investor Confidence		0.883***
Generative AI Investment Information→Investor Confidence		0.617***
Generative AI Investment Information→Investment Decision Quality→Investor Confidence		0.867***

*Note: *** $p < 0.001$.*

Table 8. Hypothesis Testing Results

Research Hypothesis	Correlation	Empirical Result	p-value	Outcome
Hypothesis 1	+	0.851***	0.00	Supported
Hypothesis 2	+	0.883***	0.00	Supported
Hypothesis 3	+	0.617***	0.00	Supported
Hypothesis 4	+	0.867***	0.00	Supported

Discussion

This study aimed to examine the impact of generative AI investment information on investment decision quality and investor confidence, while also testing the mediating role of decision quality in this process. Based on factor analysis, correlation analysis, and structural equation modeling (SEM) results, this study provides comprehensive empirical evidence with implications for both theory and practice.

Factor analysis of the generative AI investment information scale showed high reliability, indicating that investors' perceptions of AI investment information are effectively captured by the three identified factors. Task–Technology Fit reflects whether AI information aligns with investors' decision-making needs. When investors perceive that AI tools match their decision goals and strategies, their willingness to use and reliance on the system increases. Perceived Usefulness represents investors' subjective evaluation of the value of AI information, directly influencing their trust and satisfaction with the information. System Compatibility emphasizes the alignment of AI tools with existing workflows and habits; higher compatibility reduces learning costs and enhances usability. Path analysis results revealed that perceived usefulness has stronger explanatory power than task–technology fit, highlighting that investors prioritize the practical value of information in AI-assisted decision-making rather than just technical compatibility. This finding aligns with information systems use theory, which emphasizes that users' perception of a system's usefulness is a critical determinant of usage attitudes and behaviors.

Factor analysis of the investment decision quality scale also showed high reliability. Overconfidence and Judgment Bias are widely discussed behavioral finance indicators that affect capital allocation, risk assessment, and investment strategy selection. The results indicate that generative AI investment information can significantly improve investment decision quality. Specifically, the accuracy, timeliness, and structured analysis provided by AI information help reduce investors' overestimation of their abilities and misinterpretation of market information. In other words, AI information acts as an external aid that corrects cognitive biases and makes investment decisions more objective and effective. High-quality information effectively mitigates cognitive biases and improves decision-making behavior.

The investor confidence scale also demonstrated high reliability. SEM results showed that investment decision quality has the strongest effect on investor confidence, while generative AI investment information also has a significant direct positive impact, with an additional indirect effect through decision quality. This indicates that investors' confidence in their decisions is influenced not only by AI information itself but also strongly moderated by improvements in decision quality. From a psychological perspective, when investors make more rational, market-aligned decisions with AI support, their confidence in their abilities naturally increases. Conversely, poor decision quality may reduce confidence due to losses or errors. These findings highlight the interaction between overconfidence and confidence, showing that high-quality information stabilizes investors' psychological state.

Pearson correlation analysis showed that generative AI investment information, investment decision quality, and investor confidence are all significantly positively correlated, further supporting the study hypotheses. Model fit indices also indicated good overall fit, demonstrating that the SEM constructed in this study has strong explanatory power and suitability. The causal relationships among AI investment information, decision quality, and investor confidence appear highly robust, suggesting that this model can serve as a reference for future fintech research and behavioral finance empirical studies.

Notably, path analysis results revealed that within the dimensions of generative AI investment information, perceived usefulness has a stronger influence on investment decision quality than system compatibility or task–technology fit. This indicates that investors' primary motivation for using AI is the potential for improved decision outcomes rather than operational convenience alone. Regarding decision quality, judgment bias has slightly higher explanatory power than overconfidence, implying that even if investors feel confident in their abilities, biased information processing or judgment errors can still affect overall decision quality. Therefore, generative AI information should not only enhance informational value but also assist investors in improving decision processes and correcting cognitive biases.

In summary, this study offers several key insights. Perceived usefulness of generative AI investment information is the core factor influencing both decision quality and investor confidence, suggesting that AI system development should prioritize practical utility rather than technical alignment alone. Investment decision quality plays a critical mediating role between AI information and investor confidence, underscoring the importance of mitigating overconfidence and judgment bias. AI information not only improves decision quality but also directly enhances investors′ psychological confidence, forming a positive feedback loop of information → decision → confidence. This has practical value for behavioral finance and fintech applications. Finally, the findings imply that financial education and investor training should integrate AI-assisted tools to strengthen decision-making abilities and confidence, thereby reducing the negative effects of human biases on investment behavior.

Conclusion

This study aimed to examine the impact of generative AI investment information on investment decision quality and investor confidence, while also testing the mediating role of decision quality in this process. Through factor analysis, correlation analysis, and structural equation modeling (SEM), the study produced multiple empirical findings, offering important theoretical and practical implications for fintech applications and behavioral finance research.

Generative AI investment information has a significant positive effect on investment decision quality. Factor analysis confirmed that the three dimensions of AI investment information—Task–Technology Fit, Perceived Usefulness, and System Compatibility—exhibited high reliability and explanatory power. In the SEM model, the path coefficient from generative AI investment information to investment decision quality was 0.851 ($p < 0.001$), indicating that the effectiveness of AI information plays a substantial role in enhancing decision quality. This result supports behavioral finance theory, showing that high-quality information can effectively reduce cognitive biases and psychological interference, improving resource allocation efficiency and decision accuracy. In other words, when investors receive timely, comprehensive, and actionable AI-supported information, their judgment regarding capital allocation, risk assessment, and strategy selection is significantly improved. Moreover, perceived usefulness has slightly greater influence on decision quality than task–technology fit or system compatibility, highlighting that investors prioritize the practical value of information for improving decisions rather than merely the tool's ease of use or technical alignment. This finding provides practical guidance for AI system developers, emphasizing that AI investment tools should be designed with information value and decision applicability as central considerations.

Investment decision quality has a significant positive effect on investor confidence. In this study, decision quality was measured through the dimensions of Overconfidence and Judgment Bias, and SEM results showed a path coefficient of 0.883 ($p < 0.001$) to investor confidence. This indicates that higher-quality investment decisions strengthen investors' confidence in their abilities and outcomes. The finding aligns with behavioral finance and psychological literature, showing that investor confidence depends not only on external information but also on the quality of their own decisions. When investors make high-quality decisions with AI assistance, their trust in their judgment and market assessments increases, forming a positive feedback loop that helps maintain rational investment behavior in volatile or uncertain markets. This also highlights the interaction between confidence and overconfidence, showing that AI-supported information stabilizes confidence levels and reduces the risk of poor decisions.

Generative AI investment information has both direct and indirect effects on investor confidence. The direct path coefficient was 0.617 ($p < 0.001$), while the indirect effect through investment decision quality was 0.867 ($p < 0.001$). This demonstrates that AI information not only directly boosts investors' psychological confidence but also indirectly strengthens it by improving decision quality. These findings reveal the multiple values of AI-assisted investment information: it provides decision support while enhancing psychological security and resilience, enabling investors to maintain stable confidence even during market fluctuations or short-term losses. This has important implications for financial education and investor training, emphasizing that high-quality information can help mitigate overconfidence or judgment errors and improve the stability and rationality of investors' decision-making mindset.

The overall fit of the SEM model was strong, and all hypotheses were supported, indicating that the causal relationships among generative AI investment information, investment decision quality, and investor confidence are robust. The empirical results not only complement existing behavioral finance and fintech literature but also provide operationalized quantitative metrics that can be applied for validation and comparison across different markets or investor groups. For financial institutions, AI tool developers, and investment advisors, the findings offer clear operational guidance: enhancing the perceived usefulness and decision alignment of AI information should be prioritized to reinforce both decision quality and investor confidence.

In summary, this study provides empirical evidence that generative AI investment information improves both investment decision quality and investor confidence. The findings have strong relevance for behavioral finance, fintech applications, and investor education, and they offer a practical measurement framework and analytical model for future research.

Recommendations

The findings of this study indicate that generative AI investment information can significantly enhance investment decision quality, thereby boosting investor confidence, while also exerting indirect effects through decision quality. Based on these results, the following practical recommendations are offered for financial institutions, AI system developers, investment education programs, individual investors, and policymakers.

Recommendations for Financial Institutions

Financial institutions should prioritize the practical utility and decision relevance of generative AI investment information. The results show that perceived usefulness is the key factor affecting decision quality. Therefore, AI tools should deliver real-time, accurate market information and provide personalized recommendations tailored to different investment strategies and risk preferences. For example, short-term investors could receive market volatility analyses and actionable strategies, while long-term investors could receive fundamental and financial evaluation reports, ensuring that the information genuinely supports decision-making.

Institutions should also enhance system compatibility with investors' existing workflows. If AI system operations conflict with users' established habits, adoption and reliance may decline. Integration of AI tools with existing trading platforms or financial apps—providing a unified interface and synchronized data updates—can lower learning costs, increase tool usage, and improve decision outcomes. Additionally, institutions should incorporate decision support features such as scenario simulations, risk alerts, and performance backtesting, enabling investors to understand potential outcomes, reduce overconfidence and judgment biases, and strengthen confidence and decision robustness.

Recommendations for AI System Developers

Generative AI tools should emphasize transparency and explainability. When investors understand the logic and rationale behind AI analyses and recommendations, they are more likely to act on them and less likely to trust a "black-box" model blindly. AI tools should integrate behavioral finance principles, offering bias alerts, risk warnings, or decision comparison features to help investors correct overconfidence and judgment errors. Moreover, information should be contextualized and personalized according to market conditions and individual risk preferences—for instance, providing capital allocation suggestions during high-volatility periods, and long- versus short-term strategy analyses during stable markets—thereby enhancing AI information applicability and trustworthiness.

Recommendations for Investment Education and Training

Investment education should incorporate AI tools for hands-on training, helping investors link information to decision-making outcomes, and using simulated investing and performance backtesting to improve decision quality and confidence. Programs should also focus on recognizing psychological biases and fostering reflective decision practices, so investors understand how overconfidence and judgment errors can impact performance, and learn to use AI information to mitigate these biases, creating a positive cycle of information comprehension, decision application, and confidence building.

Recommendations for Individual Investors

Investors should combine AI insights with their own judgment rather than relying blindly on the tools. While AI information can enhance decision quality, its effectiveness ultimately depends on whether investors correctly interpret and apply it to their strategies. Investors can reduce overconfidence and judgment errors by comparing multiple scenarios, conducting simulations, and backtesting AI recommendations. Regular review of decision outcomes and reflection on potential biases in AI-assisted decisions is essential for adjusting strategies and improving long-term decision quality and confidence. Maintaining a simple decision log that records the rationale and outcomes of AI-assisted decisions can help track information effectiveness and support more rational decision-making.

Recommendations for Policy and Regulation

Policymakers should establish evaluation standards for AI investment tools to ensure market information accuracy, recommendation effectiveness, and comprehensive risk disclosures, safeguarding investor rights. Financial technology education and investor protection initiatives can also improve understanding and use of AI information, reducing decision risks caused by information asymmetry or misinterpretation. Regulatory agencies should continuously monitor the impact of AI investment information on markets to prevent misinformation or excessive reliance from creating systemic risks.

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