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Research Article

Big Data, Artificial Intelligence, and Financial Literacy: Exploring their Combined Influence on Investment Behavior among Chinese Household

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ABSTRACT

The investing behavior of Chinese families is undergoing a dramatic transition in the context of the digital financial era, impacted by factors such as big data use, AI adoption, financial literacy, digital literacy, and risk aversion. Although prior research has offered useful insights into certain components, a thorough examination of their linked dynamics has been lacking. The purpose of this research was to look into how big data usage, AI adoption, financial literacy, digital literacy, and risk aversion influence investment behavior among Chinese households. Additionally, it aimed to learn more about how risk aversion and digital literacy function as mediators in these relationships. A questionnaire-based survey of 370 Chinese families was employed as part of the quantitative research methodology. The study employed AMOS to find the relationship between variables. The research found that big data usage, AI adoption, financial literacy, and digital literacy significantly and favorably influenced Chinese households' investment behavior. It was discovered that digital literacy mediated the linkages between the adoption of technology and investment decisions. Furthermore, risk aversion reduced the effects of financial literacy and big data usage on investment behavior. This study added to the body of knowledge by providing a comprehensive framework that incorporates several aspects impacting investment behavior. It shed insight into the complicated dynamics of technology uptake and literacy, as well as their impact on investment decisions. The study went beyond individual components to investigate their interactions, resulting in a more complex view of modern investment behavior. This study has broad-ranging effects that will help investors, financial institutions, governments, educators, and researchers. The focus on a particular setting and self-reported data are two important constraints that must be acknowledged. Future studies can investigate longitudinal dynamics and cross-cultural variances to further our understanding of investment behavior in the digital age.

Keywords: Investment Behavior, Big Data Utilization, AI Adoption, Financial Literacy, Digital Literacy, Risk Aversion.

INTRODUCTION

Big data is crucial in the rising Chinese household investing environment. Effectively gathering and analyzing the massive amounts of financial market data created every day helps investors make better judgments. Big data helps assess risk, analyze market patterns, and understand asset performance. Big data-savvy Chinese investors

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have an edge. They can deliberately enter and exit the market, choose stocks, and diversify their portfolios using this advantage. Data-driven accuracy helps investors make better decisions and navigate complex financial markets. Due to a strong saving and investing culture and a burgeoning middle class, China dominates worldwide finance. A tremendous increase in investors has made mutual funds and equities popular. Lin, Morck, Yeung, and Zhao (2023) reported that China will have more individual stock market investors than numerous other countries by 2020. Online investment platforms and robo-advisors have also made investing easier for Chinese households (Litterscheidt & Streich, 2020). China is investing more in financial markets and using new technology. These trends are seen in patterns. AI is adding to huge data to affect investing behavior. AI technology like machine learning algorithms and robo-advisors helps investors analyze massive datasets, find investing possibilities, and reduce risk. These tools adjust financial advice and portfolio strategies to each person's goals and risk tolerance (Shanmuganathan, 2020). Chinese households can make more objective financial decisions using AI-powered solutions. AI promotes investment efficiency and plan effectiveness (Tiberius, Gojowy, & Dabić, 2022). Using AI in investment operations can boost performance and customize investments. Financial literacy is crucial in today's complex environment. This program teaches investors how to understand difficult financial principles, evaluate investment possibilities, and balance risk and return, according to S. Kumar, Rao, Goyal, and Goyal (2022). Financially literate households can build varied investment portfolios that match their risk tolerance and goals. Financial literacy improves investing knowledge and skills. This data helps investors make long-term financial stability-aligned investments, according to Cupák, Fessler, Hsu, and Paradowski (2022). Thus, financial literacy is crucial to Chinese households' prudent investment practices.

Digital literacy is essential for using technology and investing in financial services as they become more digital. Digitally literate people can use online trading platforms effortlessly. People learn to use digital investment tools and analyze data formats (Andreou & Anyfantaki, 2021). Technologically advanced Chinese families thrive at using robo-advisors, internet trading, and digital interfaces (Litterscheidt & Streich, 2020). Thus, digital literacy helps investors make smart investments in a world where digital technology dominates the financial industry. It boosts big data, AI, and financial literacy, which influence investing behavior. Technology adoption, investment behavior, and financial literacy have been thoroughly studied, yielding noteworthy discoveries. Financial literacy studies reveal that financially literate investors make better investments. The results above show that financial education influences investor behaviour (S. Kumar et al., 2022). Tech adoption research has highlighted the growing relevance of digital investing platforms and robo-advisors (Zhang, Lu, & Xiao, 2023) for efficiency and customized investment advice. Despite their significant contributions, the literature lacks detailed research on how these factors affect investing behavior. Few academic studies have examined how technology affects financial literacy and investing decisions (Hong, Thakuriah, Mason, & Lido, 2020). There is also little research on the complex relationship between technology adoption and investment decisions, the role of digital literacy in mediating this relationship, risk aversion as a moderating factor, and their links (Freeland, O'reilly, Fleury, Adams, & Vostanis, 2022). This study seeks to fill the knowledge gap by studying the complex interaction between Chinese family investing behavior, big data, artificial intelligence, financial literacy, digital literacy, and risk aversion.

This study seeks to understand how people invest in the fast-growing digital economy. Individual and combination elements like risk aversion, financial literacy, AI, big data, and digital literacy must be examined. This study investigates how these characteristics impact investor behavior. To stress its relevance in the current investment landscape, this study explores how digital literacy influences new technology uptake and investment decisions. This study impacts various critical areas. Facilitating domestic and global investors is crucial. Individual investors are more accountable for their financial well-being; therefore, they must understand the various elements that affect their investment decisions in the fast-changing financial environment. This study aids strategic, well-informed investing decisions. It demonstrates risk aversion, financial knowledge, AI use, and big data exploitation. Empowerment may affect their long-term financial security and riches. Financial institutions and investment organizations can learn from this study. In today's competitive financial business, services must adapt to consumer preferences. These organizations can tailor financial products and advising services to individual needs by understanding how risk aversion, technology use, and literacy affect investing decisions. This targeted technique can boost consumer satisfaction and loyalty, strengthening institution-client relationships.

LITERATURE REVIEW

Big Data Utilization and Investment Behavior

Big data is crucial for influencing investor behavior and decisions. Hu, Che, Wu, and Chang (2023) claim that big data influences financial news analysis investing and trading decisions. Investors can use sentiment research and news sentiment indicators to assess market mood and adapt their investment strategy. Using big data and market sentiment to alter investments can help investors make better judgments (Cabrera-Paniagua & Rubilar-Torrealba, 2021). Big data, especially sentiment analysis, has revolutionized portfolio management. Li (2022) emphasizes big data analytics in stock prediction and portfolio management. Big data and machine learning can help investors manage portfolios and anticipate stock prices. The ability to forecast changes in investing behavior by encouraging data-driven methods. This can influence asset allocation and investing decisions (Ahmed, Alshater, Ammari, & Hammami, 2022). Big data adoption and use have driven robo-advisory services. Tiberius et al. (2022) study how robo-advisors use machine learning and big data analytics to customize financial advice. Data-driven recommendations include investors' preferences, risk profiles, and financial goals, influencing their investment selections. Such services are helping investors construct tailored investment plans and change their investment behavior as they become more data-driven and automated.

H1: Big data utilization has a significant and positive impact on investment behavior.

AI Adoption and Investment Behavior

AI has transformed investment behaviour and decision-making. Researchers and industry executives are becoming more aware of how AI affects investing methods and results. Chua, Pal, and Banerjee (2023) say AI-powered algorithms are better at scanning large databases and finding investment opportunities. Zhu, Sallnäs Pysander, and Söderberg (2023) suggest that robo-advisors use AI algorithms to deliver individualized financial advise and manage portfolios. As these services help people create cost-effective investing plans based on knowledge, their investment behavior changes. Robo-advisors can help clients create a systematic investing plan, which may affect asset allocation (Lee, T. Kim, Choi, & W. Kim, 2022). AI-generated algorithmic trading systems are accurate and fast. Qian et al. (2022) showed that AI-driven algorithmic trading is a substantial financial market driver. Algorithm accessibility may affect market dynamics and investor behavior. As market conditions change, data-driven trading options may affect investor behavior.

H2: AI adoption has a significant and positive impact on investment behavior.

Financial Literacy and Investment Behavior

Rodrigues, Oliveira, Rodrigues, and Costa (2019) discovered that financial literacy is linked to better investment decision-making, portfolio diversification, and lower financial risk. Financial knowledge helps investors make smart judgments. Billari, Favero, and Saita (2023) examine investment diversification and financial literacy. Research suggests that financially literate investors diversify their investments, minimizing risk. This approach is fundamental to financial caution. Cupák, Fessler, and Schneebaum (2021) found that financial literacy affects retirement investment behavior. Their research shows that financially savvy people are more likely to make smart retirement savings and investment decisions, leading to improved retirement outcomes.

H3: Financial Literacy has a significant and positive impact on investment behavior.

Digital Literacy as a Mediator

It is becoming obvious how digital literacy affects investment behavior and big data use. Digitally literate investors can maximize big data prospects, per W. Liu et al. (2023). Digital literacy lets people grasp algorithms, access complex data sources, and extract critical information. More digitally literate people make data-driven financial decisions. Kouladoum, Wirajing, and Nchofoung (2022) stress digital literacy for huge investment data interpretation. Digital literacy, they say, aids in the comprehension and extraction of important facts from huge datasets. People may adjust their financial goals as they study this data. A shift toward data-driven spending. Advanced digital literacy helps investors employ AI. Digital literacy helps people understand, analyze, and use AI-generated data for investing decisions (Robinson 2020). Shanmuganathan (2020) explores digital literacy and AI-enabled investment decision-making. Digitally literate people can employ AI-powered algorithms and platforms, say Sylla and Gil (2020). Advanced digital literacy uses AI investing advice. As data-driven judgments become more common, this may affect behavior. Understanding digital tools and platforms may help investors use them better, which may alter their behavior, according to Lo Prete (2022). Today's investment climate is blending financial and digital literacy. Additionally, P. Kumar, Islam, Pillai, and Sharif (2023) study digital literacy and financial information processing. They observed that technologically literate people can understand complex financial data and insights. Digital literacy works with financial literacy to help customers make smarter investment decisions using technology.

H4: Digital literacy mediates the relationship between big data utilization and investment behavior.

H5: Digital literacy mediates the relationship between AI adoption and investment behavior.

H6: Digital literacy mediates the relationship between Financial Literacy and investment behavior.

Risk Aversion as Moderator

Big data affects risk aversion in portfolio diversification, a key risk management tool. Big data optimizes portfolios for risk-averse investors to balance return and risk, according to W. Xu, Murphy, X. Xu, and Xing (2021). Big data helps risk-averse investors diversify their assets. Investors' aversion to risk affects how they employ big data and data-driven insights. W. Liu, Long, Xie, Liang, and Wang (2021) warn careful investors about AI-generated financial advice. People analyze AI findings due to risk aversion, making them cautious investors even if they can earn more. AI may reduce risk for risk-averse investors. Rodgers, Hudson, and Economou (2023) suggest risk-averse investors use AI to identify and manage portfolio hazards. Real-time AI risk assessments let investors choose investments within their risk tolerance. Risk aversion affects portfolio diversification, which is crucial for risk management, especially with AI. Bisi et al. (2022) demonstrate how AI-driven insights might help risk-averse investors balance risk-return. Risk-averse investors can use data-driven AI recommendations to develop diversified portfolios that fit their aims. Financial education may help risk-averse investors. Financially literate, risk-averse people can appraise investments better, claim Litterscheidt and Streich (2020). Financial understanding lets them pick high-return, low-risk commodities. Risk aversion may restrict financial skill's impact on portfolio diversification. Mohamed, Mirakhor, and Erbaş (2019) suggest conservative, financially literate investors actively diversify their holdings to balance risk and return. Financial competency reduces risk diversification.

H7: Risk aversion moderates the relationship between big data utilization and investment behavior.

H8: Risk aversion moderates the relationship between AI adoption and investment behavior.

H9: Risk aversion moderates the relationship between financial literacy and investment behavior.

Figure 1 below clearly illustrates the conceptual framework of the study.

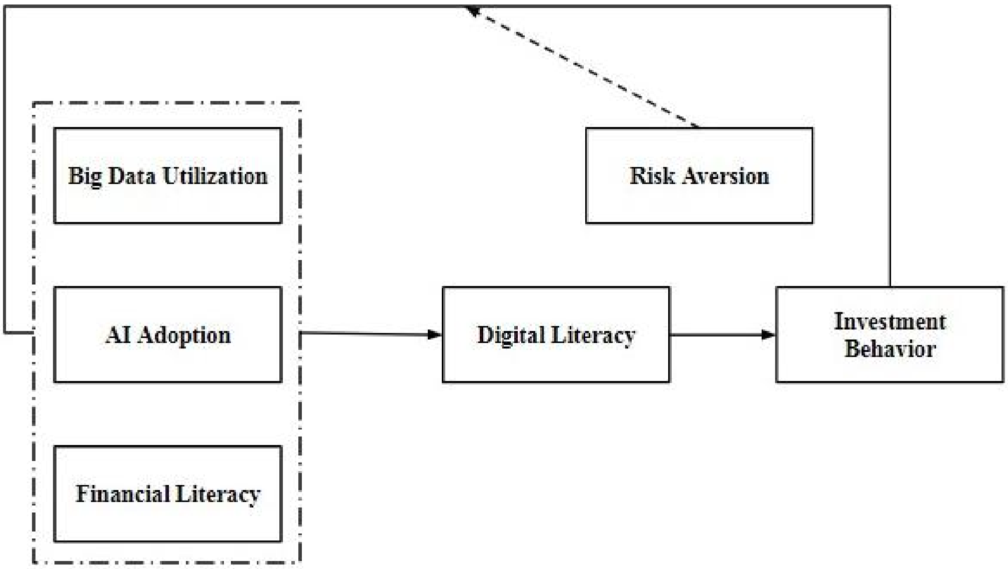

Figure 1. Conceptual Framework

METHODOLOGY

A quantitative research design was used for this study. The need to examine and quantify the linkages between big data usage, AI adoption, financial literacy, digital literacy, risk aversion, and investing behavior among Chinese families prompted this choice. Structured data, statistical analysis, and numerical findings from quantitative research are essential for validating hypotheses and establishing objective conclusions. This study benefits from quantitative research. It lets us explore variable correlations to understand how big data, AI, and financial literacy affect investment behavior. Second, it gives a larger population statistical rigor and generalizability, which is needed to generalize about Chinese houses. Quantitative studies may oversimplify complex processes and miss nuanced qualitative findings. The households in China that make up the study's population. The target demographic for understanding investment behavior in the context of big data, AI, financial literacy, and digital literacy is represented by this large group. We applied the "rule of thumb" for quantitative research to pick the right sample size. Although there is no set formula for calculating the sample size, it is generally recommended to strive for a sample size that is at least ten times the number of variables being studied. A sample size of 370 was chosen suitable because your study includes numerous variables and a complex relationship between them. The actual sample size for this study is 370 Chinese families. This sample size allows statistical studies, hypothesis testing, and relevant conclusions on Chinese households' big data usage, AI adoption, financial literacy, digital literacy, risk aversion, and investing behavior. This study used simple random sampling. A simple random sample was utilized to fairly reflect Chinese homes. This strategy gives each home in the population an equal chance of being sampled, ensuring a fair and accurate representation of demographic diversity. This method is essential for generalizing and applying findings to a larger population. Simple random sampling has limits, which must be acknowledged. One drawback is that it may not represent certain population groupings. Regional, economic, and demographic criteria were considered to guarantee that the basic random selection sample accurately represents the large Chinese investor community. Geographic representation was achieved by randomly sampling within each region and partitioning the population into regions, providing proportional urban and rural investor representation. The population was classed by income, and volunteers came from many socioeconomic backgrounds to promote economic diversity. To ensure demographic representation, the population was separated by age, gender, education, and household composition. Individuals were then randomly selected from each category to reflect demographic segments. Sufficient sample size was utilized to ensure statistical reliability and to account for Chinese investor variation. These steps were meant to reduce bias and ensure that Chinese investment matched the country's demographics, topography, and economy. Implementation can be resource- and logistically-intensive, especially with a large and diverse population. Due to random selection, sampling mistakes may occur. This study collected data using a structured questionnaire. The questionnaire was chosen for its ability to collect quantitative data from a large sample. This strategy generated consistent data and ensured that each participant received the same questions. It also made collecting numerical data for statistical analysis easier. This project's data was analyzed using Amos for structural equation modelling (SEM). AMOS, a powerful statistical tool that focuses on SEM, is perfect for examining subtle interactions between numerous factors, as in our work. SEM can assess the direct and indirect impacts of various factors and reveal mediation and moderation effects. SEM was chosen as the main analytical tool due to various variables. Complex interactions between variables can be evaluated simultaneously using SEM. This makes it excellent for investigating risk aversion, investment behavior, financial literacy, digital literacy, big data use, and AI adoption among Chinese households. SEM allows both latent and observable variables, which is useful for studying abstract concepts like digital and financial literacy. Using SEM, researchers can examine direct and indirect impacts and the framework's mediating and regulating relationships. SEM was the major analytical instrument, but additional statistical methods could have improved results. Sample characteristics and pertinent variables may have been summarized using descriptive statistics. Regression analysis and other inferential statistics may have studied investment behavior and specific factors. Additionally, mediation and moderation studies may have examined specific model pathways and interactions. Sensitivity or robustness tests may have verified the SEM results' stability and resilience.

FINDINGS

Demographic Profile of Respondents

There is a large age range among the participants. A sizeable proportion is found in the 18–24 (12.2%), 25–34 (21.1%), and 35–44 (17.6%) age groups, indicating a large presence of people in their 20s and 30s. Individuals 65 and over make up 19.7% of the sample, therefore there is also representation among older age groups. The study maintains a gender balance, with roughly 50% of participants being male and female. The inclusion of potential gender-based disparities in financial decision-making gives a well-rounded perspective on investing behavior. The participants have a variety of educational backgrounds. With 27.6% having a bachelor's degree and 16.8% having a master's, the majority have at least that level of education. 8.6% of people have a doctorate, which is a tiny yet significant amount. Contrarily, 18.4% of the sample had a high school diploma or its equivalent, demonstrating a range of educational attainment levels. The participants display a variety of employment scenarios that reflect different professional contexts. A sizable fraction (34.6%) of people hold a full-time job, while others work part-time (12.2%) or on their own (7.8%). The sample also includes homemakers (10.3%), students (3.2%), and retirees (11.6%). A smaller subset (4.1%) of participants reported being unemployed, highlighting the variety of financial situations among them. The marital status of the participants demonstrates diversity, with single people making up 24.9%, married people making up 47.6%, divorced people making up 12.2%, and widowed people making up 15.4%. This range in marital status enables a careful analysis of investment behavior in various types of relationships. The participants have a diverse range of investment experience. Significant amounts fell into the categories of intermediate (28.4%) and experienced (32.4%), showing a high level of expertise with investment procedures. In order to explore investment behavior across different expertise levels, there is also representation from novice investors (16.8%) and expert investors (22.4%). Participants had a variety of financial objectives, with wealth accumulation (39.2%) and retirement planning (45.4%) dominating the list. However, participants also have objectives for supporting their education (8.6%), achieving short-term financial objectives (14.3%), diversifying their investments (21.1%), and reducing risk (7.3%). This diversity of investing objectives offers important insights into the factors influencing investment choices. Participants display a range of investing time horizons, with a strong emphasis on medium-term objectives (38.4%). The investing horizons of the short-term (24.9%) and long-term (36.8%) are both quite well-represented. As it affects participants' risk tolerance and investment strategies, understanding the distribution of investment horizons is essential for evaluating participants' methods for making investment decisions (see statistics in **Table 1** for details).

Table 1. Demographic Details

Demographic Variables	Frequency	Percentage (%)
Age		
- Under 18	12	3.2%
- 18-24	45	12.2%
- 25-34	78	21.1%
- 35-44	65	17.6%
- 45-54	55	14.9%
- 55-64	42	11.4%
- 65 and over	73	19.7%
Gender		
- Male	185	50.0%
- Female	185	50.0%
Education		
- Less than high school	14	3.8%
- High school diploma or equivalent	68	18.4%
- Some college or associate degree	92	24.9%
- Bachelor's degree	102	27.6%
- Master's degree	62	16.8%
- Doctoral degree	32	8.6%
Employment Status		
- Employed full-time	128	34.6%
- Employed part-time	45	12.2%
- Self-employed	29	7.8%
- Unemployed	15	4.1%
- Retired	43	11.6%
- Student	12	3.2%
- Homemaker	38	10.3%
Marital Status		
- Single	92	24.9%
- Married	176	47.6%
- Divorced	45	12.2%
- Widowed	57	15.4%
Investment Experience		
- Novice	62	16.8%
- Intermediate	105	28.4%
- Experienced	120	32.4%
- Expert	83	22.4%
Investment Goals		
- Wealth accumulation	145	39.2%
- Retirement planning	168	45.4%
- Education funding	32	8.6%
- Short-term financial goals	53	14.3%
- Diversification	78	21.1%
- Risk mitigation	27	7.3%
Investment Horizon		

Demographic Variables	Frequency	Percentage (%)
- Short-term (less than 2 years)	92	24.9%
- Medium-term (2 to 5 years)	142	38.4%
- Long-term (more than 5 years)	136	36.8%

Measurement Model

Table 2 provides key insights into the construct reliability and validity of the study's primary variables, establishing the framework for its measurement technique. The study's accuracy and rigor depend on these criteria. BDU construct dependability is stable with a strong Cronbach's alpha of 0.912. Its parts are quite consistent. BDU items' outer loadings range from 0.802 to 0.833, demonstrating they accurately reflect big data utilization. Variance Inflation Factor (VIF) values below 5 imply that multicollinearity is not a concern for this construct, enhancing its dependability. AIA has a Cronbach's alpha of 0.831, indicating internal consistency. AIA elements' outer loadings of 0.562 to 0.819 confirm that they capture the hidden idea of AI adoption. Some VIF values are more than one but within acceptable ranges, indicating collinearity. DL's Cronbach's alpha of 0.881 indicates great component internal consistency and construct dependability. The outer loadings for DL items, 0.828 to 0.841, show how well they capture digital literacy. DL items' VIF values are much below 3, indicating no multicollinearity issues. FL has great construct dependability, with a Cronbach's alpha of 0.876. FL components' outer loadings range from 0.789 to 0.833, confirming that they accurately measure financial literacy. FL items have VIF values below 3, indicating no substantial multicollinearity. Cronbach's alpha of 0.916 indicates good construct dependability and internal consistency for IB items. Investment behavior latent constructs are appropriately represented by IB items with outer loadings between 0.776 and 0.870. IB item VIF values are well below 3, showing that multicollinearity is not a problem in this architecture. RA's Cronbach's alpha of 0.819 indicates good construct reliability and item internal consistency. RA items' outside loadings range from 0.696 to 0.833, indicating they accurately represent risk aversion. No major multicollinearity concerns exist because RA component VIF values are less than 3.

Table 2. Construct Reliability and Validity

Construct	Items	Outer Loading	VIF	Cronbach's Alpha
BDU	BDU1	0.802	1.507	0.912
	BDU2	0.830		
	BDU3	0.819		
	BDU4	0.832		
	BDU5	0.833		
AIA	AIA1	0.781	3.157	0.831
	AIA2	0.650		
	AIA3	0.819		
	AIA4	0.572		
	AIA5	0.575		
	AIA6	0.562		
DL	DL1	0.840	2.117	0.881
	DL2	0.828		
	DL3	0.841		
	DL4	0.735		
FL	FL1	0.789	2.831	0.876
	FL2	0.789		
	FL3	0.803		
	FL4	0.833		
IB	IB1	0.843	2.731	0.916
	IB2	0.793		
	IB3	0.870		
	IB4	0.776		
	IB5	0.862		
RA	RA1	0.803	2.587	0.819
	RA2	0.833		
	RA3	0.696		

Note: IB = Investment Behavior, BDU = Big Data Utilization, AIA = AI Adoption, FL = Financial Literacy, DL = Digital Literacy, RA = Risk Aversion.

In **Table 3**, the study's core variables—Financial Literacy (FL), AI Adoption (AIA), Big Data Utilization (BDU), Risk Aversion (RA), Digital Literacy (DL), and Investment Behavior (IB)—are distinguished. The table shows these variables' correlation coefficients, revealing their relationships. Only slightly positive correlations exist between financial literacy and the use of artificial intelligence (0.615), big data (0.434), and digital literacy (0.657). According to this, financially literate people are more likely to adopt AI technology, use big data to invest, and have superior digital literacy. These connections suggest financial literacy and receptivity to technology and data-driven investment methods may be linked. Financial Literacy (0.615), Big Data Utilization (0.511), and Digital Literacy (0.767) have weak positive associations with AI adoption. The application of artificial intelligence in investment activities is associated with higher financial literacy, big data use, and digital literacy. These results demonstrate how AI and financial competence work together. The correlations between financial literacy ($r = 0.434$), AI Adoption ($r = 0.511$), and Digital Literacy ($r = 0.471$) and Big Data Utilization are all positive. Those that actively use big data to make investing decisions likely to be financially literate, use AI, and comprehend digital technology. It links financial knowledge to data-driven decision-making. Risk Aversion (RA) marginally positively correlates with Financial Literacy (0.652) and Digital Literacy (0.631). This shows that risk-averse people have superior financial literacy and digital literacy skills. This study links risk aversion, financial literacy, and digital competence. Digital literacy has relatively positive correlations with Financial Literacy (FL), AI Adoption (AIA), Big Data Utilization (Big Data) (0.471), and Risk Aversion (0.631). Digital Literacy skills are linked to financial literacy, AI adoption, big data use, and risk aversion. Digital competency is essential for informed investment decisions nowadays. Financial and digital literacy revealed weak positive correlations with Investment Behavior (IB) (0.514 and 0.581). Better financial and digital literacy leads to more engaged and knowledgeable investing decisions. It highlights how financial literacy and digital skills affect investing behavior.

Table 3. Discriminant Validity

	FL	AIA	BDU	RA	DL	IB
FL						
AIA	0.615					
BDU	0.434	0.511				
RA	0.652	0.717	0.548			
DL	0.657	0.767	0.471	0.631		
IB	0.514	0.355	0.498	0.417	0.581	

Note: IB = Investment Behavior, BDU = Big Data Utilization, AIA = AI Adoption, FL = Financial Literacy, DL = Digital Literacy, RA = Risk Aversion.

Structural Model

Goodness-of-Fit Statistics

Table 4 of the publication evaluates the structural equation model's fitness. This evaluation determines how well the model matches observable data, revealing its quality and reliability. The first is that the X2/DF (Chi-Square to Degrees of Freedom Ratio) is 1.245, well below the recommended 3. This is encouraging because the model and data match nicely. It implies that the model's correlations match the data, supporting the study's findings. A goodness-of-fit index of 0.823 is obtained by the GFI. The ideal number is greater than 0.9, however, this value is within the allowed range of 0.7 to 0.9. This suggests that while the model fits the data well, it may be improved to align better. **Table 4** of the publication evaluates the structural equation model's fitness. This evaluation determines how well the model matches observable data, revealing its quality and reliability. The first is that the X2/DF (Chi-Square to Degrees of Freedom Ratio) is 1.245, well below the recommended 3. This is encouraging because the model and data match nicely. It implies that the model's correlations match the data, supporting the study's findings. A goodness-of-fit index of 0.823 is obtained by the GFI. The ideal number is greater than 0.9, however, this value is within the allowed range of 0.7 to 0.9. This suggests that while the model fits the data well, it may be improved to align better. The Tucker-Lewis Index (TLI) is 0.686, which is reasonable but below the 0.9 threshold. It suggests the model fits the data well but not perfectly. Finally, the RMSEA is 0.071, below the recommended 0.1. This is a good sign that the model matches the data (see **Table 4** and **Figure 2** for details).

Table 4. Model Fitness

Fitting Coefficient	Evaluation Criteria		Actual Value	Fitting Situation
	Good	Acceptable		
X2/DF	<3	3.0–5.0	1.245	Good
GFI	>0.9	0.7–0.9	0.823	Acceptable
AGFI	>0.9	0.7–0.9	0.862	Acceptable
CFI	>0.9	0.7–0.9	0.743	Acceptable
RMR	Close to 0	<0.5	0.026	Acceptable
TLI	>0.9	0.7–0.9	0.686	Good
RMSEA	<0.008	0.008–0.12	0.071	Good

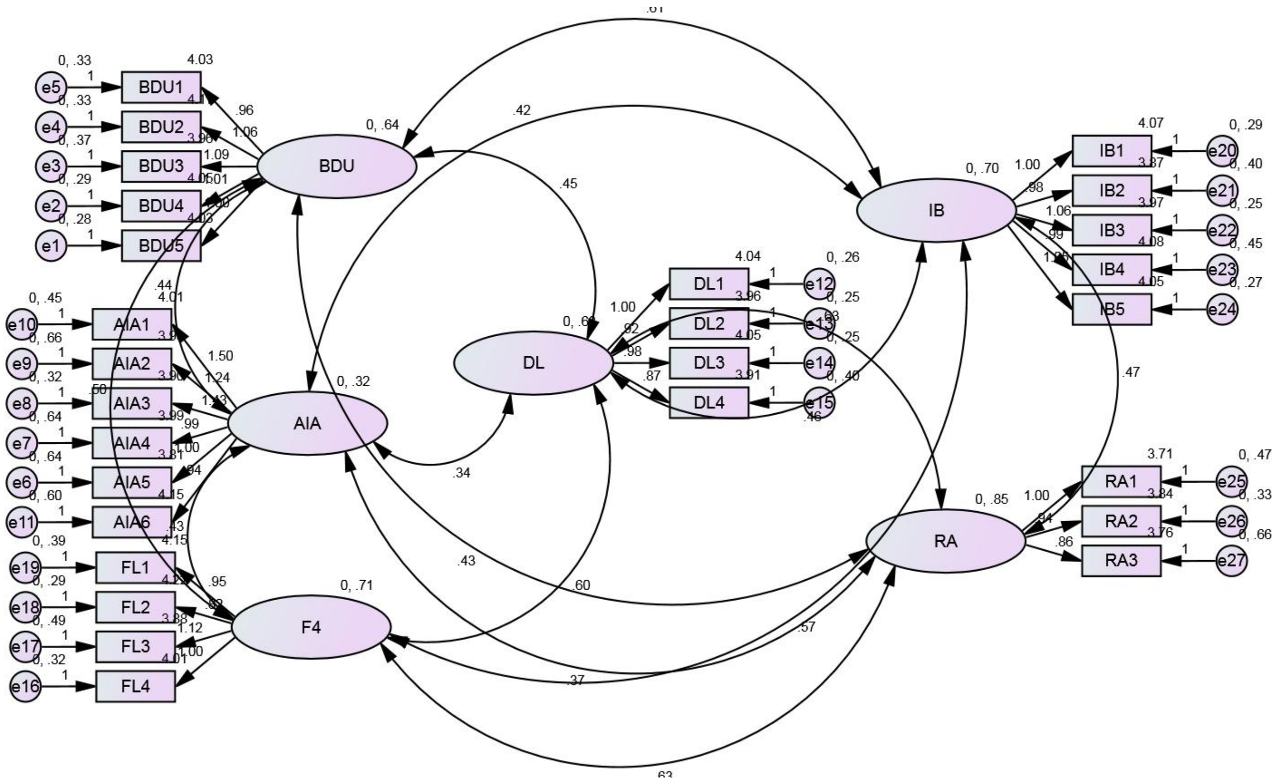

Figure 2. Measurement Model

Structural Model

Table 5 shows the route analysis results, which analyzed the study's variables' potential linkages. The table shows coefficients, critical ratios (CR), p-values, and hypothesis acceptance/rejection. A high critical ratio (CR) of 15.925 and a p-value of 0.0001 make the path coefficient of 0.565 statistically significant. This reveals that Big Data Utilization (BDU) and Investment Behavior (IB) are strongly correlated, supporting H1. The route coefficient of 0.064 is highly significant with a CR of 18.760 and p-value of 0.0001. This shows that AIA and Investment Behavior (IB), which lead to H2 acceptance, are positively correlated. A critical ratio (CR) of 11.464 and a p-value of 0.0001 make the route coefficient of 0.445 statistically significant. H3 is accepted because Financial Literacy (FL) and Investment Behavior (IB) are positively correlated. The path coefficient of 0.208 is significant with a CR of 10.087 and p-value of 0.0001. This shows that Digital Literacy (DL) mediates the association between Big Data Utilization (BDU) and Investment Behavior (IB), supporting H4. The path coefficient of 0.286 is significant with a CR of 6.254 and p-value of 0.0001. This shows that Digital Literacy (DL) mediates the relationship between AI Adoption (AIA) and Investment Behavior (IB), supporting H5. A Critical Ratio (CR) of 6.524 and a p-value of 0.0001 make the route coefficient of 0.478 crucial. This suggests that Digital Literacy mediates the relationship between Financial Literacy (FL) and Investment Behavior (IB). So H6 is true. The path coefficient of 0.064 is significant with a CR of 11.836 and p-value of 0.0001. H7 is valid because Big Data Utilization (BDU) moderates the risk-investment behavior relationship. A Critical Ratio (CR) of 21.176 and a p-value of 0.0001 make the route coefficient of 0.121 extremely significant. AI Adoption (AIA) moderates Risk Aversion (RA) and Investment Behavior (IB), supporting H8. A critical ratio (CR) of 35.941 and a p-value of 0.0001 make the route coefficient of 0.193 statistically significant. This supports H9 because Financial Literacy (FL) moderates the link between Risk

Aversion (RA) and Investment Behavior (IB) (see **Table 5** and **Figure 3** for details).

Table 5. Path Analysis

Hypothesis	Path	Coefficient	Critical Ratio (CR)	P value	Result
H1	BDU -> IB	0.565	15.925	0.0001	Accepted
H2	AIA -> IB	0.064	18.760	0.0001	Accepted
H3	FL -> IB	0.445	11.464	0.0001	Accepted
H4	BDU -> DL -> IB	0.208	10.087	0.0001	Accepted
H5	AIA -> DL -> IB	0.286	6.254	0.0001	Accepted
H6	FL -> DL -> IB	0.478	6.524	0.0001	Accepted
H7	RA*BDU -> IB	0.064	11.836	0.0001	Accepted
H8	RA*AIA -> IB	0.121	21.176	0.0001	Accepted
H9	RA*FL -> IB	0.193	35.941	0.0001	Accepted

Note: IB = Investment Behavior, BDU = Big Data Utilization, AIA = AI Adoption, FL = Financial Literacy, DL = Digital Literacy, RA = Risk Aversion.

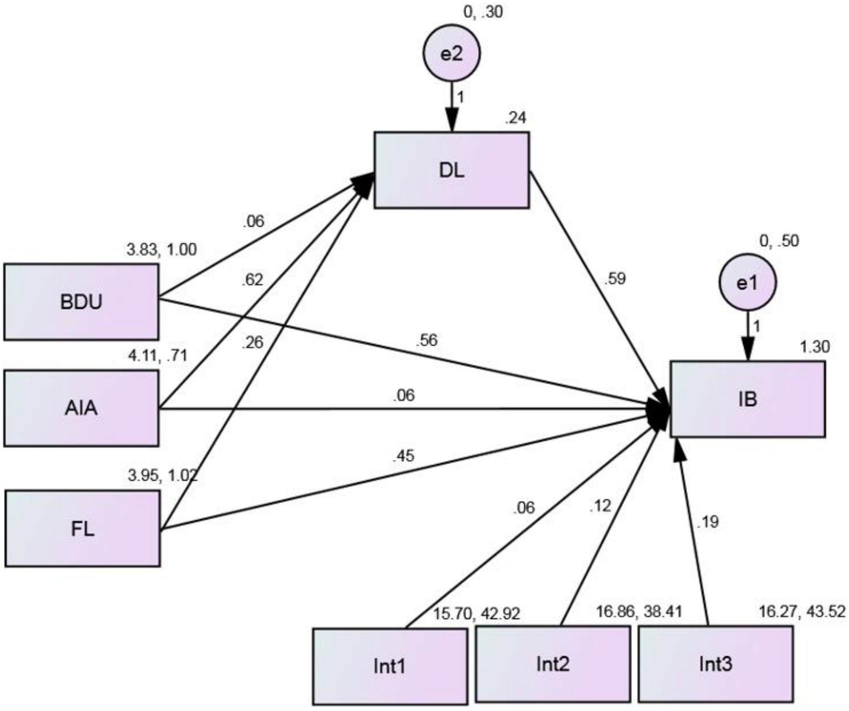

Figure 3. Structural Model

DISCUSSION

Hypothesis H1 suggests big data improves investment behavior. The financial industry is moving toward data-driven decision making. Big data analytics' ability to give investors more comprehensive and timely information is driving its application in investment operations, according to Rodgers et al. (2023). Big data may help investors make educated judgments about asset performance, market trends, and risk. Using huge data sets efficiently is associated with favorable investment behavior. Hu et al. (2023) stress big data and predictive analytics' investing benefits. Big data prediction models may find investment possibilities and forecast market trends, improving investment decision-making. This suggests that big data can affect investment behavior by giving clients data-driven insights. AI improves investment behavior, says Hypothesis 2. The widespread use of AI in finance, which now provides sophisticated financial decision-making tools, supports this claim. Shanmuganathan (2020) claims that AI systems can instantly examine massive financial data to help investors make better decisions. In algorithmic trading and portfolio management, AI may improve investing techniques and results. AI can eliminate investment biases and improve risk management, according to Hyun Baek and Kim (2023). Risk assessment algorithms enabled by AI help investors identify and remove hazards. AI helps people make informed investment decisions, improving investment behavior.

Numerous studies support Hypothesis H3, that financial literacy enhances investment behavior. Van Nguyen, Ha, Nguyen, Doan, and Phan (2022) emphasize financial literacy in investment decisions. Better financial literacy helps consumers grasp complex financial concepts, appraise investments, and weigh risks and rewards. With this information, they can invest better. Rodrigues et al. (2019) believe financial expertise influences portfolio diversification. Smart investors build diverse portfolios that fit their financial goals and risk tolerance. This suggests that financially educated investors choose diversified, well-informed, goal-oriented assets. Through digital literacy, hypothesis H4 ties big data consumption to investment. Research shows big data investment decisions require digital literacy. People with more digital literacy can use big data platforms. They can gather, analyze, and evaluate complex investment data thanks to digital literacy. Digital literacy is needed to support big data utilization's positive impact on investing.

Hypothesis H5 claims that digital literacy ties AI adoption to investing methods. Since AI implementation generally uses digital interfaces and AI-driven technology, this is encouraged. Digital literacy aids AI comprehension and evaluation (Wang, Yin, & Jiang, 2023). Digitally literate investors may use AI-powered algorithms to plan their investments. Digital literacy is needed to utilize AI to enhance investing behavior. Hypothesis H6 states that digital literacy impacts financial literacy and investment. This hypothesis suggests that internet investing platforms and financial services digitalization have changed investment decision-making financial literacy. Modern investors need digital literacy to comprehend the hazards of sharing financial information online (Yang, Wu, & Huang, 2023). Digital technology allows financial specialists to navigate digital financial platforms securely. Hypothesis H7 suggests risk aversion mediates big data use and investment behavior. This reveals risk aversion affects big data investment information reactions. W. Liu et al. (2021) suggest risk-averse investors use data analytics to guide their investments amid market volatility. Since risk-averse persons may use data-driven insights to navigate volatile markets more cautiously, big data utilization moderates its effect on investment behavior. According to H8, risk aversion affects AI adoption and investment behaviors. Risk aversion affects AI recommendations. AI decreases investing bias and improves risk management, argues Rodgers et al. (2023). Averse investors may benefit most from AI-powered risk assessment tools that identify and manage portfolio risks. Aversion alters the favorable effects of AI adoption on investment behavior, especially for risk-averse people who use AI to make risk-averse investment decisions. Hypothesis 9 says that risk aversion moderates financial literacy and investment behavior. Research shows that financial literacy is essential for smart investment decisions. Financial literacy helps clients evaluate risk-reward trade-offs, which is critical to investment behavior, according to Kaustia, Conlin, and Luotonen (2023). Financial literacy helps risk-averse investors invest wisely (Fong, Koh, Mitchell, & Rohwedder, 2021). Risk aversion may moderate the positive effects of financial literacy on investment behavior, especially among individuals who prioritize risk reduction.

CONCLUSION

This study examined the complicated dynamics of Chinese household investment behavior. The research considered big data, AI, financial literacy, digital literacy, and risk aversion. Our analysis illuminated the investing climate. Data-driven decision making and technology-integrated investing are growing, according to our research. They demonstrate how big data and AI can improve investment behavior. Financial education is important because financial literacy affects investment behavior, according to growing data. We also found that risk aversion slightly lowered these attributes' impact on investors' investing choices. Investor digital literacy affected the relationship between technology and investment choices. The results of our investigation are as follows. Personalized investing methods that consider each person's distinct attributes and talents are essential for financial institutions, decision-makers, and investors in this age of rapid technological progress. Comprehending the dynamic interplay among information, inventiveness, and risk mitigation is vital for thriving in the contemporary financial markets.

IMPLICATIONS

Practical Implications

This study has implications for a large number of individuals in the banking sector and beyond. The first use of the study's results is to support banks and financial organizations in giving their clients better service. Investment strategies should be able to be tailored to each customer's unique risk tolerance, financial literacy, and digital literacy levels through the funding of modern data analytics and artificial intelligence techniques. If they want to promote financial and digital literacy, financial institutions should prioritize customer education with user-friendly digital interfaces and teaching tools. Legislators and regulators must consider digital literacy and financial education for the public. To make secure financial decisions in the digital age, financial literacy education is essential. To keep up with the fast-changing financial industry, regulatory bodies should emphasize client safety and encourage data-driven and AI-powered financial services innovation. Finally, individual investors can benefit from the study's real-world applicability by realizing the necessity of continual education. They should look for techniques to improve their financial literacy and digital literacy. In reality, people will need to consult specialists, learn about AI-powered financial instruments, and make risk aversion decisions.

Theoretical Implications

The study theoretically advances our understanding of financial literacy, technological adoption, and literacy studies. This study delves deeply into the intricate dynamics of decision-making in the era of digital finance. The adoption of artificial intelligence, financial literacy, digital literacy, risk aversion, and investment behavior are all explained. This study adds to theories of investment behavior by illuminating the ways in which literacy levels and contemporary technology impact investment decisions. Because of increased digital and financial literacy, we now have a better understanding of the variables that affect the relationship between technology use and investment behavior. The importance of including risk aversion in models for financial decision-making is further emphasized by the study.

LIMITATIONS AND FUTURE DIRECTIONS

It is critical to acknowledge a number of limitations, despite the fact that this study provides crucial insights into the intricate realm of digital-era Chinese household investment behavior. Response bias and the possibility of respondents providing socially desired responses are the main challenges with collecting self-reported data from surveys. Research in the future could benefit from using observational studies or behavioral experiments to supplement self-report data. The research also lacked the capacity to draw qualitative conclusions regarding the feelings and motivations that impact investing choices as it was entirely interested in quantitative metrics. The intricacies of investment behavior can be better understood with a mixed-methods approach that mixes qualitative interviews with open-ended survey questions. It was also impossible to incorporate all potential elements that could influence investor behavior, despite the extensive consideration of many variables. Unquantifiable external environmental elements or intangible personal traits should be the subject of future studies.

The results of this investigation can serve as a foundation for future academic investigations on investment behavior, which could focus on a wide range of issues. The best method to help with cultural comparisons is to do research that looks at things like literacy rates, investment behavior, and technology adoption rates in particular. Additionally, people's reactions to new financial technology and educational initiatives can be better understood by looking at the historical progression of investment behavior and financial knowledge. The effects of different forms of financial education programs and digital literacy on investment behavior should also be studied. Policymakers and educators may learn a lot from program and tool evaluations that focus on better financial decision-making. The potential impact of blockchain and cryptocurrency on investment behavior should be the subject of future research as technology develops. Research on how these technologies influence investment decisions will benefit academics and businesses alike.

CONFLICT OF INTEREST

There was no conflict of interest declared by the authors.

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