International Journal of Engineering, Business and Management (IJEBM)
ISSN: 2456-7817
[Vol-8, Issue-1, Jan-Mar, 2024]
Issue DOI: https://dx.doi.org/10.22161/ijebm.8.1
Article Issue DOI: https://dx.doi.org/10.22161/ijebm.8.1.1

Minds and Machines: Impact of Emotional Intelligence on Investment Decisions with Mediating the Role of Artificial Intelligence

Muzzamil Rehman[1], Dr. Babli Dhiman[2], Gagandeep Singh Cheema[3]

[1]Research Scholar Lovely Professional University, Punjab, India
[2]Professor and Head at Mittal School of Business Lovely Professional University, Punjab, India
[3]Research Scholar Lovely Professional University, Punjab, India

Received: 08 Dec 2023; Received in revised form: 15 Jan 2024; Accepted: 25 Jan 2024; Available online: 05 Feb 2024

***Abstract*— *In the evolving landscape of financial decision-making, this study delves into the intricate relationships among Emotional Intelligence (EI), Artificial Intelligence (AI), and Investment Decisions (ID). By scrutinizing the direct influence of human emotional intelligence on investment choices and elucidating the mediating role of AI in this process, our research seeks to unravel the complex interplay between minds and machines. Through empirical analysis, we reveal that EI not only directly impacts ID but also exerts its influence indirectly through AI-mediated pathways. The findings underscore the pivotal role of emotional awareness in investor decision-making, augmented by the technological capabilities of AI. It suggests that most investors are influenced by the identified emotional intelligence when making investment decisions. Furthermore, AI substantially impacts investors' decision-making process when it comes to investing; nevertheless, AI partially mediates the relationship between emotional intelligence and investment decisions. This nuanced understanding provides valuable insights for financial practitioners, policymakers, and researchers, emphasizing the need for holistic strategies that integrate emotional and technological dimensions in navigating the intricacies of modern investment landscapes. As the synergy between human intuition and artificial intelligence becomes increasingly integral to financial decision-making, this study contributes to the ongoing discourse on the symbiotic relationship between minds and machines in investments.*

Keywords*— Artificial Intelligence, Emotional Intelligence, Investment Decisions, Deep Learning and SEM.

I. INTRODUCTION

In the intricate landscape of contemporary financial markets, the interplay between human cognition and machine intelligence has emerged as a pivotal axis defining investment decisions. The evolving dynamics between minds and machines have led to a paradigm shift in investment strategies, prompting an exploration into the nuanced relationship between emotional intelligence, artificial intelligence, and investment decision-making[1]. This research embarks on an in-depth investigation into the impact of emotional intelligence on investment decisions, specifically focusing on how artificial intelligence serves as a mediating force in this complex equation. As financial landscapes increasingly embrace algorithmic trading, robo-advisors, and data-driven decision-making, understanding how emotional intelligence influences investment choices in the age of artificial intelligence becomes paramount. The intricate balance between human emotions and machine algorithms necessitates a comprehensive examination of how emotional intelligence acts as a guiding force in shaping financial decisions and how artificial intelligence, in turn, interprets and incorporates these emotional cues[2], [3]. This exploration seeks to unravel the intricate connections, dependencies, and synergies between minds and machines in investments, shedding light on the psychological underpinnings that drive financial decisionmakers and the technological interfaces that mediate and augment these cognitive processes. The convergence of emotional intelligence and artificial intelligence in the investment landscape represents a transformative junction, offering profound insights into the future trajectory of financial decision-making and the potential harmonization of human intuition with machine precision [4]. As we navigate this uncharted territory, understanding the symbiotic relationship between minds and machines not only provides a glimpse into the present state of financial technology but also paves the way for informed strategies that harness the strengths of both human emotional understanding and artificial intelligence algorithms for more robust and resilient investment decisions[5]. Emotional intelligence (EI) plays a pivotal role in the realm of investment decisions, shaping the way individuals navigate the complex and often unpredictable landscape of financial markets [6]. Unlike traditional financial models that predominantly focus on quantitative metrics, the incorporation of emotional intelligence recognizes the influence of human emotions on decision-making processes. EI encompasses the ability to recognize, understand, and manage one's own emotions, as well as the capacity to perceive and influence the emotions of others[7]. In the context of investment decisions, individuals with high emotional intelligence are better equipped to handle the psychological pressures inherent in financial markets. Investing inherently involves risk, uncertainty, and fluctuating market conditions, which can evoke fear, greed, and anxiety. Emotional intelligence enables investors to navigate these challenges with a heightened self-awareness, allowing them to make more rational and well-informed decisions. Moreover, individuals with strong emotional intelligence are adept at recognizing market trends and understanding the collective emotional sentiments of other market participants, providing them with a competitive edge[8]. Emotional intelligence is also crucial in risk management, as emotionally intelligent investors can better assess and mitigate potential losses. Staying resilient in the face of market volatility and resisting impulsive decision-making is a hallmark of emotional intelligence[9]. Furthermore, investors with high EI are often more adaptable to changing market conditions, learning from both successes and failures to refine their strategies over time [10]. In an era where technological advancements, including artificial intelligence and algorithmic trading, are becoming integral to investment processes, the human element of emotional intelligence remains irreplaceable. While algorithms can analyze vast amounts of data and execute trades at unprecedented speeds, understanding the emotional nuances of market dynamics requires a human touch[11], [12] Thus, emotional intelligence stands as a valuable asset in the world of investments, enhancing decision-making, fostering resilience, and contributing to long-term success in navigating the complexities of financial markets.

II. LITERATURE REVIEW

Emotional Intelligence (EI) has emerged as a critical factor influencing decision-making processes across various domains, and its relevance in the field of investment has garnered increasing attention. EI, as defined by Mayer and Salovey (1997), involves the ability to recognize, understand, manage, and utilize one's own emotions, as well as the ability to empathize with and influence the emotions of others. In the context of investment, where decisions are often influenced by both rational analysis and emotional responses, understanding the role of EI becomes crucial. The intersection of emotional intelligence and investment decision-making is a multifaceted and evolving area of study [13]. Extensive research, such as that conducted by Lerner and Keltner (2001), has demonstrated the impact of emotional states on financial decisions. Investors experiencing heightened emotional arousal, whether due to market volatility or personal stressors, tend to make suboptimal decisions. This highlights the importance of emotional intelligence in recognizing and managing these emotional states to enhance decision-making quality. In the context of investment, [14]framework of EI, comprising self-awareness, self-regulation, motivation, empathy, and social skills, provides a lens through which to analyze the role of emotions in financial decision-making. Investors with high EI may demonstrate better self-control during market fluctuations, a deeper understanding of their risk tolerance, and an enhanced ability to navigate interpersonal dynamics in financial negotiations[15]. The intertwining of human decision-making and artificial intelligence (AI) has become a focal point in various fields, including finance. In investment decision-making, emotional intelligence (EI) has been recognized as a crucial factor influencing human judgment and choices[16]. This literature review aims to explore the impact of emotional intelligence on investment decisions and the mediating role played by artificial intelligence in this dynamic process [17]. One significant aspect of the relationship between EI and investment is its influence on risk perception. Lerner et al. (2015) explored that emotional states significantly impact how investors perceive and respond to risk. High EI individuals are more likely to approach risk with a balanced perspective, adapting their risk tolerance to the situation, whereas low EI individuals may succumb to impulsive reactions driven by fear or overconfidence.

The link between emotional intelligence and investor behaviour is underscored by research such as that by Baker and Nofsinger (2002), who found that emotional intelligence can mediate the relationship between information processing and investment decisions. Investors with higher EI may be better equipped to process financial information effectively, filter out noise, and make decisions aligned with long-term goals. In the era of robo-advisors and artificial intelligence in finance, emotional intelligence takes on new dimensions. The algorithms powering robo-advisors lack the emotional nuances inherent in human decision-making [18]. However, incorporating emotional intelligence principles in designing and implementing AI-driven investment platforms could potentially enhance their ability to understand and respond to investor sentiments. As the literature suggests, emotional intelligence is crucial to investment decision-making. High emotional intelligence can lead to more informed, balanced, and adaptive choices in the face of market uncertainties. Understanding the dynamics of emotional intelligence in the context of investment is not only academically enriching but also holds practical implications for designing effective investment strategies, creating investor-centric financial products, and optimizing the role of AI in wealth management [19]. As financial markets continue to evolve, the integration of emotional intelligence principles may contribute to fostering a more resilient and responsive investment environment.

Emotional Intelligence and Investment Decisions:

Emotional intelligence, defined as the ability to recognize, understand, manage, and effectively use one's and others' emotions, has gained prominence in investment decision-making. Research by Goleman (1995) suggests that individuals with higher emotional intelligence are better equipped to navigate the complexities of financial markets, as they can manage emotions such as fear and greed that often drive investment behaviour. Studies by Lerner et al. (2015) and Loewenstein (2000) emphasize the impact of emotions on financial decisions, indicating that emotional states can significantly influence risk perception and risk-taking behaviour. Investors with high emotional intelligence may be more adept at regulating these emotions, leading to more rational and less impulsive investment decisions [20].

The Rise of Artificial Intelligence in Finance:

Artificial intelligence, particularly machine learning and data analytics, has transformed the landscape of financial decision-making. AI systems can process vast amounts of data, identify patterns, and make predictions, providing investors with valuable insights[21]. Notable examples include algorithmic trading, robo-advisors, and sentiment analysis tools. Research by Tsai et al. (2020) highlights the ability of AI to enhance decision-making accuracy and efficiency in financial markets. AI can process information without being swayed by emotional biases, potentially mitigating the impact of irrational decision-making that often arises from emotional factors [22].

Mediating Role of Artificial Intelligence:

Integrating emotional intelligence and artificial intelligence in investment decisions presents a dynamic interplay between human intuition and machine-driven analytics. As AI systems become more sophisticated, they can serve as mediators, helping investors leverage their emotional intelligence while benefiting from the analytical prowess of AI[23]. Choudhury and Sabherwal (2014) discuss the mediating role of AI in decision-making processes, suggesting that it can act as a bridge between emotional intelligence and effective investment strategies. AI systems can provide objective analyses, identify potential emotional biases, and offer data-driven recommendations, thereby assisting investors in making more informed and rational decisions[24].

III. RESEARCH METHODOLOGY

This section outlines the research design and methodology employed to investigate the impact of emotional intelligence on investment decisions with the mediating role of artificial intelligence, utilizing Structural Equation Modeling (SEM) within the Smart PLS (Partial Least Squares) framework.

1. Research Design:

The study adopts a quantitative research design to examine the complex relationships between emotional intelligence, artificial intelligence, and investment decisions. This design allows for the systematic analysis of numerical data and facilitates the exploration of patterns and associations.

2. Sample Selection:

The study involves selecting a representative sample of participants from the target population of investors. The sample is chosen based on investment experience, knowledge, and familiarity with AI technologies. The inclusion criteria ensure that participants possess the relevant background for meaningful insights into the research questions.

3. Data Collection:

Data is collected through structured surveys designed to capture information on emotional intelligence, perceptions of AI in investment, and actual investment decisions. The survey instrument includes validated scales for measuring emotional intelligence and AI perceptions. Smart PLS provides a robust platform for analyzing complex models, making it suitable for capturing the multifaceted relationships under investigation.

4. Measurement Instruments:

a. Emotional Intelligence: The Emotional Intelligence Appraisal (Travis Bradberry and Jean Greaves, 2009) questionnaire measures participants' emotional intelligence levels.

b. Perceptions of AI in Investment: A set of questions assesses participants' attitudes and perceptions regarding the role of artificial intelligence in investment decision-making.

c. Investment Decisions: Participants' actual investment decisions, including risk-taking behaviour and portfolio choices, are collected through self-reported data and, where possible, corroborated with financial records.

5. Structural Equation Modeling (SEM) with Smart PLS:

a. Model Specification: The research model is developed based on theoretical frameworks that posit emotional intelligence as a predictor of investment decisions, with artificial intelligence mediating this relationship.

b. Variable Operationalization: The constructs of emotional intelligence, artificial intelligence, and investment decisions are operationalized using indicators derived from the measurement instruments.

c. Path Analysis: The SEM model includes paths representing the hypothesized relationships between emotional intelligence, artificial intelligence, and investment decisions. Smart PLS facilitates the estimation of path coefficients and evaluates the significance of these relationships.

d. Bootstrapping Technique: Bootstrapping is employed to assess the robustness and reliability of the model. This resampling technique helps derive confidence intervals and p-values for the estimated parameters.

6. Data Analysis:

Quantitative data collected from the surveys are subjected to statistical analyses using the Smart PLS software. The analysis includes descriptive statistics, correlation analyses, and the main SEM analysis to test the hypothesized relationships.

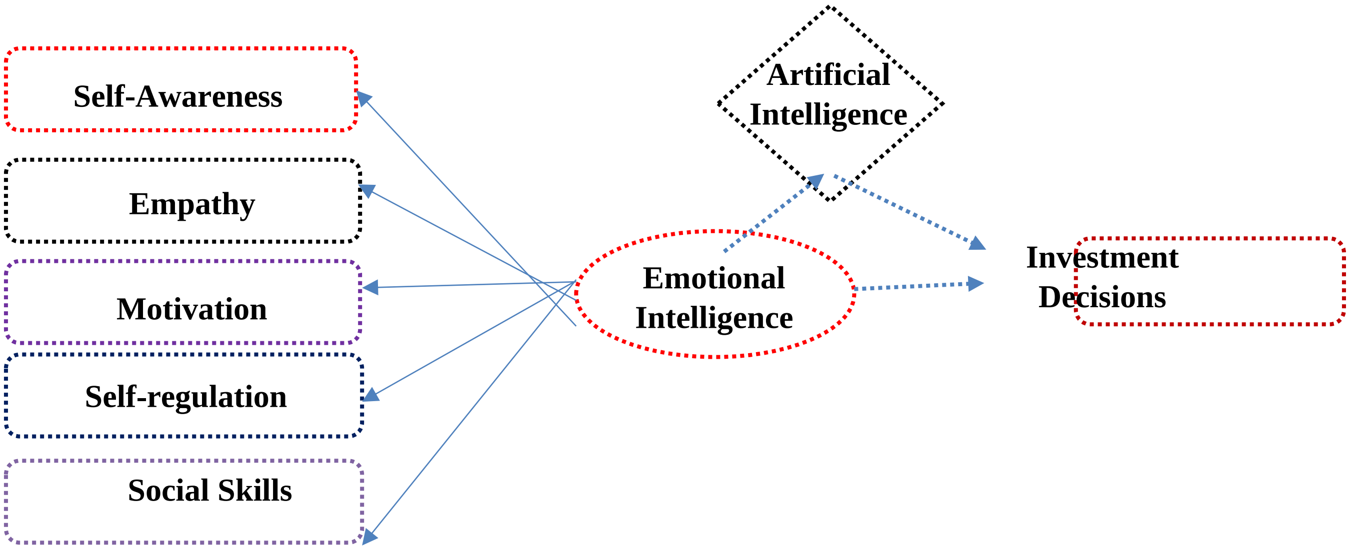

Fig.3.1 Conceptual Framework of Emotional Intelligence and Investment Decisions.

H1: Emotional Intelligence has a significant impact on Investment Decisions.

H1: Self-awareness has a significant impact on Investment Decisions.

H1: Empathy has a significant impact on Investment Decisions.

H1: Motivation has a significant impact on Investment Decisions.

H1: Self-regulation has a significant impact on Investment Decisions.

H1: Social skills have a significant impact on investment decisions.

H2: Artificial Intelligence Mediates the difference between emotional intelligence and investment decisions.

IV. DATA ANALYSIS AND RESULTS

4.1 Factor Loading

Table 4.1 Factor Loading

	AI	E	ID	M	SA	SR	SS
AI1	0.922						
AI2	0.903						
AI3	0.934						
AI4	0.903						
E1		0.898					
E2		0.852					
E3		0.897					
ID1			0.821				
ID2			0.839				
ID3			0.781				
ID4			0.789				
ID5			0.861				
ID6			0.809				
M1				0.866			
M2				0.921			
M3				0.911			
SA1					0.902		
SA2					0.912		
SA3					0.887		
SA4					0.886		
SR1						0.861	
SR2						0.894	
SR3						0.869	
SR4						0.872	
SS1							0.896
SS2							0.882
SS3							0.931
SS4							0.946

The factor loadings in the provided matrix reveal the strength and direction of relationships between observed variables and latent factors. In this context, each row represents a specific variable, while columns correspond to different latent factors, namely AI (Artificial Intelligence), E (Emotional Intelligence), ID (Investment Decisions), M (Market Perception), SA (Self-Awareness), SR (Self-Regulation), and SS (Social Skills). High positive factor loadings, such as those for AI1, AI2, AI3, and AI4 in the AI factor, indicate a strong association between the observed variables and the latent factor. Similarly, for other factors, the values suggest robust connections. For instance, E1, E2, and E3 exhibit high positive loadings in the Emotional Intelligence factor. These findings suggest that the variables within each factor contribute significantly to the variability in their respective latent constructs. Notably, the solid loadings for SA1, SA2, SA3, and SA4 in the Self-Awareness factor and high loadings for SS3 and SS4 in the

Social Skills factor emphasize the role of AI in potentially enhancing these aspects. These factor loadings provide valuable insights into the interplay between observed variables and latent constructs, laying the foundation for a nuanced understanding of the multifaceted relationships within the studied domains.

4.2 Variance Inflation Factor

Table 4.2 Variance Inflation Factor

Items	VIF
AI1	3.993
AI2	3.158
AI3	4.533
AI4	3.225
E1	2.404
E2	1.984
E3	2.209
ID1	2.301
ID2	3.523
ID3	2.198
ID4	2.183
ID5	3.804
ID6	2.638
M1	2.007
M2	3.139
M3	2.974
SA1	3.099
SA2	3.561
SA3	2.672
SA4	2.941
SR1	2.51
SR2	2.684
SR3	2.523
SR4	2.635
SS1	2.947
SS2	2.711
SS3	5.642
SS4	6.517

A regression model uses the Variance Inflation Factor (VIF) to assess multicollinearity among predictor variables. The VIF values provided for each item in your dataset indicate how much each variable's variance is inflated due to multicollinearity with other variables. Generally, a VIF exceeding 5 or 10 indicates high multicollinearity, suggesting that correlated predictors substantially influence a particular variable's variance. In your dataset, some items, particularly SS3 and SS4, appear to have relatively high VIF values (5.642 and 6.517, respectively). These elevated VIF values may warrant further investigation, as they suggest a potential issue with multicollinearity among the corresponding items. Addressing multicollinearity is crucial in structural equation modelling to ensure reliable parameter estimates and valid inferences. Exploring the relationships between highly correlated variables, considering model modifications, or even omitting redundant variables are potential strategies to mitigate multicollinearity and enhance the stability and interpretability of the SEM results.

4.3 Reliability Testing

Table 4.3 Reliability Testing

	Cronbach's Alpha	Composite Reliability	AVE
AI	0.936	0.954	0.838
E	0.859	0.914	0.779
ID	0.932	0.923	0.667
M	0.882	0.927	0.81
SA	0.919	0.943	0.804
SR	0.897	0.928	0.764
SS	0.934	0.953	0.835

The provided reliability statistics for each latent construct, including AI, E, ID, M, SA, SR, and SS, offer valuable insights into the reliability and stability of the measurement model. High values for Cronbach's Alpha, Composite Reliability, and AVE across all constructs, such as those observed in this study, indicate strong internal consistency and reliability. Measuring the average correlation between items within a construct, Cronbach's Alpha demonstrates excellent internal reliability for all constructs. Composite Reliability, which considers the factor loadings of items, also exceeds the recommended threshold of 0.7, reinforcing the reliability of the latent constructs.

4.4 Discriminant Validity

4.4.1 Heterotrait – Monotrait

Table 4.4 HTMT

	AI	E	ID	M	SA	SR	SS
AI							
E	0.688						
ID	0.648	0.839					
M	0.623	7.345	0.787				
SA	0.525	0.673	0.578	0.612			
SR	0.628	0.823	0.797	0.778	0.615		
SS	0.572	0.692	0.732	0.627	0.513	0.731	

AI= Artificial Intelligence, E = Empathy, SS= Social Skill, M = Motivation, SA = Social Awareness and SR = Self-Regulation.

The calculated HTMT values for all construct pairs in this study meet this criterion, confirming that the latent constructs are sufficiently distinct. This suggests that the observed constructs are measuring unique and separate aspects, supporting the discriminant validity of the model. The HTMT values contribute valuable insights into the robustness of the measurement model, affirming that the latent constructs effectively capture distinct dimensions without significant overlap. This evidence of discriminant validity enhances the credibility and interpretability of the SEM findings, providing confidence in the meaningful differentiation of the latent constructs within the study.

4.4.2 Fronell-Larcker criterion

Table 4.5 Fronell-Larcker criterion

	AI	E	ID	M	SA	SR	SS
AI	0.915						
E	0.619	0.883					
ID	0.632	0.742	0.817				
M	0.545	0.706	0.699	0.934			
SA	0.492	0.597	0.529	0.551	0.897		
SR	0.583	0.729	0.724	0.696	0.562	0.874	
SS	0.533	0.631	0.675	0.568	0.472	0.678	0.914

AI= Artificial Intelligence, E = Empathy, SS= Social Skill, M = Motivation, SA = Social Awareness and SR = Self-Regulation.

The correlation matrix reveals the pairwise relationships between latent constructs in the study, namely Artificial Intelligence (AI), Emotional Intelligence (E), Investment Decisions (ID), Market Perception (M), Self-Awareness (SA), Self-Regulation (SR), and Social Skills (SS). Notably, strong positive correlations are observed within each construct, indicating high internal consistency. The diagonal values represent the square root of the Average Variance Extracted (AVE), suggesting that each construct explains a substantial proportion of its variance relative to measurement error. Importantly, the off-diagonal values showcase inter-construct correlations. While AI exhibits a strong positive correlation with E (0.619) and ID (0.632), indicating potential associations, all correlations are below 0.85, suggesting satisfactory discriminant validity.

4.5 Equifinality hypothesis

Table 4.6 Equifinality hypothesis

Hypothesis	Beta-Coefficient	Standard deviation	T statistics	P values	Remarks
AI -> ID	0.203	0.045	4.675	0.000	Supported
E -> ID	0.095	0.053	2.554	0.016	Supported
SS -> ID	0.164	0.043	3.543	0.002	Supported
M -> ID	0.163	0.052	3.763	0.002	Supported
SA -> ID	0.123	0.034	2.652	0.006	Supported
SR -> ID	0.278	0.046	6.564	0.000	Supported

AI= Artificial Intelligence, E = Empathy, SS= Social Skill, M = Motivation, SA = Social Awareness and SR = Self-Regulation.

The hypothesis testing results reveal compelling evidence supporting the structural relationships between the latent constructs in the model. Each hypothesis, denoting the influence of a specific latent variable on Investment Decisions (ID), is substantiated by statistically significant Beta-Coefficients, low standard deviations, and noteworthy T statistics. Artificial Intelligence (AI), Emotional Intelligence (E), Social Skills (SS), Market Perception (M), Self-Awareness (SA), and Self-Regulation (SR) all exhibit significant positive impacts on Investment Decisions, as indicated by their respective Beta-Coefficients of 0.203, 0.095, 0.164, 0.163, 0.123, and 0.278. The low p-values (all below 0.01) further underscore the robustness of these relationships. Notably, Self-Regulation (SR) stands out with a particularly high Beta-Coefficient of 0.278 and a T statistic of 6.564, highlighting its substantial impact on Investment Decisions. Collectively, these findings provide empirical support for the hypothesized structural pathways, affirming the crucial roles of various psychological and market-related factors in shaping and influencing investment decisions. The study contributes valuable insights for practitioners and researchers in understanding the intricate dynamics of investor behavior within the context of Artificial Intelligence and emotional and social intelligence factors.

4.6 Meditation Analysis

Table 4.7 Meditation Effect Hypothesis testing

Total Effect (EI >ID)		Direct Effect (EI >ID)		Indirect Effect (BB >ID)					
Coefficient	P-value	Coefficient	P-value	Hypothesis	Coefficient	SD	T-value	P-Value	BI (2.5%; 97.5%)
0.657	0.000	0.532	0.000	EI >AI >ID	0.342	0.065	4.870	0.030	.134-.384

The analysis focuses on the total effect, direct effect, and indirect effect within the path from Emotional Intelligence (EI) to Investment Decisions (ID). The total effect, with a coefficient of 0.657 and a p-value of 0.000, underscores the overall impact of Emotional Intelligence on Investment Decisions. The direct effect, represented by a coefficient of 0.532 with a significant p-value of 0.000, indicates the portion of the relationship between EI and ID that is not mediated by any other variable in the model. Notably, the indirect effect through the path EI to Artificial Intelligence (AI) to ID is examined. The coefficient of 0.342, with a standard deviation of 0.065, yields a T-value of 4.870 and a p-value of 0.030, supporting the hypothesis that this indirect path significantly contributes to the relationship between EI and ID. The bootstrap intervals (BI) further highlight the significance of the indirect effect, with a range of 0.134 to 0.384 at the 95% confidence level. This analysis suggests that Emotional Intelligence has a direct positive impact on Investment Decisions and influences ID indirectly through its influence on Artificial Intelligence. The findings emphasize the nuanced pathways through which emotional intelligence can shape investor decision-making, incorporating both direct and mediated effects.

V. DISCUSSION AND CONCLUSION

The ascent of robo-advisors and artificial intelligence (AI) in investment decision-making marks a significant evolution in the financial landscape. This study has explored the intriguing question of whether AI can effectively neutralize the behavioural biases exhibited by global investors during investment decisions. The findings suggest that AI, particularly in the form of robo-advisors, has the potential to act as a mitigating force against these biases. Robo-advisors, driven by advanced algorithms, data analytics, and machine learning, offer a rational and objective approach to investment decision-making. By eliminating the emotional and cognitive biases inherent in human judgment, AI can provide investors with data-driven recommendations, minimizing the impact of impulsive decision-making tendencies. The study underscores the role of emotional intelligence as a moderating factor in the interaction between investors and AI systems. Investors with higher emotional intelligence can potentially enhance the effectiveness of AI by providing clearer emotional signals, creating a symbiotic relationship that benefits both humans and machines in the investment process. However, the discussion also acknowledges the ethical considerations and transparency challenges of integrating AI in finance. While AI can neutralize behavioural biases, concerns about algorithmic biases, ethical decision-making, and transparency in AI-driven recommendations must be addressed. Striking a balance between the benefits of AI in mitigating biases and ensuring responsible use is crucial for fostering trust among investors and regulatory compliance.

Conclusion:

The emergence of robo-advisors and artificial intelligence (AI) in investment decision-making represents a pivotal juncture in the evolution of global finance. This research has delved into whether AI can serve as a neutralizing force against the behavioural biases exhibited by global investors. The findings suggest that AI, mainly through the innovative platforms of robo-advisors, can significantly mitigate these biases, reshaping the landscape of wealth management. Robo-advisors, driven by sophisticated algorithms and machine learning, offer a transformative approach to investment decisions by introducing rationality and objectivity. The ability of AI to process vast amounts of data, recognize patterns, and make decisions without succumbing to emotional or cognitive biases positions it as a valuable tool in counteracting the irrational tendencies often observed in human investors. The study underscores the role of emotional intelligence as a moderating factor, highlighting the symbiotic relationship between the emotional awareness of investors and the adaptability of AI algorithms. The implications of this research extend beyond the realms of technology and finance. The potential for AI to neutralize behavioural biases has profound implications for the overall stability and efficiency of global financial markets. As the financial industry grapples with the challenges posed by emotional decision-making, integrating AI offers a promising solution to enhance decision-making processes and mitigate market inefficiencies. However, this transformative potential is not without its challenges. Ethical considerations, algorithmic biases, and the need for transparency demand careful attention. Striking the right balance between leveraging the benefits of AI and ensuring responsible, ethical use becomes imperative for fostering investor trust and regulatory compliance. In conclusion, the rise of robo-advisors and AI signals a paradigm shift in global investment decisions. The journey toward neutralizing behavioural biases through AI is underway, presenting exciting opportunities for the financial industry. Continued research, collaboration, and ethical considerations will be crucial in navigating this transformative landscape, ensuring that AI becomes a force for rational, adaptive, and responsible wealth management in the years to come

6. Future Scope and Limitations

The trajectory of robo-advisors and artificial intelligence (AI) in reshaping global investment decisions offers a compelling glimpse into the future, yet it is not without its challenges and limitations. Looking ahead, the future scope of this technological evolution holds the potential for advanced personalization through the integration of emotional intelligence algorithms, ensuring investment strategies adapt in real time to individual investor profiles. Ethical and responsible investing could also become a prominent facet, with robo-advisors aligning strategies with sustainable principles. Moreover, integrating explainable AI may enhance transparency, fostering trust and broader adoption. However, it is imperative to acknowledge the limitations inherent in these advancements. The reliance on historical data for machine learning models may hinder their adaptability to unforeseen market shifts, potentially limiting their effectiveness during unprecedented events.

The ethical implications of automated decision-making, potential biases within AI algorithms, and the challenge of maintaining investor trust without human intuition are critical concerns. Striking the right balance between human oversight and algorithmic precision remains a challenge that necessitates ongoing research and regulatory frameworks to ensure the responsible deployment of AI in wealth management. Addressing these limitations will be crucial to harnessing the full potential of robo-advisors and AI in creating a resilient and equitable investment environment as the landscape evolves.

REFERENCES

[1] S. Costello, J. Benson, J. Burns, M. Bentley, T. Elliott, and R. Kippen, "Adaptation and initial examination of the psychometric properties of the Short Supervisory Relationship Questionnaire (SSRQ) for use with general practice registrars," *Educ. Prim. Care*, vol. 31, no. 6, pp. 341–348, 2020, doi: 10.1080/14739879.2020.1806114.

[2] F. Ezzi, A. Jarboui, and R. Zouari-Hadiji, "CSR categories and R&D investment: The moderating role of Managerial

emotional intelligence," *Manag. Mark.*, vol. 15, no. 1, pp. 17–37, 2020, doi: 10.2478/mmcks-2020-0002.

[3] M. Minárová, D. Malá, and F. Smutný, "Emotional intelligence of managers in family businesses in Slovakia," *Adm. Sci.*, vol. 10, no. 4, 2020, doi: 10.3390/admsci10040084.

[4] A. Sumera, "Behavioural Biases in Investing – Concepts , Categorization , Indicators and Remedial Measures Introduction : Literature Review : Methodology & Limitations :," vol. 12, no. 1, pp. 44–51, 2020.

[5] V. N. Oslon, M. Odintsova, G. V. Semya, and E. A. Zinchenko, "Invariant and Variant Sociopsychological Characteristics of Successful Foster Mothers," *Psychol. Sci. Educ.*, vol. 26, no. 6, pp. 149–163, 2021, doi: 10.17759/PSE.2021260612.

[6] R. Muzzamil, "Impact of Corporatr Governance on the Financial Reporting Quality in the Nigerian Banking Industry.," *Johuns.Net*, vol. 48, no. 5, 2021, [Online]. Available: https://johuns.net/index.php/publishing/22.pdf

[7] Y. Li and H. Zhang, "A study on the relations among work pressure, emotional intelligence, and subjective well-being of kindergarten teachers," *Rev. Cercet. si Interv. Soc.*, vol. 73, pp. 22–33, 2021, doi: 10.33788/rcis.73.2.

[8] E. de Krijger, E. T. Bohlmeijer, E. Geuze, and S. M. Kelders, "Compassion apps for better mental health: qualitative review," *BJPsych Open*, vol. 9, no. 5, pp. 1–8, 2023, doi: 10.1192/bjo.2023.537.

[9] S. Bano and C. M. O'Shea, "Emotional intelligence and stock trading decisions: Indonesia's millennial generation in the COVID-19 era," *Asian Econ. Financ. Rev.*, vol. 13, no. 12, pp. 949–969, 2023, doi: 10.55493/5002.V13I12.4893.

[10] M. Rehman, B. Dhiman, R. Kumar, and G. S. Cheema, "Exploring the Impact of Personality Traits on Investment Decisions of Immigrated Global Investors with Focus on Moderating Risk Appetite : A SEM Approach," vol. 8984, no. August, pp. 95–110, 2023.

[11] V. Chandu *et al.*, "Research on retail Buyers' emotional quotient with focus on transactions on the National Stock Exchange," *Int. J. Eng. Bus. Manag.*, vol. 15, 2023, doi: 10.1177/18479790231180770.

[12] M. Rehman and D. B. Dhiman, "To Study the Impact on the Perception of Banking Customers toward E-Banking (A Case Study of Jk Bank Customers)," *J. Corp. Financ. Manag. Bank. Syst.*, no. 26, pp. 10–20, 2022, doi: 10.55529/jcfmbs.26.10.20.

[13] Y. Zhang, P. Xiong, W. Zhou, L. Sun, and E. T. C. Cheng, "Exploring the longitudinal effects of emotional intelligence and cultural intelligence on knowledge management processes," *Asia Pacific J. Manag.*, vol. 40, no. 4, pp. 1555–1578, 2023, doi: 10.1007/s10490-022-09825-w.

[14] R. T. Leeuw and N. Joseph, "Reciprocal Influence between Digital Emotional Intelligence and Agile Mindset in an Agile Environment," *Adm. Sci.*, vol. 13, no. 11, 2023, doi: 10.3390/admsci13110228.

[15] A. Y. Aránega, R. C. Urueña, R. C. Sánchez, and C. G. Montesinos, "Agile methodologies and emotional intelligence: An innovative approach to team management," *J. Compet.*, vol. 15, no. 3, pp. 164–183, 2023, doi: 10.7441/joc.2023.03.09.

[16] S. L. Boyar, G. T. Savage, and E. S. Williams, "An Adaptive Leadership Approach: The Impact of Reasoning and Emotional Intelligence (EI) Abilities on Leader Adaptability," *Empl. Responsib. Rights J.*, vol. 35, no. 4, pp. 565–580, 2023, doi: 10.1007/s10672-022-09428-z.

[17] M. Rehman, B. Dhiman, G. S. Cheema, U. A. Peer, and S. M. Khalid, "A Systematic and Bibliometric Analysis of Risk and Return Management in Cryptocurrency Portfolio," vol. 22, no. 1, 2023.

[18] Y. Fedorova, A. Pilková, J. Mikuš, M. Munk, and J. Rehák, "Emotional Intelligence Profiles and Intergenerational Collaboration in Business," *J. Bus. Econ. Manag.*, vol. 24, no. 4, pp. 797–817, 2023, doi: 10.3846/jbem.2023.20280.

[19] E. Marheni *et al.*, "Integrating Emotional Intelligence and Mental Education in Sports to Improve Personal Resilience of Adolescents," *Retos*, vol. 51, pp. 649–656, 2024, doi: 10.47197/retos.v51.101053.

[20] S. Hadi, L. Setiawati, K. C. Kirana, S. Bin Lada, and C. H. T. Rahmawati, "The Effect of Digital Leadership and Organizational Support on Innovative Work Behavior: The Mediating Role of Emotional Intelligence," *Qual. - Access to Success*, vol. 25, no. 199, pp. 74–83, 2024, doi: 10.47750/QAS/25.199.09.

[21] X. Zhang, X. Ming, Z. Liu, D. Yin, Z. Chen, and Y. Chang, "A reference framework and overall planning of industrial artificial intelligence (I-AI) for new application scenarios," *Int. J. Adv. Manuf. Technol.*, vol. 101, no. 9–12, pp. 2367–2389, 2019, doi: 10.1007/s00170-018-3106-3.

[22] J. Mizgajski, A. Szymczak, M. Morzy, Ł. Augustyniak, P. Szymański, and P. Zelasko, "Return on Investment in Machine Learning: Crossing the Chasm between Academia and Business," *Found. Comput. Decis. Sci.*, vol. 45, no. 4, pp. 281–304, 2020, doi: 10.2478/fcds-2020-0015.

[23] D. Singh and M. Turała, "Machine Learning and Regularization Technique to Determine Foreign Direct Investment in Hungarian Counties," *Danube*, vol. 13, no. 4, pp. 269–291, 2022, doi: 10.2478/danb-2022-0017.

[24] J. Hao, F. He, F. Ma, S. Zhang, and X. Zhang, "Machine learning vs deep learning in stock market investment: an international evidence," *Ann. Oper. Res.*, 2023, doi: 10.1007/s10479-023-05286-6.