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ChatGPT, financial literacy, and individual investment decisions

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Abstract: This study investigates the use of ChatGPT across different investment tasks in the French stock market. Based on a PLE-SEM approach, the findings indicate that investors primarily use these tools for data analysis, risk management, and sentiment analysis, leveraging their ability to process complex information, identify potential risks, and assess market sentiment effectively. The results also reveal that investors moderately rely on ChatGPT to optimize portfolios and forecast market trends, reflecting an awareness that AI-based tools may not fully capture the complexity and inherent unpredictability of financial markets. Moreover, the findings highlight the nuanced moderating role of financial literacy in shaping investors' use of AI-driven insights.

Keywords: ChatGPT; investment decision making; financial literacy; risk management; data analysis; portfolio optimization; market trend forecast; sentiment analysis.

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1. Introduction

Investment decision-making in financial markets is widely recognized in the finance literature as a dynamic process that depends on the effective processing and integration of diverse information sources. Early foundational work by Fama (1970) established that asset prices reflect all available information, underscoring the central role of data analysis in shaping investment outcomes. Building on this, studies in financial econometrics demonstrate that systematic analysis of historical returns, macroeconomic variables, and firm-level financial data enhances predictive accuracy and informs investment strategies (Campbell et al., 1997). Forecasting market trends using time-series models and factor analyses has been shown to improve expected return estimates and timing decisions (Rapach et al., 2010). Forecasts are increasingly complemented by sentiment analysis, which captures behavioral and informational signals embedded in news, social media, and textual disclosures (Baker & Wurgler, 2006; Kumar & Goyal, 2015).

Risk management, which quantifies and controls exposure to uncertainty, is another pillar of sound investment decision-making. Markowitz's (1952) portfolio selection theory formalized the trade-off between risk and return and laid the foundation for modern risk measurement. Subsequent work, including Jorion (2007) and Merton's (1973) intertemporal framework, highlights how effective risk assessment contributes to optimal timing of investment and hedging decisions. Sharpe's (1964) capital asset pricing model further links systematic risk to expected returns, making risk quantification integral to investment evaluation.

Portfolio optimization synthesizes information on expected returns and risks into asset allocation rules. The literature demonstrates that optimized portfolios outperform naive diversification approaches when informed by robust estimates of expected returns and covariances (Jagannathan and Ma, 2003; DeMiguel et al., 2009). These approaches operationalize the integration of data analysis and risk constraints to enhance portfolio performance.

Taken together, this body of literature supports a view of investment decisions as an adaptive, information-driven process that systematically combines data analysis, forecasting, sentiment analysis, risk management, and portfolio optimization to improve investment outcomes.

Recent literature highlights that the emergence of artificial intelligence (AI) has fundamentally transformed investment decision-making (El Hajj & Hammoud, 2023; Osterrieder, 2023; Wu et al., 2025; Pal et al., 2025). AI technologies have enabled more sophisticated approaches to analyzing market trends, managing risks, optimizing portfolios, and making investment decisions. Among these innovations, large language models (LLMs) such as ChatGPT represent a novel tool for investors, offering real-time assistance in interpreting complex financial information (El Hajj and Hammoud, 2023; Riani, 2023; Trinh and al., 2025). ChatGPT facilitates the analysis of large volumes of financial and textual data, enabling investors to interpret market information and forecast trends more efficiently (Sutiene et al., 2024; Asemi et al., 2025). Through advanced natural language processing, ChatGPT supports sentiment analysis by extracting qualitative signals from news, corporate disclosures, and online discussions, complementing traditional quantitative indicators (Lefort et al., 2024; Feng et al., 2025). Moreover, ChatGPT enhances investment outcomes through advanced risk management and portfolio optimization. Machine learning algorithms, such as ChatGPT, dynamically update risk estimates, capture nonlinear relationships, and adapt to changing market conditions, leading to more resilient portfolios (Bartram et al., 2020; Wang & Liu, 2025). However, the literature also emphasizes that the benefits of AI for investment outcomes depend on human–AI complementarity, where investor expertise and financial literacy play a crucial role in interpreting and applying AI-generated insights (Nguyen & Nguyen, 2015; Choi & Kim, 2023). Overall, the use of ChatGPT represents a structural shift in investment practice, reshaping the mechanisms through which information is transformed into superior investment outcomes (Gu et al., 2020; Trinh et al., 2025; Pal et al., 2025).

Despite growing interest in using ChatGPT as an investment support tool, research on its role in shaping investment decision-making remains limited. Existing studies on artificial intelligence in finance primarily focus on algorithmic trading, machine learning–based asset pricing, and robo-advisory systems, with relatively little attention given to large language models such as ChatGPT. Moreover, the literature has yet to systematically examine how ChatGPT influences the key tools of investment—namely, data analysis, market forecasting, sentiment analysis, risk management, and portfolio optimization—or how these tools translate into investment outcomes. In addition, the moderating role of investors' financial literacy in the effective use of ChatGPT-generated insights remains largely unexplored. Addressing these gaps, this study contributes to the emerging literature by providing empirical evidence of the mechanisms by which ChatGPT affects investment decisions and highlighting the conditions under which its use enhances decision quality.

Based on a survey of 121 individual French investors and employing a PLS-SEM approach, the results show that investors primarily use ChatGPT for data analysis, risk management, and sentiment analysis, leveraging its ability to process complex information, identify potential risks, and assess market sentiment effectively. The findings, however, indicate that investors rely moderately on these AI-based tools to optimize portfolios and forecast market trends. Investors are aware that such tools may not fully capture the complexity and inherent unpredictability of financial markets. Moreover, the findings highlight the nuanced moderating role of financial literacy, which shapes how investors interpret and apply AI-driven insights within their investment strategies.

This study contributes to the literature on AI and finance in several ways. First, it advances understanding of human-AI interaction in finance and offers practical value for investor decision-making. This study explores the multidimensional use of generative AI

(ChatGPT) in data analysis, risk management, portfolio optimization, market trend forecasting, and sentiment analysis. Second, unlike prior studies that have largely focused on institutional investors or U.S.-based markets, this study offers novel insights by examining the use of ChatGPT in investment decision-making within a European context. France is a particularly relevant case due to its expanding base of retail investors, accelerating adoption of digital financial tools, and robust regulatory framework that prioritizes investor protection and ethical AI deployment. Third, by examining the moderating role of financial literacy, this study offers a nuanced perspective on when and how AI-driven tools can enhance or hinder investor outcomes.

This study has direct implications for investors and financial education programs. Investors should consider ChatGPT as a decision-support tool rather than a substitute for human judgment. They have to maintain critical thinking and combine AI-generated insights with personal experience, market knowledge, and diversified information sources. Moreover, training programs should not only enhance traditional financial knowledge but also teach investors how to interpret, question, and appropriately apply AI-generated outputs. Improving investors' understanding of AI limitations—such as model assumptions, data bias, and the inability to capture market uncertainty fully—can help prevent overreliance and misinformed decisions.

The remainder of this paper is organized as follows: Section 2 presents the literature review and hypotheses development. Section 3 describes the data and design. Section 4 exposes the results and discussion. Section 5 the conclusions.

2. Literature Review

2.1. Investment decision and ChatGPT

Traditional finance theory posits that superior investment outcomes arise from the efficient processing of information and the accurate evaluation of risk–return trade-offs. Markowitz's (1952) portfolio theory formalizes this principle by demonstrating that rational investors can optimize expected returns by diversifying assets and carefully managing risk through covariance structures. Building on this foundation, Fama's (1970) Efficient Market Hypothesis argues that financial markets incorporate available information into asset prices, implying that investment performance depends critically on investors' ability to analyze and interpret information more effectively than others. Within this framework, informed decision-making—grounded in rigorous data analysis, risk assessment, sentiment analysis, and return forecasting—enables investors to construct portfolios aligned with their risk preferences and market expectations, thereby improving risk-adjusted performance (Bodie et al., 2021; Musfidah et al., 2022).

AI technologies extend this framework by enabling the analysis of large-scale, high-frequency, and unstructured data that exceeds human cognitive and computational capacities. AI-based tools not only support investors in making more informed decisions by providing rapid and reliable information but also deliver objective analyses and timely alerts that help mitigate the influence of herd behavior (Ashta & Herrmann, 2021; Nefla & Jallouli, 2025). By processing diverse textual sources such as earnings reports, news articles, and social media commentary, ChatGPT can enhance the understanding of market movements and sentiment-driven fluctuations (Ding et al., 2015). In the same vein, Coskun (2022) reports that AI-driven techniques, including ChatGPT, support investment decision-making by enabling the efficient extraction of relevant insights from large, complex data sources—a critical function for identifying market opportunities. Indeed, ChatGPT can analyze market data and detect indicators of irrational collective behavior, such as market panics or speculative bubbles. Examining historical investor behavior can help users avoid common cognitive pitfalls—such as overconfidence and herd mentality—while offering personalized, data-driven recommendations (Chen & Guestrin, 2021).

Based on the discussion above, we assume that investors use ChatGPT to enhance the processing and interpretation of complex financial data when making stock market decisions.

H1. ChatGPT-based data analysis is helpful for individual investment decision-making in the stock market.

Managing risks is a key component of investment decision-making. By leveraging machine learning algorithms and predictive analytics, ChatGPT can identify, assess, and quantify various types of financial risks with greater accuracy and speed than traditional methods (Kraus et al., 2021; Osterrieder, 2023). ChatGPT can process vast amounts of structured and unstructured data from diverse sources, allowing investors to anticipate potential threats and respond proactively (El Hajj & Hammoud, 2023). Furthermore, ChatGPT facilitates continuous monitoring and real-time risk assessment, allowing organizations or investors to implement timely mitigation strategies. ChatGPT-driven risk management supports dynamic adjustment of mitigation strategies as new information becomes available, ensuring that responses remain effective in rapidly changing environments (Kraus et al., 2021). Consequently, integrating ChatGPT into investment decision-making not only enhances the accuracy of risk identification but also significantly improves investors' agility and resilience in managing complex risks.

H2: ChatGPT-based risk management is helpful for individual investment decision-making in the stock market.

Portfolio optimization plays a crucial role in investment decision-making. ChatGPT can enhance asset allocation and improve investment performance through data-driven strategies (Chong et al., 2017; Jiang et al., 2017). ChatGPT can help investors generate natural-language explanations of portfolio decisions and simulate hypothetical investment scenarios (Olorunnimbe & Viktor, 2023). ChatGPT can consider various factors such as risk, return, and diversification while optimizing portfolios (Bartram et al., 2020). It can also be used to identify undervalued assets that may be good investment opportunities.

H3: ChatGPT-based portfolio optimization is helpful for individual investment decision-making in the stock market.

Forecasting market trends plays a pivotal role in shaping investment strategies by informing expectations about future market movements and supporting proactive decision-making. Large language models (LLMs) such as ChatGPT have emerged as powerful tools to support investors (Milana & Ashta, 2021; Osterrieder, 2023). ChatGPT has demonstrated considerable potential in assisting the forecasting of market trends by analyzing vast and diverse financial data sources, including news articles, earnings reports, and social media sentiment (Feng et al., 2025). By synthesizing this unstructured information into coherent insights, ChatGPT can help investors identify emerging patterns and signals that may precede market movements. Although not a predictive model in the traditional statistical sense, ChatGPT's natural language understanding capabilities enable it to support qualitative assessments and scenario analyses, complementing quantitative forecasting tools (Osterrieder, 2023). This hybrid approach can enhance the accuracy and timeliness of market trend predictions, particularly in rapidly evolving financial environments.

H4: ChatGPT-based forecasting of market trends is helpful for individual investment decision-making in the stock market.

Sentiment analysis can provide valuable insights into emerging market trends and investor attitudes, allowing market participants to adjust their strategies accordingly (Nassirtoussi et al., 2014; Valle-Cruz et al., 2022). By determining whether the overall sentiment is positive or negative, this approach helps assess potential impacts on asset prices and market dynamics. ChatGPT significantly enhances this process by interpreting vast volumes of unstructured financial text—ranging from news articles and earnings calls to analyst reports and social media posts (Fatouros et al., 2023). Unlike traditional sentiment analysis models that rely on predefined dictionaries or simple polarity scoring, ChatGPT can capture nuance, tone, and contextual meaning. According to Lefort et al. (2024), combining ChatGPT-derived sentiment scores with financial stress indicators improved risk-adjusted returns and reduced drawdowns. By transforming narrative data into actionable insights, ChatGPT serves as a valuable decision-support tool in the increasingly complex and fast-paced world of financial markets.

H5: ChatGPT-based sentiment analysis is helpful for individual investment decision-making in the stock market.

2.2. The role of Financial Literacy

The Organization for Economic Co-operation and Development (OECD) defines financial literacy as the process through which consumers/investors enhance their comprehension of financial products and concepts and, with the help of unbiased information, guidance and advice, improve their skills and confidence to understand financial risks and opportunities better, make more informed choices, become more aware of available assistance, and take appropriate steps to enhance their financial well-being (OECD, 2005). Financial literacy is increasingly recognized as a critical means of helping individuals with limited financial knowledge make sound investment decisions (Lusardi & Mitchell, 2014; Madi & Yusof, 2018; Son & Park, 2019). According to Cox et al. (2015), insufficient financial literacy can generate uncertainty and confusion, undermining investors' ability to make sound financial decisions. Besides, Choi et al. (2023) argue that investors with limited financial literacy are more prone to misreading financial data, which can lead to poor decision-making in equity trading. Lusardi and Mitchell (2014) also report that investors with lower financial literacy may experience financial and self-exclusion. These investors frequently misinterpret the facts and make judgments based more on subjective opinions than on independent analysis (Amisi, 2012). The authors also state that uninformed investors are more prone to make illogical or negative investing decisions. Furthermore, these investors tend to maintain undiversified portfolios and avoid investing in the stock market. Moreover, Lusardi and Mitchell (2014) report that financial literacy matters in determining the various risks involved in investing decisions. Financial literacy equips investors with the skills to critically analyze financial data, including ratios, financial statements, and relevant economic information, enabling them to make more objective and informed investment decisions. This knowledge enables investors to identify the telltale signs of irrational market behavior.

H6: Financial literacy significantly influences investment decision-making in the stock market.

Despite the advanced analytical, forecasting, and sentiment analysis capabilities of AI tools like ChatGPT, their contribution to investment decision-making is highly dependent on investors' financial literacy (Son & Park, 2019; Riani, 2023). The effectiveness of such tools depends not only on their technical capabilities but also on investors' financial literacy. AI-based systems, such as ChatGPT, are designed to process large volumes of structured and unstructured financial information, generate forecasts, assess risks, and extract sentiment from textual data. However, these outputs do not constitute decisions on their own; rather, they serve as decision-support inputs that require interpretation, contextualization, and judgment by investors (Ashta & Herrmann, 2021).

Financial literacy enhances investors' ability to understand financial concepts, evaluate risk–return trade-offs, and recognize the limitations of analytical models (Lusardi & Mitchell, 2014). Investors with higher levels of financial literacy are therefore better equipped to assess AI-generated insights critically, distinguish relevant signals from noise, and integrate these insights into coherent investment strategies (Van Rooij et al., 2011; Bartáková et al., 2025). In contrast, investors with lower financial literacy may either over-rely on AI recommendations or underutilize them due to mistrust or misinterpretation, potentially leading to suboptimal investment decisions. In AI-assisted environments, this capability becomes even more critical, as investors must evaluate the relevance, reliability, and contextual applicability of AI-generated insights (Haleem et al., 2022). The human–AI complementarity perspective suggests that AI improves decision quality when combined with human expertise rather than replacing it (Rai et al., 2019; Shrestha et al., 2019). Accordingly, financial literacy may have a moderating influence on the various dimensions of ChatGPT use and investment decision-making, conditioning the extent to which AI-driven insights are effectively interpreted and applied. Investors with higher financial literacy are therefore more likely to leverage AI tools to enhance decision quality, whereas lower literacy may lead to overreliance or misinterpretation, potentially weakening investment outcomes.

H7. Financial literacy moderates the relationship between ChatGPT-based data analyses and individual investment decision-making in the stock market.

H8: Financial literacy moderates the relationship between ChatGPT-based risk management and individual investment decision-making in the stock market.

H9. Financial literacy moderates the relationship between ChatGPT-based portfolio optimization and individual investment decision-making in the stock market.

H10. Financial literacy moderates the relationship between ChatGPT-based forecasting market trends and individual investment decision-making in the stock market.

H11. Financial literacy moderates the relationship between ChatGPT sentiment analyses and individual investment decision-making in the stock market.

3. Data and Methods

3.1. Sample and data collection

The study focuses on individual investors from France. The French context is chosen for several reasons. First, France represents a mature financial market with a high level of digital financial infrastructure and increasing adoption of fintech and AI-based tools by retail investors. Second, individual investors in France play an increasingly important role in financial markets, especially following recent market events and the expansion of online trading platforms.

We use a survey to collect data from individual investors on the French stock market. With the help of «Palace des Investisseurs»-an independent non-profit association and member of the World Federation of Investors, we prepare a list of active traders in the stock market and use stratified random sampling to obtain an appropriate sample size. A total of 220 questionnaires were distributed. Of these, 181 questionnaires were received: 121 were fully completed and used in the analysis, and 60 were discarded due to incomplete or missing information.

3.2. Measurement of construct

The survey is divided into two parts. The first part presents the demographic profile: gender, age, marital status, education, annual income, and frequency investment. The second collects information about the five dimensions of ChatGPT use in investment decision-making in the stock market (See Appendix). 7 questions are used, and each question is composed of items: Analyzing data (3 items), managing risk (3 items), optimizing portfolio (3 items), forecasting market trend (3 items), conducting Sentiment analysis (5 items), Financial literacy ‘FL’(5 items), Investment decision (5 items).

All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), consistent with prior survey-based and PLS-SEM research (Likert, 1932; Hair et al., 2022). A Likert scale (Likert, 1932) is a psychometric measurement instrument widely used in survey-based research to capture respondents’ attitudes, perceptions, or behaviors. It typically asks respondents to indicate their level of agreement or frequency on a symmetric, ordered scale. In finance and behavioral research, Likert scales are commonly used to assess latent constructs such as risk tolerance, confidence, information use, and technology acceptance that cannot be directly observed in market data (Barber & Odean, 2001; Glaser & Weber, 2007). Moreover, in AI- and fintech-related finance research, Likert scales are essential for measuring investors' perceptions of decision-support tools, trust in algorithms, and perceived usefulness, making them compatible with structural modeling approaches such as PLS-SEM (Hair et al., 2022).

3.3. Data analyses

We employ Harmons's one-factor test to examine common method bias (Doty & Glick, 1998). Common method variance (CMV) is a systematic measurement error that occurs when data for multiple variables are collected from the same source using the same method (e.g., a single survey). The results of principal axis factoring indicate that the single factor explains only 41.36% of the total variance, well below the 50% threshold (Podsakoff et al., 2003).

Moreover, we evaluate the variance inflation factor (VIF) to identify potential collinearity issues. All variance inflation factor (VIF) values are below the conservative threshold of 5, indicating that multicollinearity is not a concern (Hair et al., 2019).

Finally, we use the Kolmogorov-Smirnov and Shapiro-Wilk tests to assess the normality of the data. The results indicate a significant departure from normality ($p < 0.05$) for all latent variables. Consequently, the null hypothesis is rejected, suggesting that the data deviates from a normal distribution. Accordingly, this study employs variance-based structural equation modeling (PLS-SEM) rather than covariance-based SEM, as PLS-SEM is well-suited for complex models and robust to non-normal data distributions (Leong et al., 2019).

4. Results and Discussion

We use SmartPLS data regression to examine the joint effect of financial literacy and ChatGPT use on investment decision-making. According to Henseler et al. (2009), PLS-SEM is a prediction-oriented method that works better for exploratory testing of current hypotheses. In fact, small sample sizes and non-normal data are two contexts in which the PLS-SEM approach makes sense (Sarstedt et al., 2021).

Within the PLS-SEM framework, this theoretical structure implies (i) direct paths from ChatGPT usage dimensions to investment decision-making, and (ii) an interaction effect, whereby financial literacy moderates these paths by influencing how AI-generated information is translated into investment actions. This modeling approach allows for capturing both the explanatory power of AI-based tools and the conditional role of investor capabilities in shaping investment outcomes, consistent with prior evidence on information processing and decision-support systems (Rai et al., 2019; Shrestha et al., 2019)

4.1. Demographic profile

Table 1 displays the demographic information of investors. The results show that 40.5% of the respondents are female and 59.5% are male. Moreover, 57,9% are married, and 42,1% are single. As for age, 15,7% are under 25 years, 57,0% between 26 and 35 years, 6.6% between 36 and 45 years, and 20.7% are 46 years or older. Furthermore, 2.5% hold a bachelor's degree, 9.1% hold a master's degree, and 17.8% hold a doctoral degree. About experience, 52.1% of investors have 5 years or less, 18.2% between 5 and 10 years of experience, 9.1 % between 11 and 15 years, and 20.7% more than 16 years. Besides, 58,7% of investors have an annual income of less than 96,000€. Finally, only 17.4% of investors report investing in the stock market daily.

Table 1. Demographic profile of the respondents.

Description	Frequency	(%)	Mean	SD
Gender:				0,493
Male	72	59,5		
Female	49	40,5		
Marital status:				0,496
Single	51	42,1		
Married	70	57,9		
Age:			2,32	0,977
≤ 25 years	19	15,7		
Between 26 and 35 years	69	57,0		
Between 36 and 45 years	8	6,6		
≥ 46 years	25	20,7		
Education:			3,38	0,756
Bachelor	3	2,5		
Licence	11	9,1		
Master	44	36,4		
Doctorate/PhD	63	52,1		
Annual Income:			1,98	1,204
36000€	63	52,1		
36001 - 72000€	22	18,2		
72001 - 96000€	11	9,1		
> 96001€	25	20,7		
Investment frequency:			2,55	0,972
Daily	21	17,4		
Weekly	26	21,5		
Monthly	60	49,6		
Annualy	14	11,6		

4.2. Hierarchical regression analysis

Table 2 presents the results of the hierarchical regression analysis examining the effects of demographic variables, including gender, marital status, age, education, experience, annual income, and investment frequency, on investment decision-making in the French stock market.

In Model 1, gender explains 1.9% of the variance ($R^2 = 0.019$) and has no significant effect. Model 2 shows that adding marital status slightly increases the explained variance to 2.1% ($R^2 = 0.021$), although gender remains insignificant and marital status exhibits only a weak effect. In Model 3, the inclusion of age does not improve the explanatory power ($R^2 = 0.021$), and all predictors remain insignificant, with a negligible change in variance ($\Delta R^2 = 0.001$). Model 4 includes education, but the explained variance remains unchanged ($R^2 = 0.021$), indicating that demographic factors contribute minimally. In Model 5, adding experience increases the explained variance to 7.1% ($R^2 = 0.071$), with age, education, and marital status showing significant effects, although the overall increase remains modest ($\Delta R^2 = 0.049$). Model 6 further raises the explanatory power to 9.2% ($R^2 = 0.092$) after including annual income, but most predictors remain insignificant, and the incremental change is small ($\Delta R^2 = 0.021$). Finally, Model 7 shows that all demographic variables jointly explain 11.1% of the variance ($R^2 = 0.111$), with mixed significance levels and limited additional explanatory power ($\Delta R^2 = 0.018$). Overall, the results indicate that demographic characteristics contribute only marginally to explaining investment decision-making.

Table 2. Regression results of the demographic variable

Variables	B	SEB	95% CI		β	R^2	Δ R^2	F	Δ F
			LL	UL					
Step 1						0,019	0,019*	2,280	2,280
(Constant)	4,046	0,322	3,409	4,684					
Gender	-0,291	0,193	-0,673	0,091	-0,137				
Step 2						0,021	0,002	1,252	0,238
(constant)	4,178	0,421	3,345	5,012					
Gender	-0,280	0,195	-0,666	0,105	-0,132				
Marital status	-0,095	0,194	-0,478	0,289	-0,045				
Step 3						0,021	0,001	0,854	0,077
(constant)	4,196	0,428	3,349	5,044					
Gender	-0,265	0,203	-0,667	0,137	-0,125				
Marital status	-0,078	0,204	-0,481	0,326	-0,037				
Age	-0,030	0,107	-0,242	0,183	-0,28				
Step 4						0,021	0,000	0,635	0,001
(constant)	4,180	0,611	2,969	5,391					
Gender	-0,265	0,204	-0,669	0,139	-0,125				
Marital status	-0,078	0,205	-0,483	0,328	-0,037				
Age	-0,030	0,108	-0,244	0,184	-0,028				
Education	0,005	0,127	-0,247	0,257	0,003*				
Step 5						0,071	0,049*	1,753	6,111
(constant)	4,334	0,602	3,143	5,526					
Gender	-0,267	0,200	-0,662	0,128	-0,126				
Marital status	-0,126	0,201	-0,525	0,272	-0,060				
Age	0,139	0,126	-0,110	0,388	0,130*				
Education	0,004	0,125	-0,243	0,251	0,003*				
Experience	-0,234	0,095	-0,421	-0,46	-0,269				
Step 6						0,092	0,021*	1,929	2,682
(constant)	4,494	0,605	3,296	5,693					
Gender	-0,288	0,199	-0,681	0,106	-0,135				
Marital status	-0,045	0,206	-0,452	0,363	-0,021				
Age	0,198	0,130	-0,060	0,455	0,184*				
Education	-0,005	0,124	-0,251	0,240	-0,004				
Experience	-0,227	0,094	-0,413	-0,041	-0,261				
Annual income	-0,142	0,087	-0,313	0,030	-0,166				
Step7:						0,111	0,018*	2,006	2,334
(constant)	4,653	0,611	3,444	5,863					
Gender	-0,251	0,199	-0,645	0,143	-0,118				
Marital status	0,003	0,207	-0,407	0,413	0,001*				
Age	0,173	0,130	-0,084	0,431	0,162*				
Education	0,014	0,124	-0,231	0,259	0,010*				
Experience	-0,209	0,094	-0,395	-0,022	-0,240				
Annual income	-0,106	0,089	-0,283	0,070	-0,125				
Frequency investment	-0,168	0,110	-0,387	0,050	-0,147				

Note: CI is confidence interval. LL is the lower limit. UL is the upper limit. SE is the standard error. *p < 0,05.

4.3. Measurement model

The measurement model was assessed by examining item factor loadings, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity.

4.3.1. Reliability analysis and convergent validity

Table 3 exposes the composite reliability (CR) coefficients for the latent variables, which range from 0.834 to 0.873, indicating good internal consistency reliability (Hair et al., 2022). The results also show that the average variance extracted (AVE) for the investment decision, the dependent variable, is 0.654. The AVE values of the dimensions of ChatGPT use are 0.671, 0.507, 0.641, 0.593, and 0.632, respectively. Moreover, the AVE value of financial literacy, as a moderator, is 0.541. The AVE values are all higher than 0.50, indicating good convergence validity (Hair et al., 2019).

Table 3 also reports that the Factorial loading (FL) is about 0.7, indicating that the construct explains at least 49% of the variance in the indicator. Moreover, the analyses show that the variance inflation factor (VIF) values for all constructs are primarily below 3, suggesting no excessive multicollinearity among the variables. In addition, Cronbach's alpha coefficients for most constructs exceed 0.80, indicating strong internal consistency and suggesting excellent reliability of the measurement model.

Table 3. Factors loadings, VIF, reliability, and validity.

Constructs	FL	VIF	Alpha	CR	AVE
Analyzing Data (AD)			0,848	0,855	0,671
AD1	0,924	2,401			
AD2	0,896	2,881			
AD3	0,598	1,732			
Managing Risk (MR)			0,745	0,746	0,507
MR1	0,467	1,401			
MR2	0,802	1,507			
MR3	0,813	1,615			
Optimizing portfolio (OP)			0,841	0,842	0,641
OP1	0,699	1,801			
OP2	0,803	2,269			
OP3	0,845	2,073			
Forecasting Market Trend (FMT)			0,812	0,813	0,593
FMT1	0,699	1,990			
FMT2	0,835	2,085			
FMT3	0,769	1,548			
Conducting Sentiment Analysis (CSA)			0,874	0,890	0,632
CSA1	0,766	2,937			
CSA2	0,814	2,946			
CSA3	0,722	2,593			
CSA4	0,790	2,295			
CSA5	0,690	1,348			
Financial Literacy (FL)			0,785	0,717	0,541
FL1	0,415	1,838			
FL2	0,932	1,635			
FL3	0,122	2,016			
FL4	0,509	1,603			
FL5	0,628	1,762			
Investment Decision-Making (ID)			0,828	0,905	0,654
ID1	0,766	2,856			
ID2	0,808	2,337			
ID3	0,914	3,159			
ID4	0,316	1,818			
ID5	0,636	2,053			

Note: CR is the composite reliability. FL is the factorial loading. AVE is the average variance extracted. VIF is the Inflation Factor value. Alpha is the Cronbach's alpha coefficient.

4.3.2. Discriminant validity

We use the Heterotrait-Monotrait (HTMT) ratio to estimate discriminant validity. The HTMT ratio measures the similarity between latent variables by calculating the ratio of the average correlations between indicators across constructs (heterotrait) to the average correlations within the same construct (monotrait). HTMT values below 0.85 or 0.90 confirm that constructs are sufficiently distinct (Henseler et al., 2015).

Table 4 shows that most HTMT ratios are below 0.85, indicating no concerns about correlations.

Table 4. HTMT ratio and Formell-Larcker criterion

HTMT Ratio							
	AD	MR	OP	FMT	CSA	FL	ID
Analyzing Data							
Managing Risk	0.667						
Optimizing Portfolio	0.177	0.138					
Forecasting Market Trends	0.390	0.502	0.178				
Conducting Sentiment Analysis	0.286	0.322	0.169	0.078			
Financial Literacy	0.558	0.403	0.171	0.284	0.398		
Investment Decision Making	0.711	0.580	0.162	0.601	0.254	0.580	0.654
Formell-Larcker criterion							
Analyzing data	0.819						
Managing risk	0.663	0.767					
Optimizing portfolio	0.183	0.152	0.585				
Forecasting Market Trend	0.391	0.501	0.180	0.770			
Conducting sentiment analysis	0.308	0.303	0.097	-0.037	0.718		
Financial literacy	0.560	0.497	0.132	0.291	0.401	0.712	
Investment Decision-making	0.718	0.581	0.167	0.602	0.259	0.572	0.8

Table 4 presents the results of discriminant validity using the Heterotrait-Monotrait (HTMT) ratio and the Formell and Larcker criterion.

Additionally, we run the Formell and Larcker criterion (Formell & Larcker, 1981). The findings show that the square root of its AVE exceeds its correlations with other constructs, supporting discriminant validity. For example, the AVE for Analyzing Data is 0.819, exceeding the recommended threshold of 0.50, thereby confirming adequate convergent validity. Similarly, Managing Risk exhibits an AVE of 0.767, confirming both convergent and discriminant validity.

4.3.3. Coefficient of determination (R^2) and predictive relevance (Q^2)

Following Hair et al. (2022), we measure the coefficient of determination (R^2). This coefficient indicates the proportion of variance in the endogenous (dependent) variable that is explained by the exogenous (independent) constructs in the model. Table 5 reports an R^2 of 0.563, indicating that the use of ChatGPT explains 56.3% of the variance in investment decision-making in the French stock market. Additionally, the Q^2 value of 0.495 indicates good predictive relevance.

Table 5. Coefficient of determination (R^2) and predictive relevance (Q^2)

	R^2	Adj R^2	Q^2 predict
Investment decision-making	0,563	0,209	0,495

Table 5 presents the coefficient of determination (R^2) between the dependent variable and the exogenous constructs in the model.

4.4. Structural model

Following Henseler et al. (2009) and Hair et al (2022), we rely on bootstraped samples to evaluate the significance of path coefficients. We use 5,000 bootstrap samples to improve the stability of the estimated standard errors and confidence intervals. To further assess the adequacy of the sample size, we conduct a post-hoc statistical power analysis using G*Power 3.1. Following Cohen's (1988) recommendations, we assume a medium effect size ($f^2 = 0.15$), a significance level of 0.05, and six predictors corresponding to the structural paths leading to the dependent variable. With a sample size of 121 observations, the analysis indicates a statistical power of approximately 0.95. This value exceeds the commonly recommended threshold of 0.80, suggesting that the sample size is sufficient to detect meaningful relationships in the proposed model. Table 6 presents the results of the structural model.

Table 6. Path coefficients for direct and moderating effects.

Hypotheses	β value	p value	Decision
Panel A: Exogenous variable			
H1: AD -> ID	0,209	0,000	Supported
H2: MR -> ID	0,287	0,000	Supported
H3: OP ->ID	-0,057	0,000	Not supported
H4: FMT -> ID	-0,511	0,000	Not supported
H5: CSA -> ID	0,225	0,000	Supported
H6: FL -> ID	0,118	0,000	Supported
Panel B: Moderating terms			
H7: FL× AD -> ID	0,789	0,000	Supported
H8: FL×MR -> ID	0,021	0,000	Supported
H9: FL× OP -> ID	-0,541	0,000	Not supported
H10: FL×FMT -> ID	-0,065	0,000	Not supported
H11: FL× CSA -> ID	-0,047	0,000	Supported

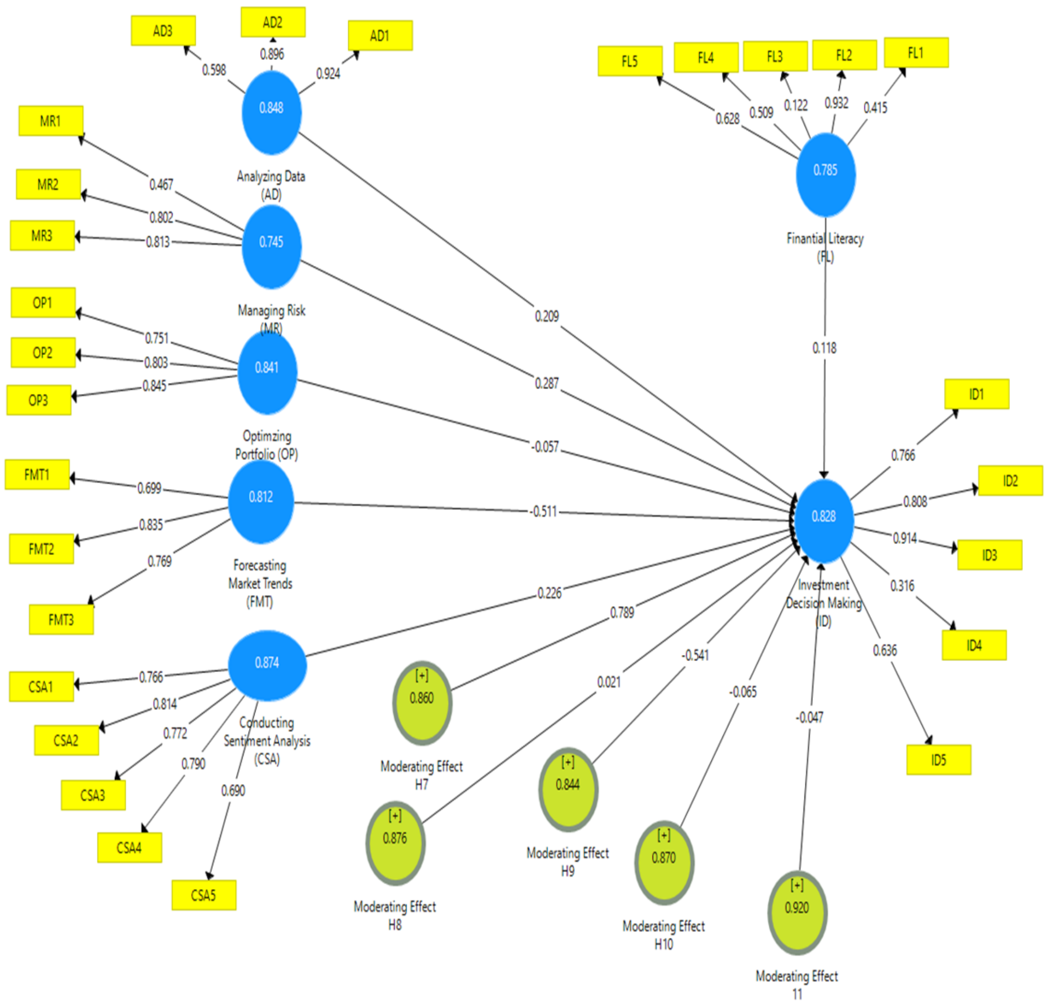
Table 6 reports the results of using ChatGPT across various investment tasks, including analyzing data, managing risks, optimizing portfolios, forecasting market trends, and analyzing market sentiment (Panel A). Panel B presents the moderating effect of financial literacy.

Table 6 reports a positive relationship between the ChatGPT-based data analysis and investment decision-making, suggesting that leveraging AI-driven data processing enables investors to extract actionable insights from complex financial information ($\beta1 = 0.209$; p-value = 0.000). As Saravanos and Kanavos (2025) note, this enhanced analytical capability helps investors better understand market conditions, identify investment opportunities, and make more informed, evidence-based decisions. Consequently, the use of ChatGPT in data analysis workflows appears to strengthen investors' confidence and effectiveness in navigating the stock market. Importantly, this positive effect is amplified among investors with higher financial literacy, who are better equipped to interpret and critically evaluate AI-generated data insights ($\beta7 = 0.789$; p-value = 0.000). As Nguyen and Nguyen (2015) note, financially literate investors effectively integrate these insights into their broader investment strategies, thereby maximizing the benefits of AI tools like ChatGPT while mitigating risks associated with misinterpretation or overreliance.

The findings also indicate that investment decision-making in the French stock market is positively associated with ChatGPT-based risk management ($\beta2 = 0.287$; p-value = 0.000). Consistent with Coskun (2022) and Osterrieder (2023), the results show that ChatGPT is widely used to identify and mitigate risks, thereby supporting safer, more informed investment decisions. ChatGPT enables French individual investors to manage risk more effectively, optimize returns, and minimize potential losses through data-driven insights and real-time analysis. The results also indicate that this positive relationship is further strengthened among investors with higher financial literacy, who possess the knowledge and skills necessary to effectively interpret AI-generated risk assessments and incorporate them into their risk management frameworks (β8 = 0.021; p-value = 0.000).

Figure 1, however, shows that ChatGPT-based portfolio optimization has no significant effect on investment decision-making (β3 = -0.057; p-value = 0.00). Inconsistent with Yue et al. (2023), the use of ChatGPT to optimize portfolios may introduce complexity or uncertainty that hinders investors' ability to make confident or timely decisions. Moreover, Figure 1 shows that this relationship is negatively moderated by financial literacy, suggesting that French individual investors with higher financial literacy are more selective and cautious in their use of ChatGPT for portfolio optimization, relying on it occasionally rather than routinely (β9 = -0.541; p-value = 0.000). Financially literate investors are likely more aware of the limitations of algorithmic recommendations and the importance of contextual judgment, market cycles, and personal investment objectives (Milana & Ashta, 2021).

Figure 1. Structural model



Moreover, the results indicate that ChatGPT-based forecasting of market trends has no significant effect on investment decision-making in the French stock market (β4 = -0.511; p-value = 0.000). This counterintuitive finding suggests that, despite AI's advanced capabilities in processing vast amounts of financial data, reliance on ChatGPT-generated forecasts may lead to overconfidence or misinterpretation of predictive signals. Consistent with Bartáková et al. (2025), the findings reveal that investors are aware that ChatGPT may not fully capture or adequately contextualize the complexity inherent in market forecasting. Indeed, predicting market trends remains a highly complex task, as it is influenced by a multitude of unpredictable and interrelated factors—such as geopolitical developments, abrupt shifts in investor sentiment, and sudden macroeconomic changes. These elements often fall outside the scope of static or data-driven algorithms, which may struggle to account for real-time dynamics, behavioral biases, and structural economic disruptions. This negative relationship is more pronounced among investors with higher financial literacy, suggesting that financially knowledgeable individuals are more critical and discerning in their use of AI-generated market forecasts ($\beta10$ = -0.065; p-value = 0.000).

Regarding sentiment analysis, the results indicate that French individual investors actively use ChatGPT-based market sentiment analysis to improve investment decision-making ($\beta5$ = 0.225; p-value = 0.000). The results, however, show that this positive relationship becomes negative among investors with higher levels of financial literacy ($\beta11$ = -0.047; p-value = 0,000). This suggests that financially literate investors may be more skeptical of the accuracy and reliability of AI-generated sentiment interpretations. They may perceive such outputs as overly simplistic or lacking in contextual nuance, especially when dealing with ambiguous or emotionally charged content (Nguyen and Nguyen, 2015). Consequently, rather than enhancing decision quality, sentiment analysis via ChatGPT may be viewed by these investors as a source of noise or distraction.

5. Conclusions

This study examines how investors use generative artificial intelligence (ChatGPT) across different investment tasks. It also investigates the moderating role of financial literacy in shaping how they interpret and apply AI-generated insights. Based on a survey of 121 individual French investors and employing a PLS-SEM approach, the findings indicate that investors primarily use ChatGPT for data analysis, risk management, and sentiment analysis, leveraging its ability to process complex information, identify potential risks, and assess market sentiment effectively. However, the results reveal a negative relationship between the use of ChatGPT for portfolio optimization and market trend forecasting, as well as investment decision-making. This suggests that investors rely moderately on these AI-based tools, reflecting an awareness that such models may not fully capture the complexity and inherent unpredictability of financial markets. Moreover, the finding highlight the nuanced moderating role of financial literacy, which shapes how investors interpret and apply AI-driven insights within their investment strategies.

This study has direct implications for investors and regulators. By offering important insights into how tools like ChatGPT can be effectively integrated into the investment decision-making process, investors are encouraged to adopt AI-assisted tools and apply AI-generated insights responsibly. Investors should also critically assess AI-generated insights and avoid relying on them uncritically, especially in high-stakes decision-making environments. They should remain cautious of potential hallucinations when using ChatGPT. Financial regulators and policymakers are also required to implement guidelines that promote digital financial literacy and responsible AI adoption, thereby safeguarding investors against potential misuse or overreliance on automated tools. Policymakers should actively promote the integration of AI tools with human judgment and financial literacy to enhance the quality of investment decision-making.

This study has several limitations. First, the sample is limited to individual investors in the French stock market, which may restrict the generalizability of the findings to other countries or institutional investor contexts. Second, the use of self-reported survey data may introduce response biases, including social desirability bias or overestimation of financial literacy. Third, given the rapid evolution of AI technologies, particularly large language models like ChatGPT, the study captures investor perceptions and behaviors at a single point in time, which may change as the technology matures. Future research could address these limitations by using longitudinal data, incorporating cross-country comparisons, and applying experimental designs to assess causality more robustly.

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AI Use Statement: The authors used ChatGPT (OpenAI) to refine grammar and language. All content was carefully reviewed and verified by the authors.”

Appendix A: Items used in the survey

Constructs/ Items	Définition
Analyzing data (AD):	
AD1	ChatGPT is quite helpful for analyzing a large amount of data.
AD2	ChatGPT offers reliable analysis to assist in making investment decisions.
AD3	ChatGPT helps investors identify more profitable investment opportunities than traditional methods.
Managing risk (MR)	
MR1	I can get detailed information about investment risks via ChatGPT.
MR2	I can evaluate and manage the risks associated with my investments using ChatGPT.
MR3	I trust my capacity to make well-informed decisions on investment risk management.
Optimizing portfolio (OP):	
OP1	I can locate the best assets for my portfolio with ChatGPT's assistance.
OP2	I can maximize my portfolio's return by using ChatGPT.
OP3	I have no confidence that managing my financial portfolio using ChatGPT would be advantageous.
Forecasting market trend (FMT):	
FMT1	I rely on ChatGPT for precise and succinct predictions of market trends.
FMT2	ChatGPT helps me make informed investment decisions by anticipating market shifts.
FMT	ChatGPT enables me to adjust my investment tactics in response to market changes.
Conducting sentiment analysis (CSA):	
CSA1:	ChatGPT helps me monitor and analyze market sentiment.
CSA2:	ChatGPT provides me with information about investors' opinions about specific investments.
CSA3:	ChatGPT helps me make more informed decisions based on market sentiment.
CSA4:	I trust ChatGPT to provide me with a precise and succinct analysis of my feelings.
CSA5:	ChatGPT helps me identify potential investment opportunities based on market sentiment.
Financial literacy (FL)	
FL1:	I am comfortable with the process of investing.
FL2:	I have faith in my ability to make investments.
FL3:	The market helps forecast activity, returns, and prices.
FL4:	Considering that during a 10- to 20-year period, the activities often yield the highest return.
FL5:	Normally, they have the most variation over time.
Investment decision making (ID):	
ID1:	Are you satisfied with the profit you made from your most recent investment?
ID2:	I consider the news about the company.
ID3:	You are happy with the number of transactions and the frequency of negotiations.
ID4:	Before investing, I consider the company's past performance.
ID5:	Prior to investing in the company's operations, I consider how I feel about its goods and services.

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