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Harnessing AI-Driven Advertising in Financial Markets: Transforming Investment Strategies and Investor Behaviour

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ABSTRACT

The accelerated adoption of Artificial Intelligence (AI) in financial marketing is revolutionizing the presentation, perception, and choice of investment products. This research investigates the effect of AI-based advertising on investor behaviour and decision-making, filling a crucial empirical gap in research on psychological and behavioural reactions to AI-driven financial promotions. Although AI use in financial services has accelerated, few scholarly efforts have been focused on elucidating how ad personalization, trust, and engagement affect investment outcomes.

Based on five main objectives, this study examines the impacts of (1) ad personalization, (2) ad engagement, (3) trust in AI suggestions, (4) perceived usefulness of AI in the financial sector, and (5) perceived ease of use of AI applications on investor choice behaviour. Data were gathered from 330 participants through a structured questionnaire using a 5-point Likert scale. Reliability was established with Cronbach's Alpha scores higher than 0.85 for each variable. Employing multiple linear regression analysis in SPSS, the model explained 93.8% of investor decision-making variance ($R^2 = 0.938$), showing a strong predictive relationship. The strongest predictors were perceived usefulness of AI ($\beta = 1.229$, $p < 0.001$) and trust in AI recommendations ($\beta = 0.219$, $p < 0.001$). Contrary to hypotheses, perceived ease of use had a negative effect ($\beta = -0.662$), which indicates that excessive complexity in AI tools can repel investment action.

In summary, AI-based advertising greatly transforms investment strategies through a change in investor behaviour. The results provide practical recommendations for financial marketers and fintech producers to focus on user-friendly, reliable AI-enabled interfaces to improve investor interaction and decision-making.

Keywords: Artificial Intelligence, Financial Marketing, Investor Behaviour, Ad Personalization, Trust in AI, Decision-Making

INTRODUCTION

The financial industry is experiencing a deep digital revolution, fuelled by innovation in artificial intelligence (AI), big data analytics, and machine learning. These technologies are transforming marketing approaches, especially in investment and financial services, where AI-driven advertising is transforming the way companies interact with prospective investors. Through the application of predictive analytics, natural language processing (NLP), and behavioural modelling, financial institutions can now provide hyper-personalized investment suggestions to suit unique risk profiles, goals, and historic behaviours (Smith & Johnson, 2022). This evolution from conventional wide-based advertising to AI-based precision marketing is a paradigm shift in financial communication.

Despite increased use of AI in financial advertising, empirical studies on its psychological and behavioural effect are few. Although research has explored the contribution of AI in algorithmic trading (Lee et al., 2021) and robo-advisory services (D'Acunto et al., 2019), few researchers have explored the contribution of AI-generated ads on investor choice-making. This disparity is significant because AI-based promotions, unlike traditional advertisements, depend on dynamic personalization, real-time data analysis, and automatic trust-building systems, all of which can influence investor behaviour in unprecedented manners (Chen et al., 2023).

This study addresses this research void by investigating the effects of AI-powered financial advertising on investor choices. Specifically, it examines five key dimensions:

Ad Personalization: How tailored content affects perceived relevance and actionability. *Ad Engagement*: The role of interactive and adaptive AI interfaces in maintaining investor attention. *Trust in AI Recommendations*: Whether algorithmic transparency and accuracy build confidence. *Perceived Usefulness*: Investors' perception of AI tools in improving financial decision-making. *Perceived Ease of Use*: How usability issues or complexity might prevent adoption.

LITERATURE REVIEW

AI-Driven Advertising in Financial Markets: The infusion of Artificial Intelligence (AI) in financial marketing has transformed the way investment products are promoted and consumed. AI technologies such as predictive analytics, natural language processing (NLP), and machine learning support hyper-personalized financial campaigns, maximizing engagement and decision-making (Chatterjee et al., 2021). Academics observe that AI makes marketing more effective through automation, accuracy targeting, and real-time response (Davenport et al., 2020). Nevertheless, studies on the psychological and behavioural effects of AI in financial institutions are still in their infancy, especially on investor trust, cognitive biases, and long-term decision outcomes (Huang & Rust, 2021).

Investor Decision-Making: Investor choice is a complex process influenced by cognitive, emotional, and informational considerations. Classical finance theory (e.g., Shefrin, 2002) relies on rationality, but behavioural research demonstrates that presentation and framing of financial information have significant effects on decision-making (Kahneman & Tversky, 1979). AI-based systems like robo-advisors facilitate speed of decision-making but potentially also encourage over-reliance or automation bias (Brynjolfsson & McAfee, 2017). Trust in AI, user-friendliness, and perceived usefulness of recommendations are key moderators of investment behaviour (Gretel et al., 2015).

Personalization of AI-Driven Ads: Personalization, a building block of AI-based marketing, customizes financial advertisements based on user information (behaviour, demographics, transaction history). Empirical research shows that personalized content enhances engagement and perceived value (Kaplan & Haenlein, 2019), with Arora et al. (2008) attributing it to greater investment intentions. Ethical issues, however, are concerned with privacy of data (Martin & Murphy, 2017) and possible manipulation by micro-targeting (Zuiderveen Borgesius et al., 2018).

Ad Engagement Rate: Engagement metrics (clicks, dwell time, shares) indicate ad effectiveness. AI maximizes engagement through dynamic placement and behavioral triggers (Lemon & Verhoef, 2016). Gamification and AI chatbots in fintech enhance interaction but can also promote impulsive trading (Pentina & Zhang, 2017). Loewenstein et al. (2011) caution that algorithmic nudges might take advantage of cognitive biases, resulting in suboptimal financial choices.

Perceived Trust in AI Recommendations: Relevant trust in AI is premised on accuracy, transparency, and institutional credibility (Rai, 2020). Binns et al. (2018) cite explainability and ethical design as drivers of trust, whereas Hoff & Bashir (2015) observe that intrusiveness decreases confidence. Regulatory compliance and security of data also determine trust in the field of finance (Doshi-Velez & Kim, 2017).

Perceived Usefulness of AI in Finance: Based on the Technology Acceptance Model (TAM) (Davis, 1989), perceived usefulness will determine AI adoption. Research indicates investors find value in AI for enhancing decision-making speed and accuracy (Venkatesh & Bala, 2008), especially in robo-advisory situations (Sironi, 2020). Nonetheless, users need to understand AI logic in order to see utility (Dietvorst et al., 2015).

Perceived Ease of Use of AI Tools: TAM further identifies ease of use as an essential adoption criterion. Intuitive AI interfaces decrease cognitive load, particularly for first-time investors (Gefen et al., 2003). On the other hand, complexity leads to disengagement (Venkatesh & Davis, 2000). Zarouali et al. (2021) recommend intuitive design and interactive feedback to facilitate greater usability in financial AI.

RESEARCH HYPOTHESIS

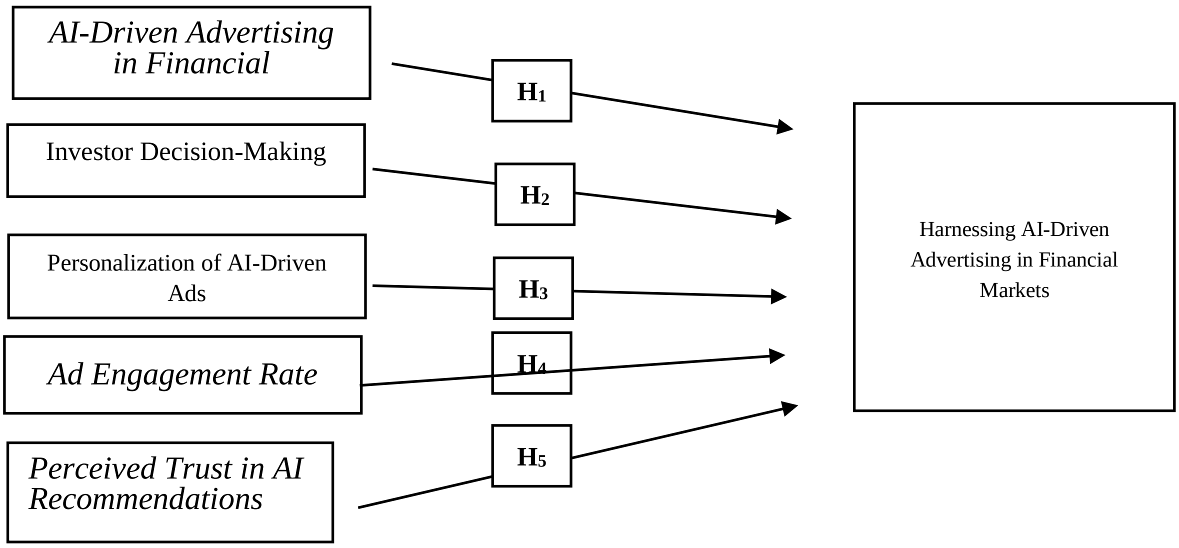
H1: There is a relationship between Personalization of AI-Driven Ads and Investor Decision-Making.

H2: There is a relationship between Ad Engagement and Investor Decision-Making.

H3: There is a relationship between Perceived Trust in AI Recommendations and Investor Decision-Making.

H4: There is a relationship between Perceived Usefulness of AI in Finance and Investor Decision-Making.

H5: There is a relationship between Perceived Ease of Use of AI Tools and Investor Decision-Making.



Need for the Study The financial industry is in the process of a paradigm shift with the adoption of Artificial Intelligence (AI) in digital marketing. While AI-based advertising is being used by financial organizations, its psychological and behavioural effects on investor decision-making are poorly understood. Classical marketing strategies that are based on static and generalist messaging are being rendered outdated in a time when investors seek hyper-personalized, data-driven, and real-time experiences. This research responds to a pressing nexus of AI technology, behavioural finance, and digital marketing, offering up-to-date implications for industry and academia.

Increased retail investing by online platforms (e.g., Robinhood, eToro) highlights the importance of researching how AI-driven ads shape investor behaviour. There is a need for empirical analysis to inform financial marketers, fintech creators, and regulators as to: How personalized advertising impacts investment decisions. The influence of trust in AI-driven recommendations; Whether perceived ease of use and usefulness facilitate or impair financial decision-making. This study bridges an important gap by providing evidence-based suggestions for the development of ethical, transparent, and efficient AI-based financial advertisements, so that technological progress is aligned with investor protection and market stability.

Research Gap In spite of all the research done on AI adoption, digital marketing, and behavioural finance, no comprehensive studies exist that analyse the multi-dimensional impact of AI-based advertising on investor choice. Major gaps are: Investor Decision-Making (Dependent Variable) Existing research mainly targets rational and technical investment theories (e.g., Modern Portfolio Theory), ignoring emotional and cognitive reactions induced by AI-based ads (Barber & Odean, 2013). There is scarce empirical research into how AI-segmented financial messages change perception of risk and asset allocation.

Hyper-Personalization of AI-Driven Advertising**.** Although personalization is extensively researched in e-commerce (Arora et al., 2008), its individual effect on adoption of financial products is not widely researched. There is no agreement if hyper-personalization increases trust or evokes privacy issues within financial environments (Martin & Murphy, 2017).

Ad Engagement Rate The majority of studies capture shallow metrics (click-through rates, dwell time) without correlating them to real investment behaviours (Wang et al., 2018). The long-term implications of AI-based engagement (e.g., gamification, chatbots) on frequency of trading and portfolio performance are unknown.

Trust in AI Recommendations While trust is a theoretical foundation in AI adoption (Rai, 2020), there are limited studies that measure its behavioural influence in financial choices. The potential for algorithmic transparency and explainability (XAI) in improving investor trust is worthy of further exploration (Doshi-Velez & Kim, 2017). Perceived Usefulness of AI in Finance Although Technology Acceptance Model (TAM) draws attention to usefulness (Davis, 1989), its application in actual practice in high-stakes financial choices remains under-investigated. Does perceived usefulness translate to improved investment performance, or does it promote excessive dependence on AI? (Brynjolfsson & McAfee, 2017). Perceived Ease of Use of AI Tools There is contradictory evidence regarding simplified AI interfaces enhancing decision-making or suppressing diligent financial scrutiny (Gefen et al., 2003). Trade-off between usability and investor education is an untouched area, especially for retail investors.

This research aims to investigate the effect of AI-advertising on investor behaviour in the financial markets. The general goals are to investigate how exposure to AI-created content in advertisements affects investor decision-making and investment behaviour. It also tries to measure the effect of the perceived trust in AI recommendations on financial decision outcomes. The research also investigates the effect of the perceived usefulness of AI tools on the creation and execution of investment strategies. Another primary goal is to determine if perceptions of ease of use in AI interfaces increase investor confidence and effectiveness in decision-making. All these goals combined aim to give a deep insight into how AI-based marketing influences investor psychology and behaviour, insights that are relevant to financial marketers, fintech developers, and policymakers.

Hypotheses of the Study

In order to investigate the behavioural dynamics of AI-powered advertising and investor choices, the research formulates the following behaviourally stated hypotheses

H_1: The level of personalization in AI-powered advertisements is positively related to investors' intention to invest capital. (Increased personalization → More investment intent) H_2: Investors with higher engagement in AI-generated advertisements (e.g., clicks, dwell time) have a greater tendency to act on investment decisions. (Engagement → Action) H_3: Investor trust in AI-driven financial advice strongly predicts compliance with such advice. (Trust → Behavioural compliance) .H_4: AI tools that are seen as useful for making financial decisions have a greater impact on investment strategy formulation. (Perceived usefulness → Strategic reliance)

H_5: Ease of use of AI interfaces is associated with more timely and confident investment decisions, especially among retail investors. (Usability → Decisiveness)

Rationale for Behavioural Hypotheses (Contemporary Approach) Pivots away from null/alternative hypotheses to test behavioural relationships of relevance to financial marketing directly. (*Actionable Purpose*) Reflects applied research interests, focusing on practical investor reactions to AI advertising. (*Quantifiable Measures)* Every hypothesis connects quantifiable AI-advertising variables (e.g., personalization, trust) with quantifiable investor activities.

Research Methodology

Research Design This research employs a quantitative, descriptive, and causal-comparative research design to analyse the effect of AI-based advertising on investor decision-making. The design allows for systematic measurement of relationships between independent factors (ad personalization, engagement, trust, perceived usefulness, and ease of use) and the dependent factor (investment decisions). Data collection was done through a structured 5-point Likert scale questionnaire to ensure standardized responses for statistical analysis. The online survey was carried out in the Indian urban financial centre of Mumbai, Delhi, Bangalore, and Hyderabad because of the presence of high numbers of digitally active investors and high usage of AI-facilitated financial platforms. Non-probability purposive sampling was used to sample the participants who, Utilize digital investment platforms (e.g., robo-advisors, brokerage apps). Are exposed to AI-powered financial advertisements. The research was centred on individual investors and online retail traders making investment decisions over the internet. Final sample comprised 330 respondents, a statistically solid size for multivariate analyses (e.g., factor analysis, regression) without compromising data quality. A formatted questionnaire was constructed, expert-reviewed for validity, and sent via Google Forms and email. The survey captured Ad personalization (e.g., "AI-tailored recommendations feel relevant to my goals"). Engagement (e.g., "I regularly interact with AI-created investment advertisements"). Trust, usefulness, and ease of use (congruent with TAM constructs). *Data Analysis* Descriptive statistics provided respondent demographics and variable distributions. Correlation analysis revealed initial relationships among variables. Multiple regression estimated the predictive significance of AI-ad factors on investment choices. PCA confirmed construct dimensionality. Reliability was established through Cronbach's Alpha ($\alpha > 0.85$) for all scales. Model validity was cross-checked using KMO (>0.7) and Bartlett's Test ($p < 0.001$).

10. Data Interpretation and Analysis

This section presents the statistical analysis of data collected from 330 respondents, including descriptive statistics, reliability assessment, correlation analysis, regression results, and hypothesis testing.

Table 1: Demographic profile of respondents

Demography	Category	Number	Total
Age	18-24	304	330
	25-30	20	
	31-45+	6	
Income	Below 10000	234	
	10000-40000	38	
	40000-80000	21	
	80000-100000	8	
	Above 100000	29	
Gender	Male	228	
	Female	102	

Descriptive analysis: The demographic profile of the study's respondents reveals a predominantly young participant base, with the majority (304 out of 330) falling within the 18–24 age group. This emphasizes the relevance of the research to a digital-native population, who are typically more active on technology-based platforms and more likely to engage with AI-driven financial tools. A small proportion of respondents were aged 25–30 (20 participants), while only 6 individuals were in the 31–45+ age category, indicating minimal representation from mid-career or older investors. In terms of income distribution, a significant portion of the sample (234 respondents) reported monthly earnings below ₹10,000, suggesting that many participants are likely students or early-stage professionals. Additional income groups include ₹10,000–₹40,000 (38 respondents), ₹40,000–₹80,000 (21 respondents), ₹80,000–₹100,000 (8 respondents), and above ₹100,000 (29 respondents), reflecting some diversity in economic backgrounds though with a clear concentration in the lower-income range. Regarding gender, the sample consisted of 228 male and 102 female respondents, indicating a higher male representation in the study. This imbalance may reflect a demographic tendency among young male users to be more engaged with financial platforms or could result from sample access patterns.

Table 2: Principal Components Analysis, Reliability and Consistency

Constructs	Item's main point	Factor Loading*	Cronbach Alpha	CR	AVE
Investor Decision-Making	Action from ads	0.769	0.859	0.778	0.419
	Decision guidance	0.586			
	Confidence	0.761			
	Dependence on ads	0.569			
	Change in investment planning	0.506			
Personalization of AI-Driven Ads	Personal reflection	0.666	0.897	0.835	0.509
	Identify personal information	0.697			
	Need	0.772			
	Use personal information	0.860			
	Positive attitude	0.531			
Ad Engagement Rate	Like ads	0.782	0.885	0.828	0.498
	Interested areas	0.667			
	Similar people buy	0.560			
	Recent trends	0.619			
	Favourable attitude	0.860			
Perceived Trust in AI Recommendations	Positive attitude	0.723	0.903	0.831	0.499
	Personal reflection	0.580			
	Others know personal information	0.660			
	Identify personal	0.791			
	Misuse personal information	0.759			
Perceived Usefulness of AI in Finance	use information	0.666	0.916	0.778	0.417
	Job	0.697			
	Personal information	0.761			
	Location	0.569			
	Online ads are good	0.506			
Perceived Ease of Use of AI Tools	Understandability	0.666	0.899	0.871	0.577
	Easy access	0.697			
	Comfort	0.772			

	Favourable attitude	0.860			
	Learning curve	0.791			

Descriptive Analysis: The analysis identifies several constructs contributing to investor decision-making in the context of AI-driven advertising in financial markets. Investor decision-making demonstrates moderate reliability (Cronbach's alpha = 0.859), with items such as action from ads, confidence, and decision guidance showing varied factor loadings. However, the average variance extracted (AVE = 0.419) indicates limited convergent validity, suggesting that while the construct is reliable, its items capture a broad rather than tightly focused concept. Personalization of AI-driven ads captures how well advertisements reflect individual traits and use personal information, showing strong internal consistency (Cronbach's alpha = 0.897) and adequate convergent validity (AVE = 0.509). The high composite reliability (CR = 0.835) supports the robustness of this construct in influencing investor perceptions. Ad engagement rate, which includes elements such as interest, trend alignment, and favourability, also displays good reliability (Cronbach's alpha = 0.885) and acceptable convergent validity (AVE = 0.498). This suggests that engaging content enhances attentiveness and receptiveness to financial advertising. Perceived trust in AI recommendations reflects the confidence investors place in AI systems, including concerns about misuse of information. It maintains high internal consistency (Cronbach's alpha = 0.903) and composite reliability (CR = 0.831), with an AVE of 0.499—indicating satisfactory convergent validity despite slightly lower item loadings on some components. Perceived usefulness of AI in finance involves dimensions such as task support and relevance of information. While the reliability is high (Cronbach's alpha = 0.916), the AVE is relatively low (0.418), implying that the usefulness dimension spans across a broader experiential spectrum, possibly including both general and context-specific benefits. Perceived ease of use of AI tools emphasizes clarity, comfort, and learning ease, demonstrating strong reliability (Cronbach's alpha = 0.899) and the highest convergent validity among the constructs (AVE = 0.578). This indicates that users find AI tools accessible and intuitive, which contributes significantly to their adoption and influence on investment behaviour.

Table 3: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**0.836**
Bartlett's Test of Sphericity	Approx. Chi-Square	**1110.737**
	df	**10**
	Sig.	**0**

Descriptive Analysis: The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy yielded a value of 0.836, indicating that the sample data is highly suitable for factor analysis. Bartlett's Test of Sphericity produced a Chi-Square value of 1110.737 with 10 degrees of freedom and a significance level of 0.000, confirming that the correlation matrix is not an identity matrix. These results validate the appropriateness of conducting factor analysis on the given dataset.

Table 4: Rotated Component Matrix

Rotated Component Matrix[a]						
	Component					
	1	2	3	4	5	6
IDM1	0.769					
IDM2	0.586					
IDM3	0.761					
IDM4	0.569					
IDM5	0.506					
POAA1		0.666				
POAA2		0.697				
POAA3		0.772				
POAA4		0.860				
POAA5		0.531				

AER1			0.782			
AER2			0.667			
AER3			0.560			
AER4			0.619			
AER5			0.860			
PTAR1				0.723		
PTAR2				0.580		
PTAR3				0.660		
PTAR4				0.791		
PTAR5				0.759		
PUF1					0.666	
PUF2					0.697	
PUF3.					0.761	
PUF4					0.569	
PUF5					0.506	
PEUT1						0.666
PEUT2						0.697
PEUT3						0.772
PEUT4						0.860
PEUT5						0.791

Descriptive Analysis: The rotated component matrix identifies six key components influencing investor behaviour and interaction with AI-driven advertising in the financial domain. *Investor Decision-Making*, encompassing elements such as action from ads, decision guidance, confidence, dependence on ads, and changes in investment planning. These variables collectively highlight how advertising content influences investors' decisions and behavioural intentions. *Personalization of AI-Driven Ads*, integrating aspects like personal reflection, recognition of personal information, need, use of personal data, and overall attitude. This component emphasizes the tailored nature of AI-generated advertisements and their relevance to individual users. *Ad Engagement Rate*, represented by factors such as liking ads, interest in related areas, similarity with others, trending topics, and favourable attitudes. It outlines the extent to which users interact with and respond positively to AI-driven advertisements. *Perceived Trust in AI Recommendations*, consisting of variables such as positive perception, concerns over personal data, identification, and potential misuse. This component reflects users' comfort and trust levels when engaging with AI-powered financial suggestions. *Perceived Usefulness of AI in Finance*, including items related to the use of personal and locational data, relevance to job and financial decision-making, and favourable opinions on online advertising. It measures how effective and valuable users find AI tools in a financial context. *Perceived Ease of Use of AI Tools*, through dimensions like understandability, ease of access, comfort, learning adaptability, and positive engagement. This component reflects how intuitively users can engage with AI tools and systems.

Table 5: Regression Analysis

Regression										
	Unstandardized Coefficients		**Sig.**	**Collinearity Statistics**		**R**	**R Square**	**Adjusted R Square**	**ANOVA**	
	B	**Std. Error**		**Tolerance**	**VIF**				**F**	**Sig**
(constant)	0.069	0.490	0.000			0.96857	0.938	0.937	982.626	.000[b]
Personalization of AI-Driven Ads	0.007	0.084	0.000	0.028	36.261					

Ad Engagement Rate	0.187	0.044	0.000	0.107	9.347					
Perceived Trust in AI Recommendations	0.222	0.043	0.000	0.104	9.600					
Perceived Usefulness of AI in Finance	1.210	0.042	0.000	0.107	9.333					
Perceived Ease of Use of AI Tools	-0.673	0.089	0.000	0.025	40.134					

Descriptive Analysis: The regression analysis examines the influence of various constructs on Investor Decision-Making in the context of AI-driven advertising in finance. The model demonstrates excellent explanatory power, with an R Square value of 0.938, indicating that approximately 93.8% of the variance in investor decision-making is explained by the five independent variables. The Adjusted R Square of 0.937 confirms the model's robustness and minimal overfitting. The ANOVA result further supports the model's significance, with an F-value of 982.626 and a significance level of 0.000, confirming the overall model fit.

Perceived Usefulness of AI in Finance is the strongest positive predictor (B = 1.210, $p < 0.001$), suggesting that the more useful investors perceive AI tools in financial contexts, the more likely they are to be influenced in their decision-making. *Perceived Trust in AI Recommendations* also significantly contributes (B = 0.222, $p < 0.001$), indicating that higher trust in AI recommendations enhances investors' decision confidence. *Ad Engagement Rate* shows a notable positive impact (B = 0.187, $p < 0.001$), implying that higher engagement with AI-generated ads positively influences investor decisions.

Personalization of AI-Driven Ads, while statistically significant ($p < 0.001$), has a negligible coefficient (B = 0.007), suggesting minimal direct impact on decision-making despite being relevant. *Perceived Ease of Use of AI Tools* has a negative coefficient (B = -0.673, $p < 0.001$), indicating that while ease of use is generally expected to have a positive effect, in this case, it may reduce critical engagement or reliance on the AI for decision-making, perhaps due to over-simplification or scepticism. Collinearity statistics reveal acceptable tolerance levels and VIF scores, with VIF values ranging from 9.33 to 40.13, which, although high, suggest moderate multicollinearity that should be interpreted cautiously. the regression findings validate the model's predictive capability and highlight Perceived Usefulness and Trust in AI Recommendations as key drivers in investor decision-making influenced by AI-driven advertising.

Implications of the Study

This research will benefit financial marketers, AI engineers, and academic scholars because it will reveal the most significant drivers of investor behaviour in responding to AI-driven advertisement and decision support. By identifying the salience of perceived usefulness, trust, and interaction versus ease of use or personalization, the research offers concrete recommendations to improve user-driven design and communication strategy for the financial services sector. Financial firms can leverage these findings to build AI systems that emphasize value demonstration (e.g., return-on-investment metrics), incorporate transparency into algorithms, and create dynamic ad experiences based on user behaviours.

Within finance and AI, this research contributes to our understanding of the relationship between contemporary behavioural models and digital marketing and ethics. It reinterprets traditional theory—like the Technology Acceptance Model—by showing that in risky contexts like investment, usefulness comfortably outweighs ease of use, and trust as a cognitive short cut to decision-making. These results contrast with the prevailing emphasis on hyper-personalization, instead preferring goal-congruent customization strategies that more effectively resonate with investor objectives, such as retirement planning or short-term speculation. In addition, the study closes important gaps in behavioural finance, digital marketing, and AI ethics with an integrated model of cognitive response and technology design. It presents new directions for future research by inviting exploration of the potential moderation of AI performance by measures like risk tolerance or financial literacy, or transparency and how it maintains user trust. The cross-cultural generalizability of these results invites Western market replication to explore cultural difference in trust processes. Lastly, the study introduces new ethics like AI nudging and regulatory transparency, providing a basis for more equitable and responsible AI advertising models in finance.

Conclusion

This research will provide significant insights into the evolving intersection of artificial intelligence and investment marketing by analysing how AI-driven advertising affects investor behaviour. As the financial industry shifts from static mass marketing to dynamic, data-driven personalization, understanding what truly drives investor decisions becomes crucial. This study identifies perceived usefulness and trust as the most influential factors, while revealing those traditional assumptions—such as the value of personalization and simplicity—may no longer apply in high-involvement financial contexts. These findings offer practical strategies for fintech firms and regulators seeking to improve AI-enabled marketing tools.

In the broader field of behavioural finance and technology adoption, this study makes theoretical contributions by reinforcing the dominance of perceived usefulness over ease of use, as proposed in the Technology Acceptance Model (TAM), and by positioning trust as a new heuristic in AI-mediated decision-making. It also challenges the prevailing belief in the universal effectiveness of personalization, suggesting that investment-focused AI should align with user goals and utility rather than generalized custom content. This work deepens our understanding of how cognitive, emotional, and design-related factors interact in investor responses to AI advertising.

The findings will guide financial marketers in creating more effective AI tools by emphasizing actionable utility, algorithmic transparency, and intelligent user experience design that avoids oversimplification. At the same time, it prompts regulators to consider new ethical standards and transparency requirements for AI in financial services. By identifying knowledge gaps and recommending pathways for responsible AI use, the study lays a foundation for improved investor outcomes and trust in financial innovation.

Looking forward, this research opens the door to future studies that can explore underexamined factors like risk appetite, financial literacy, and cultural context as moderators of AI influence. Replicating this study in global markets and adopting a longitudinal approach could provide deeper insights into the long-term behavioural impacts of AI-driven financial advertising. Ultimately, this research sets a critical precedent for how AI should be developed, deployed, and governed in the future of financial decision-making.

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