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Is artificial intelligence a linking bridge between emotional intelligence and investment behaviour?

Dr. Rachna Jain[1] and Dr. Shikha Sharma[2*]

[1 2]Associate Professor, Maharaja Agrasen Institute of Management Studies, GGSIPU affiliated, Maharaja Agrasen Chowk, Sector-22, Rohini, Delhi- 110086, India

Email: drrachnajain44@gmail.com[1]

*Correspondence: sharma.shikha3684@gmail.com

Abstract

This study examines the relationships among emotional intelligence, artificial intelligence, and investment decisions within contemporary financial decision making. Drawing on data from 410 investors and applying structural equation modelling, the study tests whether emotional intelligence, captured through self-awareness, self-regulation, motivation, social awareness, and social skills, shapes investment decisions, and whether artificial intelligence mediates this relationship. The measurement model confirms strong loadings across all constructs, and the structural results show that each dimension of emotional intelligence, together with artificial intelligence, significantly predicts investment decisions, with artificial intelligence recording the strongest direct effect. Mediation analysis further indicates that artificial intelligence partially mediates the relationship between emotional intelligence and investment decisions, evidenced by both a significant direct effect of emotional intelligence and a significant indirect effect transmitted through artificial intelligence. These findings position artificial intelligence not as a replacement for human judgment but as a complementary mechanism that channels emotionally informed insight into more consistent investment behaviour. The study offers practical guidance for financial practitioners, technology developers, and policymakers seeking to integrate behavioural and algorithmic tools responsibly, while underscoring the continuing need for transparency and ethical oversight as artificial intelligence becomes more embedded in investment decision making.

Keywords: Artificial Intelligence, Behavioural Biases, Emotional Intelligence, Investment Behaviour, Investment Decisions, Mediation Analysis, Robo Advisors, Structural Equation Modelling

JEL Classification: D91, G11, G41, O33

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1. Introduction

The interaction between human and machine intelligence has become a key factor in determining investment decisions in the complex world of modern financial markets. An investigation of the complex interaction between emotional intelligence, artificial intelligence, and investment decision-making has been prompted by the paradigm shift in investing methods brought about by the evolving dynamics between human minds and machines (Costello et al., 2020). This study delves deeply into the relationship between emotional intelligence and investing choices, with a particular emphasis on the mediating role that artificial intelligence plays in this intricate relationship. The rising integration of algorithmic trading, robo-advisors, and data-driven decision-making in the financial landscape highlights the critical need to comprehend the ways in which emotional intelligence shapes investment decisions in the era of artificial intelligence. A thorough analysis of how emotional intelligence influences financial decisions and how artificial intelligence reads and takes into account these emotional cues is required due to the delicate balance that must be maintained between human emotions and machine algorithms (Ezzi et al., 2020; Minárová et al., 2020). In order to shed light on the psychological foundations that influence financial decision makers and the technological interfaces that mediate and enhance these cognitive processes, this investigation aims to disentangle the complex relationships, dependencies, and synergies between minds and machines in the investment process. The intersection of artificial intelligence and emotional intelligence in the investment domain signifies a revolutionary intersection, providing significant perspectives on the future course of financial decision-making and the possibility of balancing human instincts with automated accuracy (Abdeldayem & Aldulaimi, 2026; Sumera, 2020). Understanding the symbiotic relationship between minds and machines will help us navigate this uncharted territory by offering insight into the current state of financial technology and paving the way for well-informed strategies that combine artificial intelligence algorithms with human emotional intelligence to make more resilient and robust investment decisions (Pereira et al., 2025; Oslon et al., 2021). When it comes to making investment decisions, emotional intelligence (EI) is crucial because it influences how people traverse the intricate and frequently unpredictable world of financial markets (Rehman et al., 2023b). Emotional intelligence is incorporated into standard financial models that emphasise quantitative measures and fail to acknowledge the impact of human emotions on decision-making. Emotional intelligence (EI) includes the capacity to observe, comprehend, and regulate one's own emotions in addition to the ability to affect and influence the emotions of others (You & Zhang, 2021). People with high emotional intelligence are better able to manage the psychological demands that come with making investment decisions in the financial markets (Chaturvedi Sharma, 2025). Risk, uncertainty, and shifting market circumstances are intrinsic to investing, and these factors can arouse feelings of greed, dread, and anxiety. Investors who possess emotional intelligence are better equipped to deal with these difficulties by being more self-aware and able to make more logical and educated choices. Furthermore, those who possess high emotional

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intelligence are skilled at identifying market trends and comprehending the general emotional feelings of other market players, giving them a competitive advantage (De Krijger et al., 2023). Since emotionally astute investors are better able to recognise and minimise possible losses, emotional intelligence is also essential for risk management. The trait of emotional intelligence is the ability to withstand market turbulence and refrain from making snap decisions (Sutejo et al., 2023).

Additionally, investors with high EI are frequently better able to adjust to shifting market conditions, taking lessons from past mistakes and achievements to gradually improve their approach (Rehman et al., 2023a). Even in a time when algorithmic trading and artificial intelligence are becoming standard features of investment processes, emotional intelligence—a human component—remains indispensable. Although algorithms are capable of processing enormous volumes of data and executing trades at previously unheard-of speeds, human intelligence is still needed to comprehend the emotional subtleties of market dynamics (Chandu et al., 2023; Rehman & Dhiman, 2022). Emotional intelligence is, therefore, a great advantage in the investing sector, helping with resilience building, decision-making, and long-term success in negotiating the intricacies of financial markets.

2. Literature Review

In a variety of contexts, emotional intelligence (EI) has become recognised as a crucial component influencing decision-making processes, and its applicability to the world of investing has drawn growing interest. According to Mayer et al. (1997), emotional intelligence (EI) is the capacity to identify, comprehend, control, and make use of one's own emotions in addition to having the capacity to relate to, understand, and affect the emotions of others. Understanding the role of emotional intelligence (EI) becomes critical in the context of investing, where decisions are frequently influenced by both rational analysis and emotional responses. Research on the relationship between emotional intelligence and investment decision-making is complex and constantly evolving (Zhang et al., 2023). Numerous studies, including one by Lerner and Keltner (2001), have shown how emotional states affect financial decisions. Whether as a result of personal concerns or market volatility, investors who are emotionally aroused are likely to make poor decisions. This emphasises how crucial emotional intelligence is for identifying and controlling these emotional states in order to improve the calibre of decision-making. The Leeuw & Joseph (2023) framework of emotional intelligence (EI), which includes motivation, self-regulation, empathy, self-awareness, and social skills, offers a prism through which to examine the significance of emotions in financial decision-making in the context of investments. High emotional intelligence (EI) investors may have a better ability to handle interpersonal dynamics in financial negotiations, a deeper understanding of their risk tolerance, and more self-control during market turbulence (Yela Aránega et al., 2023). The increasing intertwining of artificial intelligence (AI) and human decision-making is a topic of discussion in numerous industries, including

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banking. In the context of investments, emotional intelligence (EI) is a crucial factor influencing human judgment and decision-making (Boyar et al., 2023). This literature review aims to examine the relationship between emotional intelligence and investment decisions, as well as the role artificial intelligence plays as a mediator in this dynamic process (Rehman et al., 2023). The impact of emotional intelligence (EI) on risk perception is a noteworthy feature of the link between EI and investing. According to research by Lerner et al. (2015), investors' perceptions and reactions to risk are greatly influenced by their emotional states. Others with high emotional intelligence (EI) are more likely to approach risk from a balanced standpoint and modify their risk tolerance based on the circumstances, while others with low EI may behave impulsively out of overconfidence or fear. Research like that done by Baker and Nofsinger (2002), who discovered that emotional intelligence might mediate the relationship between information processing and investing decisions, highlights the connection between emotional intelligence and investor behaviour. Higher emotional intelligence (EI) may make an investor more capable of processing financial data efficiently, sifting through noise, and reaching long-term objectives. Emotional intelligence assumes new forms in the world of artificial intelligence in finance and robo-advisors. The emotional subtleties present in human decision-making are absent from the algorithms that drive robo-advisors (Fedorova et al., 2023).

Nonetheless, the integration of emotional intelligence principles in the development and execution of AI-powered investment platforms may augment their capacity to comprehend and react to investor emotions. The body of research indicates that emotional intelligence plays a critical role in financial decision-making. Having a high emotional intelligence can help you make more thoughtful, sensible, and flexible decisions when the market is unclear. In addition to being intellectually stimulating, knowing the dynamics of emotional intelligence in the context of investing has applications for developing investor-focused financial products, efficient investment strategies, and maximising the use of AI in wealth management (Marheni et al., 2024). The use of emotional intelligence principles may help to create a more responsive and resilient investment environment as the financial markets continue to change.

2.1 Emotional Intelligence and Investment Decisions

The ability to identify, comprehend, control, and utilise one's own and other people's emotions is known as emotional intelligence, and it has become increasingly important when making financial decisions. According to research by Corey & Goleman (1995), those who possess higher emotional intelligence are better able to handle the emotions that drive investment behaviour, such as fear and greed, making them more adept at navigating the complexity of the financial markets. The impact of emotions on financial decisions is highlighted by studies by Lerner et al. (2015) and Loewenstein (2000), which show that emotional states can considerably alter risk perception and risk-taking behaviour. Investors who possess a high emotional intelligence level may be better able

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to control their emotions, which could result in more thoughtful and less rash financial decisions (Khan et al., 2025; Hadi et al., 2024).

2.2 The Rise of Artificial Intelligence in Finance

Financial decision-making has undergone a radical change thanks to artificial intelligence, mainly in the areas of machine learning and data analytics. AI systems can process enormous volumes of data, spot trends, and forecast outcomes, giving investors insightful information (Maheshwari & Samantaray, 2026; Zhang et al., 2019). Robo-advisors, sentiment analysis software, and algorithmic trading are a few prominent examples. According to research by Tsai et al. (2011), artificial intelligence (AI) can improve the efficiency and precision of decision-making in the financial markets. Artificial intelligence (AI) has the ability to interpret information without being influenced by emotional biases, which may lessen the impact of illogical decision-making, which frequently results from emotional elements (Mizgajski et al., 2020).

2.3 Artificial Intelligence as Mediator

A dynamic interaction between machine-driven analytics and human intuition is presented when investing decisions incorporate both artificial and emotional intelligence (Mohapatra et al., 2025). As AI systems advance in sophistication, they may act as intermediaries, enabling investors to take advantage of AI's analytical skills while utilising their emotional intelligence (Singh & Turała, 2022). In their discussion of AI's mediating function in decision-making, Brettschneider et al. (2021) & Mitchell et al. (2019) hypothesise that the technology can serve as a link between emotional intelligence and successful investing techniques. AI systems can help investors make better educated, and logical decisions by offering objective evaluations, spotting potential emotional biases, and providing data-driven recommendations (Hao et al., 2023).

3. Methodology

The study employed Structural Equation Modelling (SEM) for the investigation of the impact of emotional intelligence on financial decision-making after considering artificial intelligence as a mediator. The study uses a quantitative research approach to investigate the intricate connections between investing decisions, artificial intelligence, and emotional intelligence. A sample of 410 participants of investors is chosen for the study. The selection of the sample is based on the individual's information, expertise, and experience with artificial intelligence technology. The criteria for inclusion guarantee that participants have the necessary background knowledge to provide insightful answers to the research questions. Structured questionnaires are used to gather data on emotional intelligence, opinions about artificial intelligence in investing, and actual investment choices (Appendix 1). Validated scales for assessing emotional intelligence and AI perceptions are part of the survey instrument. SEM offers a strong analytical framework for intricate models, which makes it appropriate for capturing the complicated interactions that are being studied.

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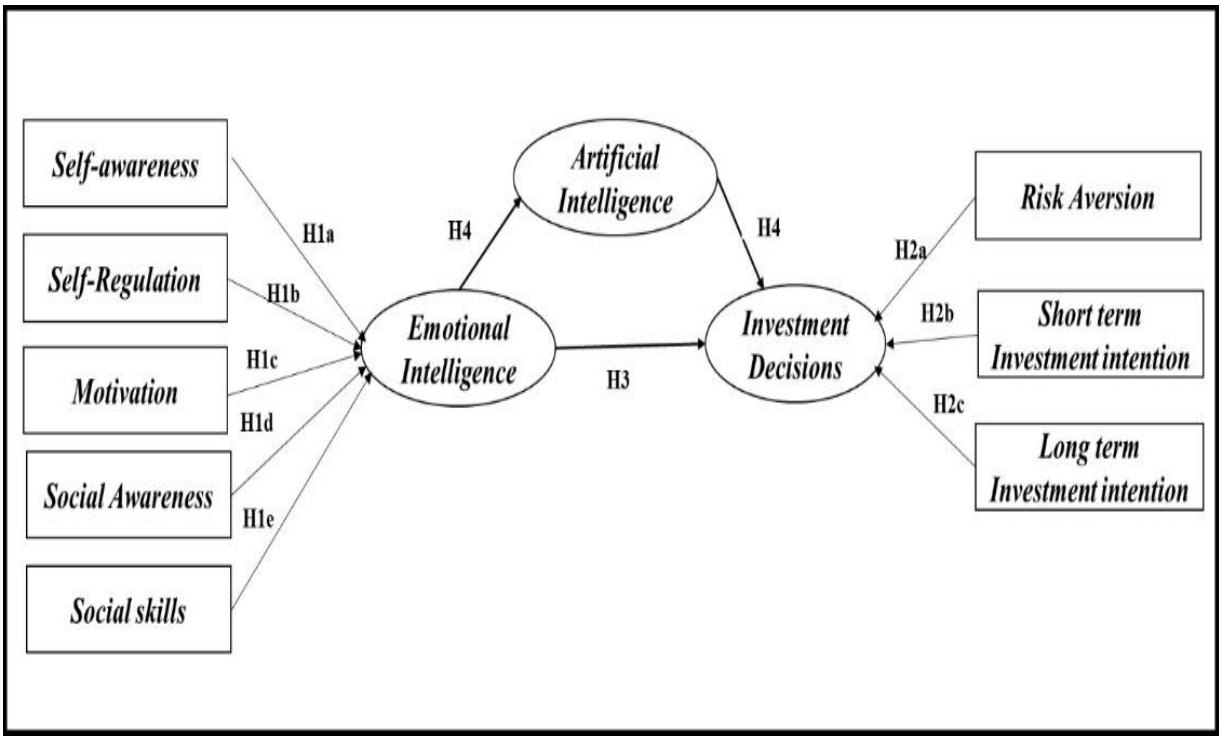
a. **Emotional intelligence:** Participants' emotional intelligence levels are determined by the Emotional Intelligence scale (Singh, S., 2004).

b. **Perceptions of AI in Investment:** Participants' opinions and attitudes on the use of AI in investment decision-making are gauged by a series of five self-developed questions.

c. **Investment Decisions:** Participants' actual investment decisions, including their risk-taking tendencies and portfolio selections, are gathered (Mayfield, et al., 2008).

Using theoretical frameworks, the study has proposed that emotional intelligence significantly impacts investment decisions and artificial intelligence acts as a mediator; the hypothesised model is developed and represented in Figure 1.

Figure 1. Hypothesised Model



3.1 Hypothesis

H1a: Self-awareness has a significant impact on Investment Decisions.

H1b: Self-regulation has a significant impact on Investment Decisions.

H1c: Motivation has a significant impact on Investment Decisions.

H1d: Social Awareness has a significant impact on Investment Decisions.

H1e: Social skills have a significant impact on Investment Decisions.

H2a: Risk Aversion has a significant impact on Investment Decisions.

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H2b: Short-term Investment intentions have a significant impact on Investment Decisions.

H2c: Long-term Investment intentions have a significant impact on Investment Decisions.

H3: Emotional Intelligence has a significant effect on Investment Decisions.

H4: Artificial Intelligence mediates the difference between Emotional Intelligence and Investment Decisions.

4. Results and Discussion

Table 1 provides the factor loadings, indicating the direction and the strength of the correlations between the observable variables and the latent factors. Each row represents a variable, and various latent factors: the constructs Self-Awareness (SA), Self-Regulation (SR), Motivation (M), Social Awareness (SAW), and Social Skills (SS) form Emotional Intelligence (EI). For the Emotional Intelligence construct, Social Skills (0.893), Social Awareness (0.870), Self-awareness (0.762), Motivation (0.693), and Self-Regulation (0.689) have significant positive factor loadings. Additionally, AI (Artificial Intelligence), represented by a series of five self-developed questions, shows a good correlation between the factor and the observable data (AI1, AI2, AI3, AI4, and AI5). The statements have strong factor loadings, which validate the relationship between the assertions and the observed variable. Each statement's factor loadings have been reported to be higher than the 0.40 acceptable threshold.

Furthermore, Investment Decisions (ID) are reflected by the components Risk Aversion (RA), Short-Term Investment Intentions (ST), and Long-Term Investment Intentions (LT). The findings demonstrate a significant factor loading value for the following investment choice constructs: Short-term investment intention (0.923), Risk Aversion (0.871), and Long-term investment intention (0.745). These findings suggest that the variables have a significant role in the variability of the associated latent construct for each component. The factor loadings offer useful information about the interactions between observable variables and latent constructs.

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Table 1. Measurement Model

CONSTRUCT	Item	Factor Loading	Cronbach α	CR	AVE
SELF-AWARENESS	SA1	0.675	**0.7621**	**0.9921**	**0.9308**
	SA2	0.590			
	SA3	0.575			
	SA4	0.561			
	SA5	0.512			
	SA6	0.495			
	SA7	0.475			
	SA8	0.464			
	SA9	0.455			
	SA10	0.405			
	SA11	0.372			
	SA12	0.321			
SELF-REGULATION	SR1	0.654	**0.6897**	**0.9955**	**0.9446**
	SR2	0.671			
	SR3	0.684			
	SR4	0.702			
	SR5	0.695			
	SR6	0.683			
	SR7	0.667			

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	SR8	0.655			
	SR9	0.632			
	SR10	0.624			
	SR11	0.601			
	SR12	0.586			
MOTIVATION	M1	0.685	**0.693**	**0.9981**	**0.9149**
	M2	0.590			
	M3	0.572			
	M4	0.563			
	M5	0.515			
	M6	0.503			
	M7	0.495			
	M8	0.482			
	M9	0.476			
	M10	0.428			
	M11	0.381			
	M12	0.335			
SOCIAL AWARENESS	SAW1	0.702	**0.8704**	**0.998**	**0.9778**
	SAW2	0.753			
	SAW3	0.655			
	SAW4	0.751			
	SAW5	0.752			

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	SAW6	0.708			
	SAW7	0.658			
	SAW8	0.602			
	SAW9	0.651			
	SAW10	0.759			
	SAW11	0.707			
	SAW12	0.752			
SOCIAL SKILLS	SS1	0.731	**0.8939**	**0.9987**	**0.9841**
	SS2	0.782			
	SS3	0.834			
	SS4	0.881			
	SS5	0.865			
	SS6	0.763			
	SS7	0.802			
	SS8	0.836			
	SS9	0.882			
	SS10	0.903			
	SS11	0.791			
ARTIFICIAL INTELLIGENCE	AI1	0.662	**0.788**	**0.9700**	**0.8750**
	AI2	0.564			
	AI3	0.543			
	AI4	0.481			

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	AI5	0.462			
RISK AVERSION	RA1	0.902	**0.871**	**0.9827**	**0.9393**
	RA2	0.671			
	RA3	0.655			
	RA4	0.564			
SHORT-TERM INVESTMENT INTENTION	ST1	0.453	**0.923**	**0.9722**	**0.8804**
	ST2	0.341			
	ST3	0.311			
	ST4	0.285			
	ST5	0.254			
LONG-TERM INVESTMENT INTENTION	LT1	0.491	**0.745**	**0.9274**	**0.7267**
	LT2	0.370			
	LT3	0.343			
	LT4	0.312			
	LT5	0.289			

Notes: Author's compilation

Table 1 gives the results of Cronbach's alpha (α), Composite reliability (CR) & Average Variance Extracted (AVE), which estimate the reliability and validity statistics for each latent construct. High values of α, CR & AVE suggest valid internal reliability and consistency. For every construct, the alpha value is higher than 0.7, which indicates the average correlation between items within a construct and demonstrates robust internal reliability. Composite Reliability provides further evidence for the validity of the latent constructs; it exceeds the recommended cutoff of 0.7 and accounts for the factor loadings of the items. Each construct's AVE value is higher than 0.70, which shows that each construct is explaining the variation caused by the observed factor substantially.

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Table 2. Fornell-Larcker Criterion

	1	2	3	4	5	6	7	8	9
Construct	**SA**	**SR**	**M**	**SAW**	**SS**	**AI**	**RA**	**STI**	**LTI**
SA	0.964								
SR	0.543	0.972							
M	0.421	0.619	0.956						
SAW	0.675	0.42	0.512	0.988					
SS	0.318	0.738	0.423	0.309	0.992				
AI	0.729	0.367	0.629	0.615	0.542	0.935			
RA	0.614	0.578	0.430	0.409	0.725	0.538	0.969		
STI	0.509	0.681	0.705	0.516	0.417	0.627	0.362	0.938	
LTI	0.443	0.324	0.512	0.603	0.521	0.421	0.645	0.53	0.852

Notes: Author's compilation

The Fornell-Larcker (F-L) criteria given in Table 2 were used to evaluate discriminant validity. The study satisfied the criterion by the estimated F-L values of every construct pair, suggesting that the latent constructs are sufficiently distinct. These values provide significant data about the robustness of the measurement model by confirming that the latent constructs properly reflect different dimensions with little overlap. The diagonal values, like the Self-Awareness construct value 0.9641, indicate that each construct accounts for a considerable amount of its variation in measurement error. This is the square root of the Average variation Extracted (AVE). Interestingly, the association between constructs is shown by values off the diagonal. As a result, the discriminant validity of the model is strengthened since it is shown that the observed constructs measure separates and independent factors.

Table 2 also represents the pairwise correlation matrix between one and another constructs: SA (Self-Awareness), SR (Self-Regulation), M (Motivation), SAW (Social Awareness), SS (Social Skills), AI (Artificial Intelligence), RA (Risk Aversion), ST (Short-term Investment Intention) & LT (Long-term Investment Intention) All of the constructs have strong positive correlations, indicating great internal consistency. Although all correlations are smaller than 0.85, this indicates sufficient discriminant validity. Artificial intelligence (AI) exhibits a strong correlation value with

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Social Awareness (0.729), Motivation (0.629) & Short-term investment intention (0.627), indicating potential linkages.

Table 3. Hypothesis Results

Hypothesis	β-Coefficient	Std. Dev. (σ)	t-stats	p-value	Results
SA->ID	0.234	0.042	2.558	0.023	Supported
SR->ID	0.089	0.055	3.554	0.005	Supported
M->ID	0.162	0.042	3.763	0.004	Supported
SAW->ID	0.169	0.056	2.625	0.007	Supported
SS->ID	0.134	0.038	6.554	0.001	Supported
AI->ID	0.282	0.049	4.564	0.000	Supported

Notes: Author's compilation

Table 3 represents the hypothesis testing results. The results prove a substantial relation between the latent constructs. Beta coefficients, standard deviation, and t-statistic values are mentioned in Table 3, which supports that investment decisions are directly influenced by latent variables. The beta-coefficient value is highest on Artificial Intelligence (0.282), which supports the model that AI has a significant impact on Investment decisions (ID). In Emotional Intelligence, Self-Awareness (SA) shows the highest beta-coefficient value (0.234), followed by social awareness (0.169), Motivation (0.162), Social Skills (0.134) & Self-Regulation (0.089) on Investment Decision. The study also shows that p-values are significant at a 5% level of significance for all constructs: SA (Self-Awareness), SR (Self-Regulation), M (Motivation), SAW (Social Awareness), SS (Social Skills), and AI (Artificial Intelligence) on Investment decision. Hence, the study provides important new insights into the intricate dynamics of investor behaviour in connection with artificial intelligence, emotional intelligence, and social intelligence for academics and practitioners.

Table 4. Mediation Results

Effect	Coefficient	SE	z-value	p-value
Total Effect	1.582	2.19	2.667	0.008
Direct Effect	0.698	0.275	2.542	0.011

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Indirect Effect	0.884	0.422	2.096	0.036

Notes: Author's compilation

The mediation analysis (Table 4) shows a substantial total effect with a p-value of 0.008 and a β-coefficient of 1.582, demonstrating the overall impact of emotional intelligence (EI) on investment decisions (ID). Without a mediating variable, the direct effect (0.011) indicates a substantial relationship between EI and ID. The mediating variable, Artificial Intelligence (AI), was used in the study to investigate the indirect relationship between EI and ID. The p-value of 0.036 indicates that the mediation effect was validated by the results. Accordingly, the study shows that artificial intelligence and emotional intelligence significantly impact investment choices.

4.1 Discussion

A notable change in the financial environment is the rise of artificial intelligence (AI) in investing decision-making. The study tried to explore how artificial intelligence successfully responds to the behavioural prejudices in investment decisions. The results imply that artificial intelligence (AI), especially in the form of robo-advisors, may be able to mitigate these changes. Robo-advisors provide a logical and impartial method for making investing decisions because they are powered by sophisticated algorithms, data analytics, and machine learning. Artificial intelligence (AI) can offer investors data-driven suggestions by eliminating the cognitive and emotional biases present in human judgment, hence reducing the influence of impulsive decision-making tendencies. The study emphasises how emotional intelligence plays a moderating influence on how investors and AI systems interact. By giving more pronounced emotional cues, investors with greater emotional intelligence may be able to increase AI's efficacy and foster a mutually beneficial partnership between machines and humans in financial decisions. Nonetheless, the conversation also recognises the problems with transparency and ethical issues around the use of AI in banking. Even though AI can counteract behavioural biases, issues with algorithmic biases, moral judgment, and openness in AI-driven suggestions still need to be investigated. Establishing a steadiness between the benefits of AI in reducing prejudices and guaranteeing accountable use is essential for building investor conviction and meeting regulatory requirements.

5. Conclusions, Implications, and Future Research Directions

The advent of AI in investment decision-making and robo-advisors marks a turning point in the development of global finance. This study investigated the possibility that artificial intelligence (AI) could counteract the behavioural biases displayed by international investors. The results imply that AI may dramatically reduce these prejudices and change the capital management landscape by using robo-advisor platforms. Robo-advisors, powered by advanced algorithms and machine learning, provide a revolutionary way to make investing recommendations by bringing objectivity and logic into the mix. The capacity of AI to analyse enormous volumes of information,

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identify patterns, and make decisions free from cognitive or emotional biases makes it an effective tool for combating the illogical inclinations that are frequently seen in human investors.

The study emphasises the function of EI as a moderating element and the mutually beneficial interaction between investors' EI and AI algorithms' adaptability. This research has ramifications outside of the fields of finance and technology. AI's capacity to counteract behavioural biases has significant ramifications for the general efficiency and stability of the world's markets. While the financial sector struggles with the problems caused by emotive decisions, mixing AI is a viable way to improve managerial procedures and lessen inefficiencies in the market. This revolutionary potential is not without difficulties, though. Careful consideration must be given to algorithmic biases, transparency requirements, and ethical issues. It becomes crucial to strike the correct balance between utilising AI's advantages and making sure it is used responsibly and ethically to build investor confidence and comply with regulations. To sum up, the emergence of AI and robo-advisors portends a paradigm change in international investing choices. AI is starting to eliminate behavioural biases, which offers the financial sector several intriguing options. To ensure that AI becomes a strength for responsible, adaptable, and logical capital management in the future, continual research, cooperation, and ethical considerations will be essential in directing the rapidly changing terrain.

5.1 Implications of the Study

The challenges of maintaining investor trust in the absence of human intuition, possible flaws in AI algorithms, and the ethical implications of automated decision-making are significant concerns. Persistent research and regulatory frameworks to readdress the difficulty in finding the ideal balance between algorithmic precision and human oversight are necessary to ensure the appropriate use of artificial intelligence (AI) in asset management.

Robo-advisors that match strategies with sustainable goals may help make ethical and accountable investing more well-known. Incorporating AI may also increase reliability and assurance, nurture confidence, and adoption of technological advancements. However, there are certain limitations associated with these technical advancements. When extreme events occur, machine learning models that rely too heavily on historical data might not be able to adapt to abrupt changes in the market, which might lower their effectiveness.

5.2 Future Research Directions

The trajectory of artificial intelligence (AI) and robo-advisors in changing international investment decisions offers an exciting glimpse into the future, despite its challenges and limitations. By incorporating emotional intelligence algorithms into investing strategies, future technology developments may potentially allow for more customisation by enabling the strategies to adapt in real time to the distinct profiles of individual investors. Certain challenges need to be

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resolved effectively by utilising artificial intelligence and robo-advisors to establish an ethical and stable investment setting as the market grows.

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