The Impact of Information Quality on the Investment Decision-Making Behavior of Chinese Institutional Investors From the Perspective of AIEmpowerment

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Abstract

The objectives of this research were: 1) To study the impact of company information quality in the securities market on the investment decision-making behavior of institutional investors. 2) To explore how information quality affects investment decisions through perception and identification. 3) To analyze the impact of the weight of information quality in the securities market on the investment behavior of institutional investors. 4) To analyze the impact of AI-enabled information quality on the long-term investment behavior of institutional investors.

The sample consisted of 448 fund managers and researchers in Beijing who influence investment decision-making. They were selected by the snowball sampling method. The research instruments for the data collection were a combination of on-site distribution and electronic questionnaires. The statistics for data analysis included SPSS 27.0 and AMOS 24.0 for reliability analysis and confirmatory factor analysis, including tests for content validity, convergent validity, and discriminant validity.

The research results were found as follows: 1) The quality of company information in the securities market has a significant impact on investment decision-making behavior. 2) AI-enabled information quality has a significant impact on investment decision-making behavior. 3) The quality of company information in the securities market has a significant impact on perceptual identification. 4) Artificial Intelligence empowerment has a significant impact on perceptual recognition. Suggestions for further research include expanding the scope to include institutional investors from different regions and industries, conducting longitudinal studies to explore causal relationships, and investigating the impact of AI on other aspects of the financial market such as risk management and market efficiency.

Keywords: Information Quality; Investment Decision-Making Behavior; Institutional Investors; AI Empowerment

Introduction

Shanghai Stock Exchange and Shenzhen Stock Exchange marked the beginning of the development of China's securities market. On December 19, 1990, the Shanghai Stock Exchange opened for business; on July 3, 1991, the Shenzhen Stock Exchange officially opened. (China Government. (1997). China Government Website. Retrieved from https://www.gov.cn). The stakeholder entities in the capital market can be broadly divided into five categories: securities regulatory authorities, stock exchanges, listed companies, securities operating and intermediary service institutions, and investors. The securities market

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is a market for information collection and distribution. These market participants are both providers and users of capital market information. Different sources of information have different properties. Securities investment information has a significant impact on the investment form, direction, scale, term, and investment psychology of investment entities, which in turn affects the rational and irrational fluctuations of security prices. Therefore, it assists institutional investors in their investment decisions and analyzes information quality based on new AI technologies. Identification with perception is imperative.

As of the end of the second quarter of 2023, the total asset management business scale, including fund management companies and their subsidiaries, securities companies, futures companies, and private equity fund management institutions, is approximately 68.07 trillion yuan, of which the scale of public funds is 27.69 trillion yuan, and the scale of securities companies is approximately 68.07 trillion yuan. The scale of the private equity asset management business of the company and its subsidiaries is 6.25 trillion yuan2, the scale of the private equity asset management business of fund management companies and its subsidiaries is 6.66 trillion yuan, the scale of pension funds managed by fund companies is 4.50 trillion yuan3, and the scale of futures companies and their The private equity asset management business scale of subsidiaries is approximately RMB 293.140 billion, the scale of private equity funds is RMB 20.80 trillion, and the scale of asset-backed special plans is RMB 1.96 trillion. (Reference China Securities Investment Fund Industry Association 2024)

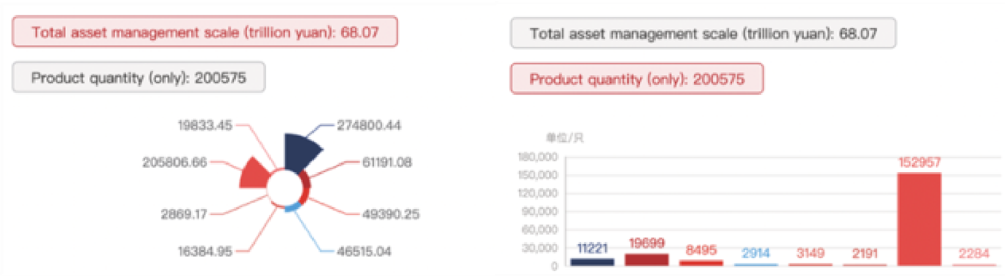

Table 1 Number and scale of various asset management products (as of the end of the third quarter of 2023)

type	Quantity (only/piece4)	Scale (100 million yuan)
Raised funds	11,221	Arsenic274,800.44
Securities company asset management plan	19,699	61,191.08
Fund company asset management plan	8,495	49,390.25
pension	2,914	46,515.04
Fund subsidiary asset management plan	3,149	16,384.95
Futures Company Asset Management Plan	2,191	2,869.17
Private Equity	152,957	205,806.66
Asset Support Special Plan	2,284	19,833.45
total	202,189	675,999.17

Figure 1 Overview of China’s asset management industry. Data comes from the website of the Asset Management Association of China (www.amac.org.cn) 2024

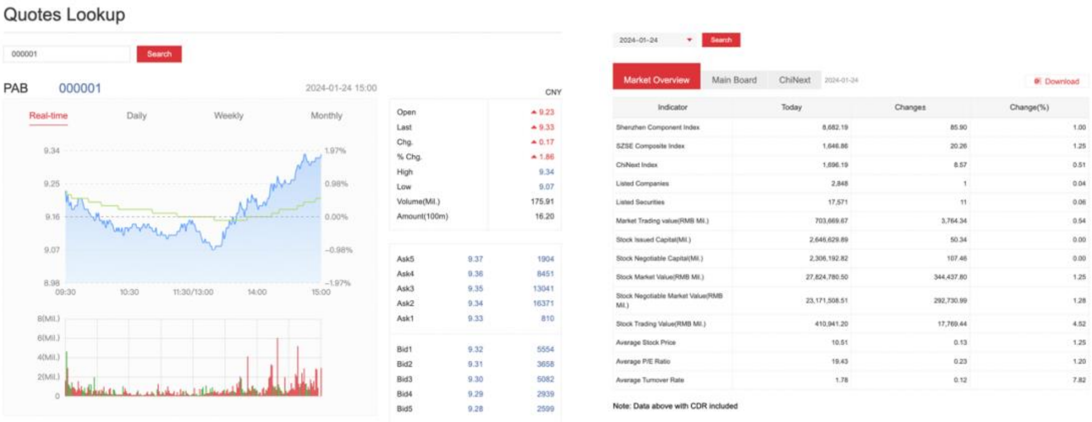

Figure 2 Overview of the daily trading market &Market Overview. Data comes from the website of the Shenzhen Stock Exchange (www.seze.cn) 2024

The institutional development of the capital market has made significant progress, and institutional investors have become major participants in the capital market. However, compared with mature markets, China's securities market still has greater volatility. Therefore, this study takes private equity funds of institutional investors as the main research object to explore the application of artificial intelligence technology finance in the capital market and the impact of information quality on investment decisions.

Research Objective

1. To Study the impact of company information quality in the securities market on the investment decision-making behavior of institutional investors
2. To through which information quality affects investment decisions through perception and identification.
3. To the impact of the weight of information quality in the securities market on the investment behavior of institutional investors
4. AI To Analyze the impact of information quality on the long-term investment behavior of institutional investors

These research objectives aim to comprehensively assess the role of information quality in securities markets, particularly how it affects the behavior and decision-making processes of institutional investors. Through these studies, valuable insights and suggestions can be provided to securities market participants and regulators, thereby promoting the healthy and efficient operation of the market.

Literature Review

Information quality is a multidimensional concept crucial for ensuring information's utility and reliability for users. According to Wang and Strong (1996), key dimensions such as accuracy, relevance, completeness, timeliness, and reliability determine the quality of information (P25). Reliability, as defined by Kahn, Strong, and Wang (2002), pertains to the consistency and trustworthiness of information, emphasizing its dependable presentation (P38). Timeliness, highlighted by Eppler and Moneymaker (2002), refers to the currency of information, ensuring it reflects the most recent updates and meets users' immediate needs (p.

42). Completeness, as described by Wang and Strong (1996), relates to the extent to which information is comprehensive and meets the breadth and depth requirements of users (P56).

Artificial intelligence (AI) is defined by Smith (2021) as the capability of machines to perform tasks that typically require human intelligence (P28). AI advancements significantly contribute to enhancing information quality by enabling accurate, timely, and reliable data processing and analysis.

Perceived identity plays a pivotal role in social psychology and sociology, particularly within social identity theory, as outlined by Tajfel and Turner (1979). This theory posits that individuals categorize themselves and others into various social groups, influencing their perceptions and behaviors based on factors such as religious affiliation, profession, and cultural identity (P26).

Mood, characterized by Myers (2019), involves subjective experiences, physiological responses, and behavioral expressions (P62). Theories on emotions vary, with the James-Lange theory suggesting emotions stem from physiological reactions to events (James, 1884), while the Cannon-Bard theory proposes simultaneous physiological reactions and emotional experiences (Cannon, 1927, P16). The Schachter-Singer theory posits that both physiological arousal and cognitive interpretations are necessary for emotional experiences (Schachter & Singer, 1962, P27).

An investment decision refers to the comprehensive process of evaluating diverse investment opportunities to align with financial goals, risk tolerance, and return expectations, as articulated by Smith (2020) (P43). Investment decision behavior, as studied by Chen (2021), involves allocating resources, particularly financial assets, across various investment options to achieve desired financial outcomes, encompassing risk assessment, portfolio diversification, market analysis, and aligning with personal or organizational financial goals (P29).

Institutional investors, defined by Investopedia (2023), include entities pooling substantial funds to invest in securities, real estate, and other assets. These organizations encompass banks, insurance companies, pensions, hedge funds, REITs, investment advisors, endowments, and mutual funds. Even non-primary investing companies investing excess capital in such assets are considered institutional investors (P19).

This literature review synthesizes key concepts in information quality, AI, perceived identity, emotions, investment decision-making, investment behavior, and institutional investors. These areas underscore the complexities and interdependencies influencing both individual behaviors and organizational strategies across various disciplines.

The conceptual framework of this study is designed to explore the impact of information quality on the investment decision-making behavior of Chinese institutional investors, emphasizing the role of AI empowerment. The framework integrates several theories, including behavioral finance, information asymmetry, and organizational behavior, to analyze how information quality affects investment decisions through perceptual identification and emotions.

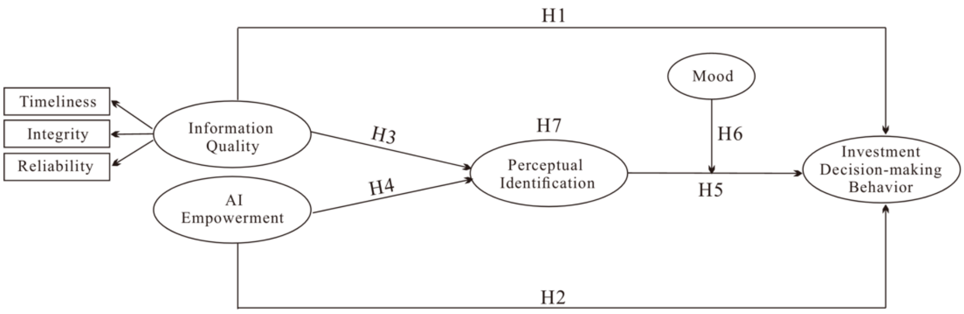

Figure 3 The conceptual model of this article

Based on the literature review and theoretical framework, the following hypotheses were proposed:

H1: The quality of company information in the securities market has a significant impact on investment decision-making behavior.

H2: AI-enabled information quality has a significant impact on investment decision-making behavior.

H3: The quality of company information in the securities market has a significant impact on perceptual identification.

H4: Artificial Intelligence empowerment has a significant impact on perceptual recognition.

H5: Perceptual Identification has a significant impact on investment decision-making behavior.

H6: Mood plays an important role in the relationship between perceived identity and investment decisions.

H7: Perceptual Identification plays a significant mediating role in the relationship between the quality of artificial intelligence empowerment information and investment decisions of listed companies.

Research Methodology

In studying how institutional managers influence investment decisions, this research integrates behavioral finance, information asymmetry, and organizational behavior theories. Behavioral finance highlights the impact of psychological factors and cognitive biases on investment choices. Information asymmetry emphasizes the role of information quality and availability, while organizational behavior focuses on how internal culture and policies shape decisions. By examining various institutional managers in Beijing and exploring their behavioral patterns and motivations, the study aims to understand the factors influencing investment decisions. This research also considers the role of perceived identification and emotions in moderating and mediating these relationships. The primary research method employed is a questionnaire survey, which has passed STIU-HREC065/2024 certification. This study aims to examine the impact of information quality in the securities market on the investment decisions of Chinese institutional investors from an AI-enabled perspective.

The source of data for this research includes both primary and secondary data. Primary data were collected through a structured questionnaire survey administered to fund managers and researchers in Beijing who influence investment decision-making. Secondary data were obtained from existing literature, financial reports, and relevant market data to support and contextualize the findings from the primary research.

The population for this study comprises institutional investor managers in Beijing. The sampling method employed is snowball sampling, where initial participants (fund managers and researchers) were asked to distribute the questionnaire further within their professional networks. This approach facilitated reaching a broad and relevant audience for the research. A total of 448 questionnaires were distributed, and 426 were returned. After data cleaning and preprocessing, including handling missing data and outliers, and excluding invalid questionnaires with missing values, contradictory items, or identical answers, 400 valid questionnaires were obtained, meeting the sample size requirements.

The data collection process involved several stages to ensure the reliability and validity of the data. Initially, a pre-survey was conducted to revise and finalize the formal questionnaire. From May 1, 2024, to May 20, 2024, a simultaneous online and offline questionnaire survey was conducted. The collected formal sample data were then analyzed using SPSS 27.0 and AMOS 24.0. Descriptive statistical analysis was first conducted to reflect the overall characteristics of the sample data. Reliability tests, including Cronbach's alpha and composite reliability, were performed, and validity was tested using content validity, convergent validity, and discriminant validity. Confirmatory factor analysis was conducted to examine whether the relationships between items and dimensions met the research objectives. The model fit and the relationship between model hypotheses were verified through path analysis. The study results were then analyzed to explore factors influencing the information quality impact on Chinese institutional investors' investment decisions and suggest improvement methods.

Research Result

Research Objectives

This study aims to investigate the influence of the quality of company information and AI-empowered information on investment decision-making behavior in the securities market. Additionally, it explores the role of perceptual identification in this process and examines the moderating effect of mood on the relationship between perceptual identification and investment decisions. Moreover, the study assesses the mediating role of perceptual identification in the relationship between AI-empowered information quality and the investment decisions of listed companies. The objective is to provide a comprehensive understanding of how different factors interplay to affect investment behaviors, ultimately aiding in the formulation of better investment strategies and improving information disclosure practices.

1. Reliability and validity analysis

The Alpha values of the five variables in this questionnaire range from 0.721 to 0.97, and the coefficient values all exceed the minimum value. It can be seen that the five variables have good internal consistency and the measurement reliability of each variable component is high.Each latent construct (Information quality, AI empowerment, Perceptual identification, Mood, and Investment decision-making behavior) is associated with several observed variables (T, II, RI for Information quality, AI1, AI2, AI3, AI4 for AI empowerment, etc.). all standardized estimates (Std. Estimate) are relatively high, indicating strong relationships between the observed variables and their respective latent constructs. the T-values are all quite high, suggesting high significance for the factor loadings. the p-values are all very low (significantly less than 0.05), indicating that the relationships between the observed variables and their latent constructs are statistically significant. the AVE and CR values are generally high, indicating good convergent validity and reliability for the measurement model.

As can be seen from the above table, first of all, in terms of measurement relationships, the absolute values of the standardized load system are all greater than 0.6 and show significance, which means that there are better measurement results. Secondly, the AVE values corresponding to a total of four factors are all greater than 0.55, and all CR values are higher than 0.7, and the value of one factor AVE is still lower than 0.5, which indicates that there may be room for improvement in convergent validity. The final result means that the data analyzed this time has good convergent validity.

2. Discriminant validity

Discriminant validity refers to the degree to which a aspect is truly different from other aspects according to empirical standards. The evaluation method is to test the discriminant validity of the questionnaire by studying the relationship between the value after the root sign of AVE and the correlation coefficient between each variable. Normally, good discriminant validity between latent variables needs to meet the following two requirements: first, the root-rooted value of AVE of each latent variable needs to be greater than the value of the correlation coefficient between itself and other latent variables，the other Second, the correlation coefficient between each latent variable cannot exceed 0.85, and the smaller the correlation coefficient of each latent variable is compared to 0.85, the better. From the results in Table 1, we can see that the model variables meet the above conditions, so it can be considered that the scale in this study has good discriminant validity.
discriminant validity

Table 1 discriminant validity

	Mood	IDB	PI	AIE	INQ
Mood	**0.7510**				
IDB	0.536***	**0.762**			
PI	0.468***	0.536***	**0.7752**		
AIE	0.417***	0.575***	0.412***	**0.7745**	
INQ	0.666***	0.81***	0.665***	0.621***	**0.6473**

*Note: ***p<0.001*, the value on the diagonal represents the root mean square of AVE, and the correlation coefficients between variables are below the diagonal.

Analyzing the discriminant validity, for AIE, its AVE square root value is 0.26, which is greater than the maximum absolute value of the inter-factor correlation coefficient of 0.666, which means that it has good discriminant validity. Regarding information quality, its AVE square root value is 0.481 and the maximum absolute value of the inter-factor correlation coefficient is 0.621, which means it has good discriminant validity. For perceived identity, its AVE square root value is 0.279, which is greater than the maximum absolute value of the correlation coefficient between factors, 0.665, which means it has good discriminant validity.

Table 2 Model Fit Analysis

Indicators	CMIN/DF	GFI	AGFI	CFI	RMSEA	RMR	SRMR	IFI	TLI
Value	1.034	0.998	0.945	.998	0.009	0.044	0.271	0.998	0.998
Criterion	≤3	≥0.95	≥0.90	≥0.95	≤0.05	≤0.07	≤0.05	>0.9	>0.9
Reference	Kline (1998)	Kline (2005)	Tabachnick & Fidell(2007)	West et al (2012)	Macallumet al (1996)	Steiger (2007)	Diamantopoulos & Siguaw (2000)		

the evaluation criteria of model fitting index, in the confirmatory factor analysis model of this study, CMIN / DF 0.889, standard value ≤3; GFI 0.98, standard ≥0.95， A GFI 0.97 , standard ≥ 0.90 ， C FI 1, standard ≥ 0.95 , R MSEA 0 , standard ≤ 0.05 , R MR 0.037 , standard ≤ 0.07 , I FI 1.003 , T LI 1 Most of the model fitness indicators such as .004 meet the standards, so the model fitness is very good.

Table 3 Structural equation model and its standardized output results

path			Unstandardized Estimate	Standardized Estimate	S.E.	C.R.	P
PI	<---	IQR	0.191	0.2	0.065	2.919	0.004**
PI	<---	IQT	0.146	0.16	0.064	2.299	0.022*
PI	<---	IQI	0.226	0.252	0.061	3.732	***
PI	<---	AIE	0.154	0.157	0.063	2.432	0.015*
IDB	<---	PI	0.166	0.162	0.063	2.611	0.009**
DB	<---	IQT	0.19	0.203	0.059	3.217	0.001**
IDB	<---	IQI	0.116	0.125	0.057	2.039	0.042*
IDB	<---	IQR	0.25	0.256	0.062	4.039	***
IDB	<---	AIE	0.251	0.249	0.06	4.164	***

*Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$*

According to the model standardized coefficient and significance level, the final structural equation path coefficient diagram of this study is shown in Figure 4.2. Among them, significant paths are represented by solid lines, and insignificant paths are represented by dashed lines. Moreover, the coefficient on the solid line path is the standardized coefficient of AMOS output. The larger the coefficient, the greater its influence. The significance level is reflected by the number of * signs after the number. *** means significant at the 0.001 level, ** means significant at the 0.01 level, and * means significant at the 0.05 level. As can be seen from the table:

H1: The quality of company information in the securities market has a significant impact on investment decision-making behavior;

H2: AI Empowerment information quality has a significant impact on investment decision-making behavior;

H3: The quality of company information in the securities market has a significant impact on Perceptual Identification.;

H4: Artificial Intelligence empowerment has a significant impact on perceptual recognition.;

H5: Perceptual Identification has a significant impact on investment decision-making behavior

3. Mediating effect

According to Wen Zhong et al. (2014), the mediating effect is tested first, using model 1 4 in the spss27 process. The independent variable is information quality, the dependent variable is investment decision-making behavior, and the mediating variable is perceived identity. This study used the bias-corrected non-parametric percentile Bootstrap confidence interval method to test the mediating effect existing in the model. The Bootstrap method refers to a method of repeatedly sampling with replacement from the initial sample to obtain a sample close to the population distribution (Hayes, AF2009). If the confidence interval does not include 0, it means that the mediation effect exists; if the confidence interval of the direct effect does not include 0, it means that the mediation effect is partial mediation; if the confidence interval of the direct effect includes 0, it means that the mediation effect is complete mediation (Wen, Z, Zhang, L, Hou, J, et al. 2004). As shown, information quality significantly predicts investment decision behavior.

Table 4 Analysis of the mediating effect of INQ as the independent variable

INQ-->P-->ID		**Effect**	**se**	**t**	**LLCI**	**ULCI**
Total effect		0.7463	0.0524	14.2435	0.6433	0.8493
Direct effect		0.6322	0.0587	10.7641	0.5167	0.7476
Indirect effect	INQ-->P-->ID	0.1141	0.0322		0.0528	0.1773

Note: Model:4，Sample size:400 Y: ID ; X: INQ ; M : P ; W : M ; Int_1: P × M ;

Total Effect (0.7463): This indicates the overall impact of Information Quality (INQ) on Investment Decision-making Behavior (ID) without considering any mediators. The high t-value (14.2435) and the statistically significant p-value (0.0000) suggest that this effect is statistically significant. The Lower-Level Confidence Interval (LLCI) and Upper-Level Confidence Interval (ULCI) do not straddle zero (ranging from 0.6433 to 0.8493), reinforcing this significance. Therefore, we can conclude that Information Quality significantly predicts Investment Decision-making Behavior.

Direct Effect (0.6322): When the mediator (Perceptual Identification) is controlled for, Information Quality still has a strong and significant direct effect on Investment Decision-making Behavior. The significant t-value (10.7641) and p-value (0.0000) confirm the strength and significance of this relationship. The confidence intervals (from 0.5167 to 0.7476) do not include zero, which indicates a significant direct effect.

Indirect Effect (0.1141): The indirect effect represents the portion of the relationship between Information Quality and Investment Decision-making Behavior that is mediated by Perceptual Identification (P). The fact that the total indirect effect and the specific indirect path through Perceptual Identification (INQ --> P --> ID) are equal indicates that Perceptual Identification might be the only mediator in the model. The indirect effect is significantly different from zero (as the confidence interval ranges from 0.0528 to 0.1773), suggesting that

Perceptual Identification partially mediates the relationship between Information Quality and Investment Decision-making Behavior.

Table 5 Mediating effect analysis where the independent variable is AI

AI-->P-->ID		Effect	se	t	LLCI	ULCI
Total effect		0.4816	0.0458	10.5171	0.3916	0.5717
Direct effect		0.3785	0.0461	8.2133	0.2879	0.4691
Indirect effect	AI-->P-->ID	0.1031	0.0225		0.0641	0.1507

Note: Model:4，Sample size:400 Y: ID ; X: AI ; M : P ; W : M ; Int_1: P × M ;

Total Effect (0.4816): This effect size signifies the cumulative influence of AI Empowerment on Investment Decision-making Behavior without accounting for the mediator or moderator. With a significant t-value (10.5171) and a p-value of 0.0000, there is strong evidence to suggest that AI Empowerment is a robust predictor of ID. The confidence intervals (LLCI at 0.3916 and ULCI at 0.5717) are well above zero, indicating a high level of confidence in this positive relationship.

Direct Effect (0.3785): When the mediator (P) is considered in the model, AI Empowerment still has a direct, positive effect on Investment Decision-making Behavior. The significance of this effect is indicated by the t-value (8.2133) and a p-value of 0.0000, with confidence intervals (from 0.2879 to 0.4691) that reinforce this finding. It suggests that even beyond the mediating influence of Perceptual Identification, AI Empowerment plays a significant role in how investment decisions are made.

Indirect Effect through AI → P → ID Pathway (0.1031): This is the mediating effect of Perceptual Identification on the relationship between AI Empowerment and Investment Decision-making Behavior. It suggests that a portion of AI Empowerment’s influence on ID is carried through the variable P. The indirect effect is statistically significant, as the confidence interval does not include zero (ranging from 0.0641 to 0.1507), although it represents a smaller portion of the total effect when compared to the direct effect. and the confidence intervals do not include 0, indicating the hypothesis H7 is established.

H7: Perceptual Identification plays a significant mediating role in the relationship between the quality of artificial intelligence empowerment information and investment decisions of listed companies.

Table 6 Matrix of Moderating Effect Analysis

	Coefficient	SE	T	P	LLCI	ULCI
constant	3.5436	.0501	70.7602	.000	3.4452	3.6421
P	.3291	.0476	6.9097	.000	.2355	.4228
M	.3128	.0486	6.4315	.000	.2172	.4084
Int_1	.0936	.0436	2.1477	.0323	.0079	.1793

Note: Model: 1，Sample size:400 Y: ID ; X: INQ ; M : P ; W : M ; Int_1: P × M ;

Table 7 Highest Order Unconditional Interaction(s)

	R2 - change	F	df1	df2
M * W	.0086	4.6124	1.0000	396.0000

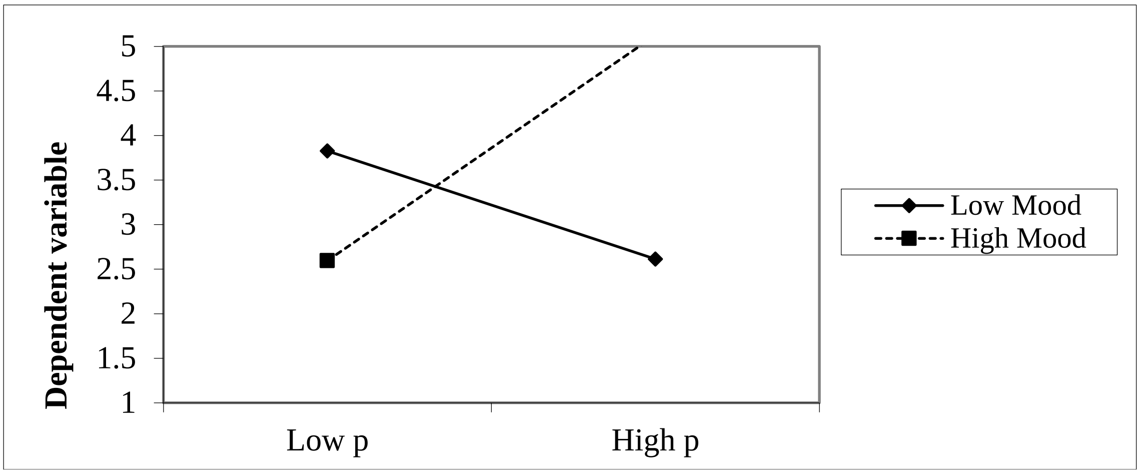

Figure4 Adjustment diagram

Total Effect (0.4816): This effect size signifies the cumulative influence of AI Empowerment on Investment Decision-making Behavior without accounting for the mediator or moderator. With a significant t-value (10.5171) and a p-value of 0.0000, there is strong evidence to suggest that AI Empowerment is a robust predictor of ID. The confidence intervals (LLCI at 0.3916 and ULCI at 0.5717) are well above zero, indicating a high level of confidence in this positive relationship.

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R2 - change (.0086): This value represents the increase in the variance explained (R2) when the interaction term (M * W) is added to the model. While the change is small, it is significant (p = .0323), indicating that the interaction term contributes additional information for predicting ID that is not explained by the main effects alone.

F (4.6124): This statistic tests the null hypothesis that the interaction term does not contribute to explaining the variability in ID. With a value of 4.6124 and a p-value of .0323, we can reject the null hypothesis, affirming the significance of the interaction.

Degrees of Freedom (df1: 1.0000, df2: 396.0000): These values are used in determining the F statistic. The model has 1 degree of freedom for the interaction term (numerator) and 396 degrees of freedom for the error term (denominator).

This study used the Bootstrap method to resample the sample 5,000 times, and test the two mediating effects in the model under the setting conditions of 95% confidence interval. The results of the mediation effect test are shown in Table 4.7 shown. And the confidence intervals do not include 0, indicating the hypothesis H6 is established.

H6: Mood plays an important role in the relationship between perceived identity and investment decisions.

In conclusion, the analysis suggests that Information Quality and Perceptual Identification are important factors influencing Investment Decision-making Behavior. Moreover, the moderating effect of M, implies that the strength of the relationship between Perceptual Identification and Investment Decision-making Behavior changes at different levels of M. Understanding this interaction can help in creating more nuanced strategies to enhance investment decision-making by considering the quality of information, how it is perceived, and the empowerment context provided by AI or other tools.

Research Findings

Table 8 hypothesis verification

	HYPOTHESIS	RESULT	Compare with predecessors
H1	The quality of company information in the securities market has a significant impact on investment decision-making behavior	accepted	Delone & Mclean (2003); Todd &Wixom (2005
H2	AI Empowerment information quality has a significant impact on investment decision-making behavior	accepted	Malik Sallam (2023)
H3	The quality of company information in the securities market has a significant impact on Perceptual Identification.	accepted	Delone & Mclean (2003); Todd &Wixom (2005
H4	Artificial Intelligence empowerment has a significant impact on perceptual recognition.	accepted	Malik Sallam (2023)
H5	Perceptual Identification has a significant impact on investment decision-making behavior	accepted	WR King & J He (2006)
H6	Mood plays an important role in the relationship between perceived identity and investment decisions.	accepted	Qi Luo & Hanqi Li (2023)
H7	Perceptual Identification plays a significant mediating role in the relationship between the quality of artificial intelligence empowerment information and investment decisions of listed companies.	accepted	Qi Luo & Hanqi Li (2023)

Conclusion

The findings conclude that both high-quality information and AI-empowered information significantly influence investment decision-making behavior and perceptual identification. Additionally, perceptual identification has a significant impact on investment decision-making behavior, with mood playing a crucial moderating role between perceptual identification and investment decisions. Moreover, perceptual identification significantly mediates the relationship between AI-empowered information quality and investment decisions. These findings emphasize the importance of information quality, AI, perceptual identification, and mood in investment decision-making.

Discussion

The study's findings reveal several significant relationships. Firstly, the quality of company information in the securities market has a substantial impact on investment decision-making behavior, confirming the hypothesis (H1). Secondly, AI-empowered information quality also significantly influences investment decision-making behavior, validating the hypothesis (H2). Thirdly, the quality of company information significantly impacts perceptual identification, supporting the hypothesis (H3). Additionally, AI empowerment has a notable effect on perceptual identification, confirming the hypothesis (H4). The study further finds that perceptual identification significantly affects investment decision-making behavior, corroborating the hypothesis (H5). Moreover, mood plays a crucial role in the relationship between perceived identity and investment decisions, supporting the hypothesis (H6). Lastly, perceptual identification significantly mediates the relationship between AI-empowered information quality and investment decisions of listed companies, validating the hypothesis (H7). These results collectively underscore the multifaceted nature of investment decision-making processes, highlighting the importance of information quality, perceptual factors, and emotional states.

This study highlights the critical roles of company information quality and AI-empowered information quality in influencing investment decision-making behavior. It emphasizes that perceptual identification and mood are significant factors that cannot be overlooked in this context. The findings indicate that investors rely not only on the quality of information but are also influenced by their perceptual identification and emotional state. This has important implications for both investors and companies. For investors, understanding these influences can lead to more informed and balanced decision-making. For companies, these insights can drive improvements in information disclosure practices and the development of AI technologies to enhance the quality of information provided to the market. The study thus provides valuable guidance for enhancing the overall efficiency and effectiveness of the securities market.

The results of this study are consistent with previous research, thereby reinforcing its credibility. The findings align with the research of Delone & McLean (2003) and Todd & Wixom (2005), which also identified a significant impact of company information quality on investment decision-making behavior and perceptual identification (H1 and H3). Furthermore, the study's results are in agreement with Malik Sallam (2023), which demonstrated that AI-empowered information quality significantly affects investment decision-making behavior and perceptual identification (H2 and H4). Additionally, the finding that perceptual identification significantly impacts investment decision-making behavior is consistent with the research of WR King & J He (2006) (H5). The study also corroborates the findings of Qi Luo & Hanqi Li (2023), showing that mood plays an important role in the relationship between perceptual identification and investment decisions (H6), and that perceptual identification significantly mediates the relationship between AI-empowered information quality and the investment decisions of listed companies (H7). These consistencies with previous research underline the robustness of the study's conclusions and their relevance to the current body of knowledge in the field.

Recommendations

Theoretical Recommendations

The findings of this study demonstrate that the quality of company information in the securities market and AI-empowered information quality have significant impacts on investment decision-making behavior. Perceptual identification plays a crucial mediating role in this process, and mood significantly moderates the relationship between perceptual identification and investment decisions. These findings extend existing investment decision-making theories by emphasizing the importance of information quality and perceptual factors. Future theoretical research should explore additional factors that may influence investment decision-making behavior, such as social influences and cognitive biases. Moreover, the impact of information quality and perceptual identification on investment decisions should be examined in different market environments and cultural contexts to develop a more comprehensive and widely applicable investment decision-making model.

Policy Recommendations

Based on the findings of this study, regulatory bodies should enhance the oversight of information disclosure quality in the securities market to ensure that investors have access to accurate, transparent, and high-quality information. This can be achieved by establishing stricter information disclosure standards and strengthening the review mechanisms for information disclosure. Additionally, policymakers should encourage and support the application of artificial intelligence technologies in the financial sector, promoting the development and use of high-quality AI-empowered information systems to improve the accuracy and timeliness of market information. Furthermore, the emotional and psychological well-being of investors should be considered, and necessary support services should be provided to help investors remain rational and calm when making investment decisions.

Practical Recommendations

For financial institutions and investors, this study provides several practical recommendations. Financial institutions should focus on improving the quality of their information disclosure, ensuring that the information provided to investors is comprehensive, accurate, and timely. Additionally, financial institutions can leverage artificial intelligence technologies to optimize information processing and analysis, thereby enhancing the quality and efficiency of information use. Investors should pay attention to their emotional state and perceptual identification when making investment decisions, in addition to the quality of information. They can use psychological counseling and emotional management techniques to remain calm and rational during the decision-making process, reducing the adverse effects of emotions on investment decisions. Lastly, financial training and education should place greater emphasis on perceptual identification and emotional management to help investors improve decision-making quality.

Despite its contributions, this study has several limitations:

1. The research is limited to institutional investors in Beijing, which may affect the generalizability of the results to other regions or investor groups.
2. The study focuses on private equity funds, potentially overlooking the behaviors of other types of institutional investors.
3. The cross-sectional nature of the study limits the ability to draw causal inferences from the findings.

Recommendations for Future Research

1. Expand the scope of the study to include institutional investors from different regions and industries.
2. Conduct longitudinal studies to explore the causal relationship between information quality and investment decisions.
3. Investigate the impact of AI on other aspects of the financial market, such as risk management and market efficiency.

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