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EMOTIONAL INTELLIGENCE AS A PREDICTOR OF INVESTMENT CHOICES: THE MEDIATING BRIDGE OF ARTIFICIAL INTELLIGENCE

Sneha S [1]*, Varshini V[1], Lena Mathews[1]
[1]Department of Commerce, St. Claret College Autonomous, Bengaluru. Karnataka, India.
Corresponding author email address: **snehasneha8200@gmail.com**

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Abstract

The rapid integration of Artificial Intelligence (AI) in financial markets has significantly transformed investment decision-making processes, shifting them from intuition-driven judgments to data-driven and algorithm-supported strategies. Alongside technological advancements, Emotional Intelligence (EI) remains a crucial human factor influencing investors' perceptions, risk assessment, and behavioural responses. This study examines the relationship between Emotional Intelligence, Trust in Artificial Intelligence, and Investment Decision-making, with a particular focus on the mediating role of trust in AI. Using a quantitative research design, primary data were collected from 100 retail investors through a structured questionnaire. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test the proposed hypotheses and assess both the measurement and structural models. The findings reveal that Emotional Intelligence has a significant positive influence on investment decisions, while trust in AI also plays a crucial role in enhancing decision quality. Moreover, trust in AI partially mediates the relationship between EI awareness and investment decisions, indicating that emotionally intelligent investors are more likely to rely on AI tools when trust is established. The study contributes to the growing literature at the intersection of behavioural finance and financial technology by highlighting the importance of integrating human emotional capabilities with AI-driven systems. The results offer practical insights for investors, financial institutions, and policymakers seeking to promote effective and responsible adoption of AI in investment decision-making.

Keywords: Emotional intelligence, Investment Decision, Artificial Intelligence, Behavioural Finance, PLS SEM

1. INTRODUCTION

The Artificial Intelligence (AI) has rapidly changed how the people think, learn and solve problems in the today's world. The finance sector has adopted many changes in the development of technologies, which led to major transformation in their fields. The changes in the Artificial Intelligence (AI), it is helping in making financial decisions making process in a very flexible manner without the help of human intervention. AI is becoming a game changer since it is able to analyze big data, determining market opportunities, and help in making balanced objective decisions. In the past, investment decision making process was depended on human intuition, which was very valuable but also had many challenges that had to be faced. Now AI comes to play by using complex algorithms which is helping in the improvement of predictability and operation efficiency. Also there is in the wide use of applications from robo-advisory services and algorithm trading for identifying the fraud detection and credit risk assessment, which is playing a huge role in the modern finance. The AI systems have enabled for quick automatic execution of trades, which helps in improving the profitability level and reducing the risks.
Our study looks at the relationships and interactions among the investment decisions (ID), artificial intelligence (AI), and emotional intelligence (EI). It shows the result that how much emotional intelligence influences on an investor's choice and as well as how AI recognizes, reacts, and modifies the emotional factors in a given financial setting. The balance and interaction between human emotion and accurate machine performance are crucial in markets that deal in

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data and algorithms. Our study shows the need to integrate and optimize the use of advanced technology and insight to attain more appropriate and successful investment outcomes.
Making an investment decision is not an easy task in the market. The investor has to be aware of the pros and cons of the risk involved during the investment. There will be a fluctuation in the stock prices. The investors also should be well aware of the stocks before making or doing the investment in the stock market. The emotions of the individuals while making investment decisions are unpredictable in the financial markets. The understanding of the individuals feelings is referred to as emotional intelligence. Emotional intelligence can include the components, how they fluctuate, and therefore see about feelings; it is also used to handle the issue and recognize one's own and others' emotions. Emotional intelligence is a significant element in the decision-making process. It affects the behaviour and thinking patterns are linked to physical and mental health, employee interpersonal relationships and job performance.

2.REVIEW OF LITERATURE

Rehman, M., Dhiman, D. B., & Cheema, G. S. (2024), primarily investigates the intricate relationships among Emotional Intelligence (EI), Artificial Intelligence (AI), and Investment Decisions (ID) in the evolving financial landscape. It aims to scrutinize the direct influence of human emotional intelligence on investment choices and to elucidate the mediating role of AI in this process. The study explores the nuanced relationship between emotional intelligence, artificial intelligence, and investment decision-making, considering the convergence of human cognition and machine intelligence as a pivotal axis defining investment decisions.
Jaiswal, C. (2024)., explores the role of Artificial Intelligence (AI) in financial decision-making within the Kathmandu Valley, focusing on how AI's social and emotional capabilities influence investment decisions. It provides a detailed analysis of the current status of AI use, its relationship with investment decisions, and its overall impact on the financial sector. The study enhances the theoretical understanding of how AI influences investment decision-making by exploring personal AI dimensions, broadening the scope of AI research in finance to include emotional and social competencies alongside technical skills.
Verma, B., Schulze, M., Goswami, D., & Upreti, K. (2025)., primarily investigates the resistance of retail investors in India to Financial Robo-Advisors (FRAs). It is grounded in the Innovation Resistance Theory (IRT), which provides a comprehensive framework for understanding user resistance to innovations. Unlike other models that focus on technology adoption through constructs like ease of use or perceived usefulness, IRT offers a better perspective by directly addressing functional and psychological resistance factors that impede technology adoption. The research also examines how users' attitudes towards Artificial Intelligence (AI) moderate the impact of these barriers on resistance.
Ahmad, M. (2018). There are numerous implications in favour of individual investors and academic researchers along with this, open latest prospects to investigate the dynamics of latent concepts of neuro finance and behavioural finance in Pakistan's stock Market. This informs through an excellent written empirical finding that individual investors are prone to investment horizon and personalization of loss while making investment in Pakistan's stock Market. The results of this research give a latest viewpoint in current body of knowledge as of collectively practical a well as academic angle.
Ammer, M. A., Ahmed, Z. A., Alsubari, S. N., Aldhyani, T. H., & Almaaytah, S. A. (2023). The behavioural tests must be applied in human-resources management and performance management to motivate qualified employees toward achieving organization's strategic goals. The study analysed behavioural data collected from 20,000 participants through a publicly available dataset on the Kaggle platform. We obtained the Big Five personality-test results to cluster the participants by type of behaviour. Supervised machine-learning models were used to analyse the responses to the questions according to personal traits. The algorithm was able to divide the individuals into a group of clusters; each cluster was a set of similar personality traits.
Chen, C., Ishfaq, M., Ashraf, F., Sarfaraz, A., & Wang, K. (2022). Economic, political, and behavioural changes influence an investor's buying and selling patterns. However, share market prices are affected by global economic fluctuations. Investors' decisions are influenced by various factors, including changes in share prices caused by different circumstances. Most investors are irrational in business activities (Pfnür and Wagner, 2020). They invest in stocks only based on their previous experience. They do not understand why share prices are reflected or vary due to the lack of business knowledge. A financial analyst who is both a chartered accountant and a CFA analyst is hired by many investors. Business students have a rudimentary understanding of how practical decisions are made and how the market fluctuates.
Verma, B., Schulze, M., Goswami, D., & Upreti, K. (2025). On the psychological basis, user resistance was prominently influenced by overconfidence bias, image barrier, and inertia. These findings revealed that cognitive bias, identity associations, and a dependence on conventional financial practices continue to impede widespread adoption of robo-advisors' platforms. Essentially, resistance itself had a negative and significant influence on both the usage

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intentions and recommendations to FRAs, validating resistance as a key barrier in user decision-making process.
Meyer, J. H., Friederich, F., Matute, J., & Schwarz, M. (2024). The findings offer practical implications. First, it reveals that FOMO appeals in social network postings do not foster sustainable investment behaviour and might deter investors from engaging. This finding is particularly interesting for digital influencers and social media accounts aiming to foster sustainable investments. Given that they typically profit from the increased effectiveness of their product endorsements, they should focus on non-FOMO appeals when promoting green investment opportunities.
Overall, reading through past work suggests investment choices are more than ever swayed by emotional smarts, mental shortcuts, alongside tech like smart algorithms. Some papers point out feelings and self-awareness shape how people judge risks, whereas machines that mimic empathy tend to tweak or guide those decisions. Other findings show folks hesitate using automated helpers due to inner blocks - like thinking too highly of their own skills, fear of change, or feeling it clashes with who they are. Work in money-related psychology keeps showing plenty still act on gut feelings, old memories, without solid know-how about finances. On top of that, models using machine learning along with social media nudges - like fear of missing out - prove tech and online spaces are reshaping how investors act. Still, while we're moving toward systems where people and AI make choices together, stubborn habits and feelings keep slowing things down.

3. RESEARCH GAP

While there's been a lot of research into emotional intelligence, quick decision-making, and how AI can assist with financial decisions, a few important gaps still exist. Not many studies combine emotional intelligence, artificial intelligence, and behavioural quirks into real-world models - most focus on just one part instead of exploring how they all interact when people decide where to invest. Additionally, there's limited understanding of how AI influences this process; while some research suggests it impacts feelings and thoughts, solid proof connecting AI, emotional smarts, and money choices is still scarce. Moreover, there's a lack of local research in growing markets—most work on how people resist, manage feelings, or use AI is spread thin across different countries. Very few studies examine all these factors together, especially when it comes to everyday buyers in developing areas like India.

4. OBJECTIVES

1. To analyse the influence of Emotional Intelligence in Investment Decision-making.
2. To examine the mediating role of AI tools adoption in the relationship between Emotional Intelligence and Investment decision

4.1. Hypothesis

H1: EI positively influences Investment Decisions.
H2: AI tools adoption influences the Investment decision.
H3: AI tools adoption mediates the relationship between EI and Investment decision.

5. RESEARCH METHODOLOGY

5.1 Research Design

This study employs a quantitative, descriptive research design to explore the relationships between EI, AI tools adoption and Investment decision among retail investors. The research focuses on identifying how EI influence investors' decision-making and the mediating role of AI tools adoption.

5.2. Sample Design

The target population is the retail investors using AI tools in investment. A sample of 100 respondents were selected through purposive sampling technique. The sample size of 100 respondents was determined based on the requirements of Structural Equation Modelling (SEM), which recommends a minimum of 5-10 respondents per estimated parameter **(Hair et al., 2019) (Wolf et al., 2013)**. Given the study's 10 observed variables and medium-sized anticipated effects, a sample size of 100 ensures sufficient statistical power **(0.80)** at an alpha level of **0.05**.

5.3. Data Collection

Primary data was collected through a structured questionnaire. The survey included items for assessing the constructs EI , AI tools adoption and Investment decision. Each construct was measured using a 5-point Likert scale, ranging from 'Strongly Disagree 'to 'Strongly Agree'.

5.4. Measurement of Variables

Investment behaviour construct is measured through items analysing portfolio diversification, changes in stock selection strategies, trading frequency and reduction in emotional biases due to AI. Items were measured using Five-point Likert Scale with 1- point denoting strongly disagree and 5-point denoting Strongly agree.

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6. DATA ANALYSIS

6.1. Demographic Profile

The researcher examined the demographic profile of the respondents, for which Age, Gender, Educational qualification, Annual Income and Investment Experience of the respondents are considered. An analysis was performed on 100 valid submissions.

Table 1: Demographic Profile

Demographic Variables		**No.of Respondents**	**Percentage**
Age	Up to 25	64	64.00
	26-35	19	19.00
	36-45	6	06.00
	46-55	11	11.00
	56 and above	1	01.00
	Total	**100**	**100.00**
Gender	Male	37	37.00
	Female	63	63.00
	Total	**100**	**100.00**
Education	Up to Higher Secondary	5	05.00
	Bachelor's degree/Diploma	38	38.00
	Master's degree or higher	57	57.00
	Total	**100**	**100.00**
Annual Income	Up to Rs.5,00,000	64	64.00
	Rs.5,00,001 - Rs.10,00,000	20	20.00
	Rs.10,00,001, - Rs.15,00,000	13	13.00
	More than Rs.15,00,001	3	03.00
	Total	**100**	**100.00**
Years of Investment Experience	Less than 1 year	20	20.00
	1-3 years	65	65.00
	3-6 years	9	09.00
	More than 6 years	6	06.00
	Total	**100**	**100.00**

Source: Authors' Computation

The demographic analysis reveals that the majority of respondents **(64%)** are aged up to 25 years, indicating a predominantly young investor sample. Female respondents constitute a higher proportion **(63%)** compared to males **(37%)**. In terms of education, most respondents are well qualified, with **57%** holding a master's degree or higher and **38%** possessing a bachelor's degree or diploma.

Regarding income levels, a significant proportion of respondents **(64%)** earn up to ₹5,00,000 annually, suggesting that the sample largely comprises early-career or young earners. Most respondents **(65%)** have 1–3 years of investment experience, while **20%** are relatively new investors with less than one year of experience. Overall, the sample reflects young, educated investors with limited to moderate investment experience

6.2. Measurement Model

The study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) due to its suitability for exploratory research **(Hair et al., 2019)**

Table 2. Reliability and validity

Variables	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted (AVE)**

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AI	0.870	0.911	0.720
EI	0.940	0.949	0.650
ID	0.882	0.910	0.629

Table 2 presents the results of the reliability and convergent validity assessment of the constructs included in the research model, namely Artificial Intelligence (AI), Emotional Intelligence (EI), and Investment Decisions (ID). The evaluation covers internal consistency reliability and convergent validity to ensure the adequacy of the measurement model. Internal consistency reliability was examined using Cronbach's Alpha and Composite Reliability. All constructs exhibit Cronbach's Alpha values ranging from **0.870** to **0.940** and Composite Reliability values above **0.90**, exceeding the recommended threshold of **0.70**, thereby indicating strong internal consistency. Convergent validity was assessed through the Average Variance Extracted (AVE), with values of **0.720** for AI, **0.650** for EI, and **0.629** for ID, all above the minimum acceptable level of 0.50. These results confirm that a substantial proportion of variance in each construct is explained by its indicators. Overall, the measurement model demonstrates satisfactory reliability and convergent validity, confirming that the constructs are robust and suitable for subsequent structural model analysis.

Table 3. Fornell-Larcker Criterion for Discriminant Validity

	AI	**EI**	**ID**
AI	0.848		
EI	0.563	0.806	
ID	0.537	0.824	0.793

Table 3 presents the results of the discriminant validity assessment using the Fornell–Larcker criterion for the constructs Artificial Intelligence (AI), Emotional Intelligence (EI), and Investment Decisions (ID). According to this criterion, the square root of the Average Variance Extracted (AVE) for each construct should be greater than its correlations with other constructs. As shown in the table, the square root of AVE for AI **(0.848)**, EI **(0.806)**, and ID **(0.793)** exceeds their respective inter-construct correlation values. This indicates that each construct shares more variance with its own indicators than with other constructs in the model. Therefore, the results confirm that the constructs are empirically distinct and that adequate discriminant validity is established within the measurement model.

6.3. Structural Model Analysis

The study employs path analysis using SmartPLS to examine the relationships among emotional intelligence, use of AI-based investment tools, and investment choices. Given the exploratory nature of the study, the analysis focuses on path coefficients and explained variance.

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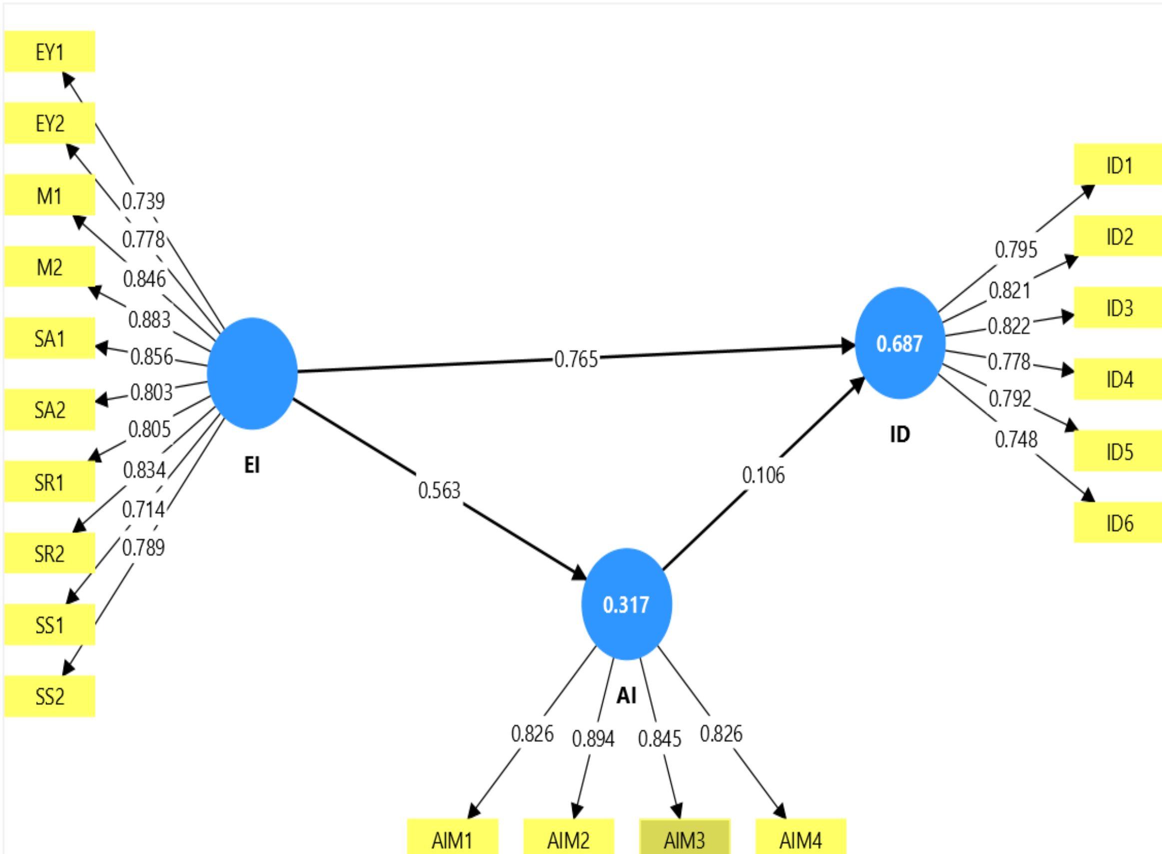

Figure 1: Structural Model

The above figure presents the structural equation model illustrating the relationships among Emotional Intelligence (EI), Artificial Intelligence (AI), and Investment Decisions (ID). All indicators show loadings above the acceptable threshold of **0.70**, indicating that the items adequately represent their respective constructs. This suggests good indicator reliability for Emotional Intelligence, AI-based Investment Tools, and Investment Decisions.

6.3.1 Path Analysis

Table 4 . Path Analysis

Path	Path Coefficient (β)
Emotional Intelligence → Investment Decisions (EI>>ID)	0.765
Emotional Intelligence → AI tools adoption (EI >> AI)	0.563
AI- tools adoption → Investment Decisions (AI>>ID)	0.106

EI shows a strong direct influence on **ID (β = 0.765)**, indicating that higher emotional intelligence significantly improves investment decision-making. EI also has a substantial effect on AI tools adoption **(β = 0.563)**, suggesting that emotionally intelligent investors are more likely to rely on AI-based tools. However, the direct effect of AI on ID is relatively weak **(β = 0.106)**, implying that AI plays a limited mediating role. The path analysis results suggest that emotional intelligence plays a dominant role in influencing investment decisions, while the role of AI-based investment tools appears to be supportive rather than decisive. The findings indicate that emotionally intelligent investors may rely more on their personal judgment than on AI-driven tools when making investment choices.

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6.3.2. R² Values

Table 5: R² Values

Endogenous Construct	**R²**
AI Tools Adoption	0.317
Investment Decisions	0.687

The model explains **31.7%** of the variance in AI tools adoption **(R^2 0.317)** and **68.7%** of the variance in investment decisions **(R^2 0.687)**, demonstrating that EI is the dominant predictor of investment behaviour, while AI provides only marginal additional explanatory power.

6.4. Mediation Analysis

Table 6: Indirect Effect

	Indirect Effect
Emotional Intelligence >> AI Tools Adoption >> Investment Decision	0.060

Table 6 presents the results of the mediation analysis examining the specific indirect effect of Emotional Intelligence (EI) on Investment Decisions (ID) through Artificial Intelligence (AI). The results indicate a positive indirect effect with a beta coefficient of **0.060**, suggesting that EI influences investment decisions through its impact on AI tools adoption. Although the magnitude of the indirect effect is modest, it confirms the presence of a mediating relationship. This implies that emotionally intelligent individuals are more inclined to adopt AI tools, which in turn contributes to their investment decision-making. Thus, Artificial Intelligence serves as a partial mediator in the relationship between Emotional Intelligence and Investment Decisions, supporting the proposed mediation hypothesis.

7. DISCUSSION AND CONCLUSION

The present study examined the influence of Emotional Intelligence (EI) on investment decision-making among retail investors, with particular emphasis on the mediating role of Artificial Intelligence Tools Adoption. The findings provide meaningful insights into how human emotional capabilities and technological adoption interact in modern financial decision-making.

The results indicate that Emotional Intelligence awareness has a significant positive influence on investment decisions, supporting Hypothesis H1. This finding aligns with earlier studies, which emphasize that emotionally intelligent investors are better equipped to manage uncertainty, control emotional biases, and make rational investment choices. Investors with higher EI are more capable of understanding market risks, handling stress during market fluctuations, and avoiding impulsive decisions driven by fear or overconfidence.

Further, the study confirms that AI Tools influence investment decisions, thereby supporting Hypothesis H2. This result is consistent with prior research by Jaiswal (2024), which highlights the growing reliance on AI-driven tools such as robo-advisors and algorithmic trading systems in financial decision-making. When investors trust AI systems, they are more likely to adopt data-driven insights, improve portfolio diversification, and reduce emotional biases, ultimately enhancing decision quality.

The mediation analysis reveals that trust in AI significantly mediates the relationship between EI awareness and investment decisions, confirming Hypothesis H3. This finding suggests that while emotional intelligence directly contributes to better investment behaviour, its impact is strengthened when investors place trust in AI tools. Emotionally intelligent investors tend to recognize the value of AI-generated insights and are more open to integrating technological support into their decision-making process. This result aligns with Rehman et al. (2024), who argue that the convergence of human cognition and machine intelligence leads to more effective investment outcomes.

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Overall, the findings suggest that investment decision-making is no longer purely human- or technology-driven, but rather a combined process where emotional intelligence, trust, and artificial intelligence jointly influence outcomes. These results also help explain why some investors resist AI adoption, as highlighted by Verma et al. (2025), where lack of trust and psychological barriers hinder effective use of AI-based financial tools.
This study contributes to the growing body of literature at the intersection of behavioural finance and financial technology by examining the combined role of Emotional Intelligence, trust in Artificial Intelligence, and investment decision-making. The findings clearly demonstrate that Emotional Intelligence awareness plays a crucial role in shaping investors' decisions, while trust in AI enhances the effectiveness of AI-driven financial tools.
The results further establish that trust in AI acts as a significant mediating factor between EI awareness and investment decisions, indicating that emotionally intelligent investors are more likely to benefit from AI systems when they perceive them as reliable and trustworthy. This highlights the importance of fostering trust alongside technological advancement to ensure successful adoption of AI in financial markets.
From a practical perspective, the study offers valuable implications for investors, financial institutions, and policymakers. Investors should focus on developing emotional intelligence skills while leveraging AI-based tools for informed decision-making. Financial institutions and fintech firms should prioritize transparency, reliability, and user education to build trust in AI systems. Policymakers may also consider formulating guidelines that promote ethical and responsible use of AI in financial decision-making.
Despite its contributions, the study is limited by its sample size and focus on retail investors using AI tools. Future research may extend this work by incorporating larger samples, cross-country comparisons, additional behavioural variables, or longitudinal designs to better understand long-term effects. Nevertheless, the study successfully highlights the importance of integrating human emotional capabilities with artificial intelligence to achieve more balanced, rational, and effective investment decisions.

8. STATEMENTS & DECLARATIONS:

Use of AI Statement

The authors declare that they have not used generative artificial intelligence, specifically ChatGPT in the writing of this manuscript and/or in the creation of images, graphics, tables, or their corresponding captions

Conflict of Interest and Declarations:

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