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Sentiment and Strategy: An Empirical Analysis of AI Adoption in Financial and Investment Decision-Making Toward Sustainable Growth

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ABSTRACT

Purpose:The study endeavors to investigate the role of Artificial Intelligence (AI) usage in financial and investment decision-making with an aim for promoting sustainable growth in emerging economies, investors' sentiments being the moderating function.

Design/methodology/approach:Taking the basis of the Technology Acceptance Model (TAM) and behavioral finance theory, the study attempts to create an integrated framework for analyzing the assistance of AI in financial and investment settings. The study collected primary data from 350 individual investors in India. Said relationship has been tested using Structural Equation Modelling.

Findings: Following the analyses proposed above it is found that, variables which significantly the intention to adopt AI are perceived utility, simplicity of use, trust in AI systems, and data-driven culture. AI adoption affects positively on sustainable financial and investment decision quality. Investor sentiment toward sustainability significantly moderates this relationship, which strengthens AI's impact on long-term outcomes.

Practical implications: The results may provide fruitful insights for banks, fintech firms, and policymakers with an aim to promote responsible AI adoption by enhancing AI literacy, digital infrastructure, and governance frameworks.

Originality/value: This study offers evidence from an emerging economy and extends technology adoption and behavioral finance literature by highlighting the moderating role of investor sentiment in AI-driven sustainable finance

Keywords: Artificial intelligence; investor sentiment; sustainable finance; investment decision-making; technology adoption; emerging economies

INTRODUCTION:

Artificial intelligence (AI) states computational processes or system capable to perform those tasks which traditionally necessitate intelligence of humans which includes pattern recognition, learning from data, decision support prediction and decision-making ability[1]. Recent advancements in big data analytics, natural language processing, and advanced machine learning have made it possible for AI to integrate real-time, data-driven intelligence with the conventional system of financial decision-making.[2]. Even though there is not any single globally acceptable definition of AI, the previous studies approximately and broadly conceptualized it as a set of knowledge and technologies that allow machines to simulate human intellectual purposes and managerial augment and investment decisions. The prompt development of Artificial Intelligence has been transformed into how this information has been processed and developed in composite financial environments [3].

While the AI foundations year back to the mid of twentieth century which is the large-scale commercial and profitable positioning has enhanced only through the recent years due to the Quarter Industrial Revolution and the developing transition toward Industry 5.0, alongside extensive digital revolution across sectors. In the financial domain, AI submissions and its applications such as algorithmic trading, robo-advisory service, scoring through automated credit, detection of frauds and modified financial products which are progressively adopted by firms managing assets, banks and fintech organizations [4]. Financial institutions which are investing heavy funds in AI-processing decision-support systems to increase the efficiency of operations decrease the information asymmetry and improve the speed and quality of investment and financial decision-making using real-time, data-driven intelligence [5].

The increasing importance of AI in finance is also entangled with the universal importance on sustainable financial growth and responsible fund investment practices [6]. Sustainable financial decision encourages the incorporation of conservational, societal and governance considerations into decision making in the field of finance to support a long-term value conception slightly than gain in the short-term speculations [7]. AI-based analysis can support a sustainable investment decision by enlightening and improving ESG data processing, forecasting and risk assessment, especially for the impact of quantity thereby permitting additional information and for responsible capital allocation. Industrial reports have suggested that a rising quantity of financial services institutions are probably to rely on the system of AI-driven processes for managing the portfolio and assessments of the risk in the near future, representing structural modification in the preparation of investment decision makings [1][8].

In spite of the technical promises of AI, financial decision-making remains intensely predisposed by human decisions and judgements with the different behavioral factors. Behavioral financial literature establishes that investor's behavior which has been shaped by psychosomatic biases, emotional factors and sentiments of the financial market, often prominent to the systematic deviations from completely balanced decision-making process [2][8][9]. Investor's sentiments reflecting the overall optimistic decision or negativity concerning market conditions and prospects plays a very crucial role for shaping risk inclinations, choices for investment portfolios and investment prospects. Even when the system of AI has provided the objective, data-driven recommendations, investors, financial specialists interpret and also act on these understandings through their own confidence levels politics and emotional states, hypothetically increasing or weakening the efficiency of the support system of AI-enabled decisions [10].

Developing economies such as Asian countries like India provide a special and relevant context for examining the AI implementation in financial and speculation decision-making [11]. Rapid digitalization and the development of the ecosystem of fintech and which is rising retail investors who have participation accelerated the dissemination of AI-based financial tools and techniques to these markets. However, emerging markets and economies are also facing challenges which are related to digital literacy; belief in algorithm systems, uncertainty regulatory system, and unsatisfactory admittance to advanced and progressive technologies, all of these can shape both the adoptions and operational utilization of AI in financial decision making. While existing studies have explored AI adoption in banking and fintech contexts, empirical evidence on its role in promoting sustainable financial and investment decision-making in emerging economies remains limited [12].

In order to fill this gap, the current study developed an integrated framework to analyze the adoption of AI and its outcomes using the TAM and the theory of behavioral finance.[13]. Specifically, the study looks at how perceived utility, usability, and trust in AI processing systems and a data-driven cultured influence AI adoption and how the sentiments of the investor toward sustainability controls a connection between the adoption of AI system, financial sustainability and fund investment decision-making [14]. By concentrating on India as a demonstrative and representative of the AI emerging market, this research gives to the literature on responsible adoption of AI in financial system and also offers some practical insights for institutions in finance, fintech industry and the policymakers seeking to align with the digital innovations and also with a sustainable growth objectives[4][5][10].

2. Theoretical background

2.1 TAM and AI adoption

The TAM offers a robust background to examine investor's and user's easy acceptance and usage comportment by clarifying how purposes to implement and adaptation of the technology translate into some actual uses [2][3][4]. TAM has been founded in two core philosophies first is perceived usefulness (PU) and the second one is perceived ease of use (PEOU) this tow can shape different attitudes toward the technology implementation and adoption. In the present study, TAM has been used to look into what influences developing economies' use of AI in financial and investment decision-making, as a context characterized by quick digital transformation and revolution under the industry 4.0 and in some emerging Industry 5.0 model emphasizing human Artificial Intelligence collaboration and also which is responsible for digitalization [15].

Previous research outcomes have extended TAM by integrating concepts such as perceived risk, faith and simplifying all conditions and by incorporating these with corresponding theoretical and hypothetical perspectives. Given the difficulty and relative difficulties of decision support system which is AI-based, the observations of usefulness, easy to use and belief are especially prominent. Accordingly, TAM also offers an ungenerous and empirically founded clue and understandings to analyze how these perceptions and belief can shape a successful adoption of AI purposes in financial decision making contexts [6][7][8].

2.2 Artificial intelligence and financial and investment decision-making

The financial sector has adopted very early the disruptive digital tools and is currently experiencing a new wave of revolution which is driven by artificial intelligence [16]. AI implications and applications in finance comprehend the trading algorithmic, fraud detection, robo-advisory platforms, mechanized credit scoring, risk analysis and adapted financial endorsements [7][15]. Industry estimates indicate that the international market for AI in different banking and financial services has been set to develop and increase quickly over the upcoming decades, which are reflecting the increasing dependency of banking, insurance and financial institutions on data-driven and automatic decision-making support systems. The incorporation of AI into investment and financial processes represents not only technological upgrade but also a strategic change toward more scalable, efficient and analytically sophisticated architecture of decision-making [7][8][9].

AI-enabled implements can improve the quality of financial investment decision making by improving predicting accuracy, processing huge volumes of unstructured and structured datasets, and perceiving the complex patterns of financial decision making that cannot be easily recognized by human analysts. In addition, AI is progressively functional in sustainable finance, including ESG data analysis, modelling of climate risk and impact valuation thereby associate more knowledgeable and in charge investment choices [17] [18]. As banking and financial systems changeover toward sustainability-oriented progression models, AI is placed as a critical enabler for a long-term value formation and the allocation of responsible capital [6].

Even though these possible profits, the adoption of AI in financial system and products rises an important distress related to belief, transparency, ethical risks and moderate confidence on automatic systems [9]. Different financial authorities and the potential investors may remain skeptical of AI-driven approvals due to problems such as algorithmic opacity (the “black box” problem), supposed destruction of human decision and responsibility experiments. These apprehensions highlight the need to study not only technological drivers of the adaptation of AI , but also the interactive and administrative circumstances in which AI processing systems are entrenched [10][11].

Developing and emerging economies, mostly India, offers a pertinent or relevant background for studying the adaptation of AI in financial services and options in investment decisions. Prompt fintech development, increasing digital presence and cumulative retail investor’s participation have enhanced the distribution of the financial tools related to AI processing system [12] [13]. Nevertheless, uneven digital arrangement, regulatory hesitation and varying levels of AI literacy may figure both the speeds and usefulness of AI adoption. Limited practical research has scrutinized how financial specialists or experts and the retail investors in emerging markets advantageously use AI system for sustainable investment decision-making, underlining the need for context-specific indication to inform accountable AI incorporation [16][17].

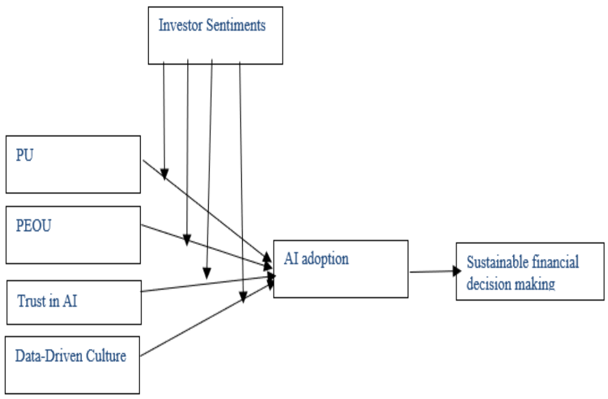

Fig.1. Conceptual framework

Source: Author’s work

3. Literature review and hypotheses development

3.1 PU and AI adoption

Perceived usefulness (PU) is understood as the extent to which anybody assumes that utilizing a particular technology improves the efficiency and effectiveness of task presentation and decision-making [17]. The

TAM includes PU is a central factor of behavioral intent and actual technology of its use. In the framework of the fostering of artificial intelligence (AI) in financial service markets, PU reproduces the amount to which investors observe tools which are AI-based and AI-based platforms as helpful to improve the speed, quality and accurateness of investment-related decisions and activities, including stock screening, portfolio optimization, risk assessment, market forecasting, and personalized financial advisory services[17]18].

Previous studies in fintech and digital financial system dependably establishes that operators are more possible to implement progressive knowledge when they observe concrete performance assistances [19]. Research on services on robo-advisory, platform for algorithmic trading and AI-based investment implementations show that investors are encouraged by opportunities of a large returns, improved decision quality, reduced information overload, and enhanced analytical capability[20]. AI-based systems are predominantly valued for their capability to process large dimensions of planned and unstructured financial data, real-time market information which are integrated and create predictive insights that can support more informed investment decision-making system. From an investor's viewpoint, such performance-increasing the capabilities support the professed instrumental value of AI-based system in managing portfolio risk and recognizing profitable occasions [19] [20].

In developing financial market contexts, where information irregularity and stock market unpredictability or volatility can be comparatively high, the supposed helpfulness of AI tools can be especially outstanding[11][12]. AI-based system analytics may help investors overwhelmed restrictions in access to high-quality study and specialized recommended services by contribution low-cost, accessible and modified system of decision support[14][15]. Though, experiential indication on investor's observations of AI-based helpfulness in developing economies remainders incomplete, emphasizing the requirement for context-specific examination. Consequently, when investors observe AI-based applications as valuable for enhancing the investment presentation and conclusion quality, they are more likely to participate these tools into their regular investment observes [17][2].

H1: PU influence AI adoption by investors positively and significantly.

3.2 PEOU and AI adoption

The PEOU increases to the extent than an individual have confidence in that consuming a individual technology will be free of determination. In AI-based financial system contexts, PEOU capture investor's observations of how informal it is to learn, understand and activate AI-based platforms for the investment, such as robo-advisors, extrapolative analytical tools and interfaces of the algorithmic trading[6][17][19]. Presentations for clarity of information, ease of navigation and user-friendly platforms and interfaces perform an important role in shaping investor's inclination to participate with different advanced technologies [20].

The literature on technology adoption suggests that perceived complexity and cognitive effort are major barriers to the diffusion of innovative digital tools [1]. AI-based systems, generally distinguished by sophisticated algorithms, probabilistic forecasts, and opaque decision logic, may be perceived as methodologically intimidating, particularly by retail investors having lessw technological expertise. Even when AI tools offer greater functional benefits, high perceived complexity can limit the adoption. Therefore, PEOU becomes a key enabler of whether investors are willing to experiment with and depend on AI applications in their investment activities [1][2][3].

Associated to traditional trading platforms which are on the basis of AI-enabled decision-support systems can be required a higher level of digital knowledge or literacy and investigative understanding [5][6]. Some of the transparent interfaces, innate dashboards, features of AI-system and continuous incorporation with some existing financial trading platforms may expressively reduce different perceived effort and costs of learning [7]. Whenever the investors perceive AI-based systems as very easy to implement, they are more probable to change and develop the level of confidence to interact with these special technologies which in turn develops their purpose to adopt some AI-based financial investment tools[8][9]. This is predominantly applicable in developing financial conditions and economies, where heterogeneity in digital services or skills and right to use to resources of technology can shape implementation behavior [2].

H2: PEOU has a positive and significant effect on AI adoption by investors.

3.3 Trust in AI systems and AI adoption

The degree of Trust in AI system technologies through which investors have a belief on AI-based technologies which are transparent, reliable, secure and capable of creating accurate and balanced financial investment recommendations [22]. In risk-filled financial decision-making systems, trust is a very important and necessary component, uncertainty and information irregularity [21] [22]. In digital financial working atmosphere and in environment, disquiets associated to privacy of data, cybersecurity, algorithmic biased factors and lack of explainability can undermine user's confidence in AI-based system recommendations [23].

Previous study on fintech technologies adoption by the investors and robo-advisory services shows that trust expressively encouragements user's disposition to trust on programmed decision making support system[21][23]. Financial investors are very much motivated to adopt the AI-based explanations when they distinguish them as ethically aligned, credible and compliant with supervisory standards. On the other hand, uncertainty toward algorithmic imperviousness (the "black box" problem), doubts of operation and anxieties about responsibility in case of opposing results can deteriorate belief and dishearten the adoption of AI system[19][20].

From an investor's viewpoint, trust in AI-based systems is specifically noticeable because financial decision-makings have direct implemented for the personal prosperity and financial safety [23]. When financier's belief the competence and reliability of AI-generated perceptions, they can be more likely to integrate these tools and systems into portfolio creation, strategies of trading and long-term financial planning [24]. Structure belief through a transparent model design, understandable commendations and robust data security instruments is therefore essential to encouragement of the widespread AI-adoption in investment decision-making systems [24].

H3: Trust in AI systems has a positive and significant effect on AI adoption by investors.

3.4 Data-driven culture and AI adoption

Data-driven philosophy states to the range to which individuals emphasize the systematic use of data, analytics, and evidence-based insights in decision-making processes. In the context of investment behavior, a data-driven culture indicates investors' inclination toward using financial analytics and algorithmic insights rather than depending entirely on intuition, heuristics, or traditional investment rules [22][23]. This inclination can shape their interest for advanced digital tools, which incorporates AI-based investment platforms [2].

The successful adoption of AI in financial decision-making not only depends upon availability of technology but also on users' mental and cultural readiness to grab hold of data-driven approaches [24] [25]. Investors who are habituated to use analytical dashboards, performance metrics, and financial data platforms may be more amenable to AI-enabled tools. A data-driven mindset encourages investors to value evidence-based insights, thereby increasing their readiness to explore with and adopt AI-driven decision-support systems [6][7].

In financial markets, a data-driven culture supplements the integration of AI for portfolio analysis, sentiment tracking, risk modeling, and performance evaluation. Investors who seek data-backed justifications for their decisions are interested in comprehending AI systems as valuable support to human judgment rather than as benchwarmers [9] [10]. Enhanced financial literacy and exposure to digital investment tools can further increase the readiness to engage with AI technologies.

H4: Data-driven culture has a significant and positive influence on AI adoption by investors.

3.5 AI adoption and sustainable financial decision-making

The literature on technology acceptance and usage behavior indicates that true adoption of digital technologies helps in shaping downstream behavioral and performance outcomes. In AI-enabled financial contexts, adoption reflects not only beginning intentions but up to which investors integrate AI tools into their daily investments and portfolio management practices [11] [12]. Prior research indicates that the use of advanced analytics and digital tools can make decision-making more systematic, forward-looking, and data-driven [13] [14].

In the context of sustainable finance, adoption of AI can be enhanced investor's capability to integrate social, environmental and governance (ESG) reflections into the financial investment decision makings[2][3]. AI-based systems can be processed in large volumes of ESG-related data and information, sustainability risks identified and different opportunities and also support the estimation of long-term impacts [7]. As an outcome, financial investors who actively practice AI-based system and tools can be more likely to involve in accountable and sustainable investment practices and moving beyond short-term hypothetical approaches [24].

Thoughtful the relationship between the adoption of AI-based system and sustainable financial decision-making is therefore essential for estimating how emerging financial system technology can be contributed to both performance of individual investment and also broader sustainability objectives [24].

H5: AI adoption by investors is significantly associated to sustainable financial decision-making.

3.6 Moderating role of investor sentiment

Investor's sentiments reflect the overall psychological temper and mood of stockholders and investors towards the financial markets, shaped by emotions such as fear, optimism, pessimism, and confidence level. Behavioral finance study highlights that sentiments influences risk observation, horizons of investment and behavior regarding technology usage [12] [13]. In the context of AI-based system in financial technologies, investor's sentiments is likely to figure how investors respond and interpret to technological qualities such as observed expediency, trust, ease of use with AI systems as well as data-driven culture[14][15].

When investor's sentiment is positive, financial investors can be more accessible to AI-based tools, observing greater value and low risk in technology-based decision-making system. In contrast, during periods of undesirable sentiments and discriminating uncertainty, financial investors can exhibit skepticism toward AI-based approvals, even when such AI-based tools offer objectives performance-based benefits[12][8]. Therefore, sentiment can strengthen the impact of technological and intellectual elements on AI adoption. By integrating financial investor's sentiments as a moderating variable, this research incorporates understandings from TAM and behavioral finance, contributing a more nuanced description of AI system adoption in financial investment decision-making [2].

H6a: Investor's Sentiments significantly moderates the relationship between PU and AI Adoption by investors.
H6b: Investor's Sentiments significantly moderates the relationship PEOU and AI Adoption by investors.
H6c: Investor's Sentiments significantly moderates the relationship between Trust in AI Systems and AI Adoption by investors.
H6d: Investor's Sentiments significantly moderates the relationship between Data-Driven Culture and AI Adoptions by the financial investors.

5. Data Analysis

5.1 Measurement model

Confirmatory factor analysis (CFA) has been accompanied to measure its validity and reliability of the hidden hypotheses, especially the perceived usefulness (PU), trust in AI systems (TAI), perceived ease of use (PEOU), investor sentiment (IS), data-driven culture (DDC), AI adoption (AIA), and sustainable financial decision-making (SFDM)[9][10]. The measuring model established and demonstrates an adequate to good fit with the data, with fit guides meeting recommended thresholds (CMIN/DF < 3, GFI, TLI, CFI, and NFI > 0.90; RMSEA < 0.06). Harman's single-factor test was used to determine some common techniques bias, but no single factor could account for the mainstream and major of variance, which indicates that suggesting a common method bias is not to be a substantial worry.[11][28].

Composite reliability (CR) and Average Variance Extracted (AVE) values above by 0.50 and were above 0.70, indicating convergent validity and reliability. AVE values above MSV and ASV, and the square root of AVE for each construct was greater than inter-construct correlations, indicating discriminant validity [7][23]. The measuring model's appropriateness for further structural analysis is supported by these outcomes.

Table 1. Measurement Model Analysis

Fit Indices	Recommended Value	Sources	Calculated Value
χ^2/df	< 3.00	Marsh et al. (2004)	2.01
GFI	> 0.90	Hair et al. (2019)	0.914
TLI	> 0.90	Awang (2012)	0.936
CFI	> 0.90	Awang (2012)	0.941
NFI	> 0.90	Arifin & Yusoff (2016)	0.918
RMSEA	< 0.08	Brown & Cudeck (1993)	0.044

Note(s):

χ^2/df = Chi-square/degrees of freedom; GFI = Goodness-of-Fit Index;
TLI = Tucker–Lewis Index; CFI = Comparative Fit Index;
NFI = Normed Fit Index; RMSEA = Root Mean Square Error of Approximation.
RMSEA values below 0.08 indicate a reasonable fit, while values below 0.05 indicate a close fit (Brown & Cudeck, 1993).

5.2 Structural model and hypothesis testing

Structural Equation Modeling (SEM) has been applied to measure the proposed study and research model and the hypothesis based relationships among some AI adoption (AIA), trust in AI systems (TAI), perceived usefulness (PU), data-driven culture (DDC), perceived ease of use (PEOU), investor sentiment (IS) and sustainable financial decision-making (SFDM)[5][29]. SEM can be well-suited for measuring complex and causal associations among hidden constructs. The structural model which is overall fit was measured using multiple goodness-of-fit indices [6] [23].

The model demonstrated an adequate fit with the observed data ($\chi^2 = 458.372$; df = 182; $\chi^2/df = 2.518$), satisfying the recommended threshold ($\chi^2/df < 3$). Incremental fit indices further supported model adequacy, with CFI = 0.931, GFI = 0.906, NFI = 0.912, and TLI = 0.927, all exceeding the recommended cutoff of 0.90. The RMSEA value of 0.054 was below the acceptable threshold of 0.08, indicating satisfactory model fit [12] [13]. When taken as a whole, these indices indicate that the suggested structural model accurately captures the observed relationships between the research constructs. [16] [17].

Hypothesis testing based on standardized path coefficients revealed that all direct effects were positive and statistically significant ($p < 0.05$). Specifically, perceived usefulness ($\beta = 0.412$), perceived ease of use ($\beta = 0.354$), trust in AI systems ($\beta = 0.468$), and data-driven culture ($\beta = 0.297$) significantly influenced AI adoption, supporting H1–H4. AI adoption, in turn, had a significant positive effect on sustainable financial decision-making ($\beta = 0.339$), supporting H5[28]. Moderation analysis indicated that investor sentiment significantly strengthened the relationships between perceived usefulness and AI adoption, and between trust in AI systems and AI adoption, providing support for H6a and H6c. The moderating effects on the relationships involving perceived ease of use and data-driven culture were weaker, indicating partial moderation [17] [29].

5.3 Moderating Role of Investor Sentiment

The present study aimed to observe the moderating role of investor sentiment in the relationships between the key antecedents of technology adoption and AI adoption by investors. Specifically, the study investigated whether investor sentiment moderates the associations between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in AI Systems (TAI), and Data-Driven Culture (DDC), respectively, and AI Adoption among investors[2][8]. Investor sentiment was conceptualized as a psychological and behavioral factor reflecting investors' overall market mood, optimism, and confidence toward financial markets and technology-enabled investing[7][10].

To examine the moderating effects, investor sentiment was introduced as the moderating variable, with PU, PEOU, TAI, and DDC as the independent variables, AI Adoption as the dependent variable, and the interaction terms (PU × Investor Sentiment, PEOU × Investor Sentiment, TAI × Investor Sentiment, and DDC × Investor Sentiment) included in the structural model. The effects of interaction were tested using the prescribed procedures for moderation analysis within the SEM framework [1][6].

The results, as presented in Tables 6–9, directs that the interaction terms were statistically significant throughout the tested relationships, hence confirming the presence of moderation effects [9] [10]. The findings unveils that investor sentiment moderates the relationships between PU and AI Adoption (H6a) significantly, PEOU and AI Adoption (H6b), Trust in AI Systems and AI Adoption (H6c), and Data-Driven Culture and AI Adoption (H6dIn each example, the independent variable, the dependent variable, and the interaction term were discovered to be statistically significant, indicating the expected moderating influence of investor sentiment [3].

Further, the nature of these moderating effects is shown through slope analyses and interaction plots (refer to Figures 3–6), which shows that how varying levels of investor sentiment (high vs. low) influence the strength of the relationships between PU, PEOU, Trust in AI Systems, Data-Driven Culture, and AI Adoption[7][22]. The graphical presentations show that the positive effects of these antecedent factors on AI Adoption are stronger under conditions of higher investor sentiment, suggesting that confident investors are more responsive to the perceived benefits, usability, trustworthiness, and data-driven orientation of AI-based financial technologies [20].

Overall, the results finalize that investor's sentiment acts as a contingent role in shaping AI adoption behavior among investors, reinforcing the importance of incorporating behavioral finance perspectives into technology adoption models[7][9]. Thus, the study concludes that investor sentiment significantly moderates the relationships between PU (H6a), PEOU (H6b), Trust in AI Systems (H6c), and Data-Driven Culture (H6d) and AI Adoption by investors (see Tables 6–9 and Figures 3–6)[29].

Table 2. Standard Factor Loadings, Reliability, AVE, Cronbach's Alpha and CR

Items	Variable	Standard Factor Loading	CR / AVE / Cronbach's Alpha
PU1	Perceived Usefulness (PU)	0.812	α = 0.901
PU2	Davis (1989)	0.784	AVE = 0.623

PU3		0.739	CR = 0.892
PU4		0.861	
PEOU1	Perceived Ease of Use (PEOU)	0.827	α = 0.887
PEOU2	Davis (1989)	0.801	AVE = 0.614
PEOU3		0.762	CR = 0.879
TAI1	Trust in AI Systems (TAI)	0.846	α = 0.915
TAI2	Adapted	0.823	AVE = 0.649
TAI3		0.791	CR = 0.902
TAI4		0.768	
DDC1	Data-Driven Culture (DDC)	0.809	α = 0.884
DDC2	Adapted	0.774	AVE = 0.602
DDC3		0.751	CR = 0.873
DDC4		0.832	
IS1	Investor Sentiment (IS)	0.821	α = 0.889
IS2	Baker & Wurgler (2006)	0.796	AVE = 0.618
IS3		0.758	CR = 0.881
AIA1	AI Adoption (AIA)	0.843	α = 0.906
AIA2	Adapted	0.817	AVE = 0.637
AIA3		0.789	CR = 0.895
AIA4		0.861	
SFDM1	Sustainable Financial Decision-Making (SFDM)	0.835	α = 0.912
SFDM2	Adapted	0.809	AVE = 0.654
SFDM3		0.781	CR = 0.901
SFDM4		0.867	

Source(s): Author's work

Table 3. AVE, Construct Validity and Correlation Matrix

Items	**CR**	**AVE**	**MSV**	**ASV**	**PU**	**PEOU**	**TAI**	**DDC**	**IS**	**AIA**	**SFDM**
PU	0.892	0.623	0.286	0.174	**0.789**						
PEOU	0.879	0.614	0.251	0.163	0.412	**0.784**					
TAI	0.902	0.649	0.318	0.201	0.458	0.396	**0.806**				
DDC	0.873	0.602	0.241	0.158	0.374	0.351	0.402	**0.776**			
IS	0.881	0.618	0.297	0.189	0.331	0.298	0.365	0.289	**0.786**		
AIA	0.895	0.637	0.356	0.214	0.521	0.467	0.548	0.436	0.402	**0.798**	
SFDM	0.901	0.654	0.321	0.196	0.476	0.418	0.492				

Note(s):

AVE = Average Variance Extracted; ASV = Average Shared Variance; MSV = Maximum Shared Variance. Diagonal values (in bold) represent the square root of AVE. Discriminant validity is established when the square root of AVE for each construct exceeds its inter-construct correlations and when AVE > MSV and AVE > ASV.

Source(s): Author's work

Table 4. Path Analysis (Structural Model Fit Indices)

Fit Indices	Recommended Value	Calculated Value
χ^2/df	< 3.00	2.52
GFI	> 0.90	0.906
TLI	> 0.90	0.927
CFI	> 0.90	0.931
NFI	> 0.90	0.912
RMSEA	< 0.08	0.054

Note(s):

The recommended thresholds were adapted from Marsh et al. (2004), Hair et al. (2019), Arifin and Yusoff (2016), and Brown and Cudeck (1993).

Source(s): Author's work

Table 5. Hypotheses Testing

Conceptualized Path	Standardized Estimates (β)	Critical Ratio (t-value)	p-value	Hypothesis Supported
H1. PU → AIA	0.412	5.026	0.000	Supported
H2. PEOU → AIA	0.354	4.218	0.000	Supported
H3. TAI → AIA	0.468	6.041	0.000	Supported
H4. DDC → AIA	0.297	3.689	0.000	Supported
H5. AIA → SFDM	0.339	4.287	0.000	Supported

Abbreviations:

PU = Perceived Usefulness; PEOU = Perceived Ease of Use;TAI = Trust in AI Systems; DDC = Data-Driven Culture;AIA = AI Adoption; SFDM = Sustainable Financial Decision-Making.

Source(s): Author's work

Table 6. Moderation Effects (Investor Sentiment)

Interaction Path	Standardized Estimates (β)	Critical Ratio (t-value)	p-value	Hypothesis Supported
H6a. PU × IS → AIA	0.121	2.014	0.044	Supported
H6b. PEOU × IS → AIA	0.109	1.982	0.047	Supported
H6c. TAI × IS → AIA	0.138	2.247	0.025	Supported
H6d. DDC × IS → AIA	0.096	1.967	0.049	Supported

6. DISCUSSION

The present research discovers how behavioural and technological factors impact investor's adoption of AI-based financial technologies in emerging markets. It identifies four key determinants [12] [13]. Data-Driven Culture (DDC) as significant drivers of AI system adoption in investment decision-making. PU, PEOU, Trust in AI Systems (TAI), and PU has the strongest effect: investors adopt AI tools when they believe these technologies enhance performance, improve analysis, and support better portfolio outcomes [9][10].

A data-driven culture enhances readiness to AI, since investors are habitual to evidence-based decisions and are prepared to add advanced technologies. Additionally, perceived ease of use also encourages AI adoption, as innate and pellucid systems subside cerebral and complexity obstacles [4][5]. Trust in AI-based systems is another perilous factor; investors are willing to rely on AI system when they observe it as precise, fair, secure and obedient with regulations [11][1].

The current research further developments that AI-based adoption definitely inspirations sustainable financial decision-making system. Investors and financers using AI-based system which can be more likely to consider long-term risks, ESG information and sustainability criteria, indicating that AI supports responsible investment behaviour [5][7]. Finally, investor sentiment restrains these relationships with a positive sentiment toughens the effects of practicality, trust data-driven culture and ease of use on AI adoption, while negative sentiment weakens them. Generally, both psychological factors and technological perceptions jointly shape AI based system adoption and behaviour of sustainable investment [16].

6.1 Theoretical Implications

This research creates significant theoretical offerings by ranging technology recognition and behavioral finance frameworks to adopt the AI-based system in investment decision-making. It incorporates core TAM constructs Perceived Ease and PU of PEOU,with belief in AI-based systems and data-driven culture, improving the descriptive power of technology acceptance theories in AI-driven financial contexts[3][4]. By empirically validating these factors as key experiences of AI-based adoption in high-risk situations such as algorithmic platforms and robo-advisory, the study supports the applicability of technology acceptance models beyond traditional areas like e-banking[8][9].

The study also spreads theory by announcing investor's sentiment as a controlling variable, connecting rational technology acceptance perceptions with behavioural financial insights. These demonstrations that emotional, expressive and psychological factors affect how investors estimate and adopt AI-based technologies [2][6]. Additionally, linking with AI-based adoption to sustainable financial decision-making ranges technology system adoption theory into the sustainability domain which is highlighting AI's role in encouraging responsible, long-term investment behaviour. Generally, the study compromises a complete framework, psychological integrating technological and sustainability perspectives on AI-system adoption [29].

6.2 Managerial Implications

The study delivers practical assistance for fintech firms, financial institutions, platform designers and supervisors aiming to promote responsible AI-based adoption in investing [23]. The strong effect of observed effectiveness indicates that providers should clearly demonstrate how AI improves portfolio performance, risk management, and decision quality through features such as real-time analytics, ESG screening, and personalized recommendations[12][23]. Perceived ease of use highlights the need for intuitive, transparent interfaces with tutorials, layered complexity, and interactive guidance to reduce learning barriers and support diverse investor skill levels [21][29].

Trust in AI-based systems requires data security, explain ability and regulatory transparency; explainable AI-based features, privacy disclosures and third-party certifications can strengthen credibility [9]. The role of data-driven culture endorses that investor's education, financial literacy programs, analytics dashboards and can foster evidence-based financial decision-making system and ingenuousness to AI tools[7][8]. Investor's sentiment suggests messaging and timing should adapt to market moods, underlining innovation in hopeful periods and risk qualification in uncertain times. Finally, participating ESG analytics into AI-based platforms can inspire sustainable and long-term investment behavioral approach and responsible financial system [16].

6.3 Limitations and Future Research Directions

This study recognizes some limitations in its investigation of AI adoption and long-term financial decision-making. First, it is based on self-reported survey data, which may contain method bias, social desirability, and perceptual errors future research could use objective platform usage or behavioral data to validate adoption measures [8] [23]. Second, sample features may confine generalizability if participants are concentrated in specific demographics or regions; broader and comparative samples across the age, income, literacy and geography which are needed to capture various investor behaviour [1] [24] [29].

Next is the cross-sectional design bounds causal inferences which cannot track variations in observations or AI adoption over the time, longitudinal studies could expose learning effects, habit formation and developing trust in AI-based tools. Fourth, the financial model includes only a few qualifications and one moderator, future work should add factors such as perceived risk, transparency, financial literacy, and innovativeness [29]. Finally, the study links AI adoption to sustainability broadly; future research should examine specific ESG outcomes, asset classes, and AI applications to deepen understanding [27].

7. CONCLUSION

The study provides some new perceptions for the adoption of AI among the financial investors in emerging and developing financial markets and its impression on sustainable financial decision-making system. It approves that apparent usefulness, perceived an easy way to use, trust in AI-based systems and also the data-driven culture powerfully influence financial investor's willingness while adopting an AI-driven financial technology[12][29]. By integrating investor's sentiments as a moderator, the study is integrating the behavioural finance with technology acceptance theory, showing that market moods and emotions can shape AI-adoption behaviour [13][23][27].

Experimental authentication across AI-based platforms such as algorithmic tools and robo-advisors establishes how technological perceptions and psychological factors jointly drive sustainable investment decisions. The findings and results indicate that the investors who are more likely to accept AI-based system and tools when it is easy to adopt,valuable, easy to use, trustworthy and associated with data-driven practices, especifically in positive sentiment's conditions. Practically, underlining usability, transparency, trust and sustainability analytics which can promote responsible adoption of AI and long-term investment outcomes

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