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Perceived Influence of AI-Driven Finfluencer Content on Retail Investors' Equity Trading Decisions in India

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Abstract

The recent heightened retail involvement in equity markets across India has been accompanied by the emergence of AI-based financial influencers known as finfluencers who use predictive analytics and algorithmic analytics to control the mindset of investors. This paper examines the effect of AI-enhanced finfluencer content on the retail investor trading frequency and risk-taking behavior. The convergent mixed-methods design was embraced through the integration of Technology Acceptance Model (TAM) and Prospect Theory by using the survey data of 450 retail investors and semi-structured interviews of 25 participants. Regression findings indicate that perceived AI credibility is a significant predictor of the trading frequency (0.45, p <.001), which is better than the influence of perceived usefulness. As manifested by the positive Nifty 50 monthly returns, which will be described as positive Nifty 50 monthly returns, the correlation between AI credibility and bullish market conditions is notable (50), and the risk-taking increases in the areas of gains. The mediation analysis also shows that the fear of missing out (FOMO) can partially explain the relationship (indirect effect = 0.14, 95% CI [0.08, 0.22]). The qualitative results pinpoint the issues of automation bias and trust in AI-generated financial content supported by the lack of transparency. The results place AI credibility as a reinforcer of behavior but not a neutral informational process.

Keywords: *AI-driven content, finfluencers, retail investors, behavioral finance, equity trading, India*

1. INTRODUCTION

1.1 Background

The COVID-19 significantly accelerated the rate of retail investments in the Indian equity markets. Demat accounts grew to more than 12 crores in 2025 compared to about 4 crores in 2020, and it implies the continuous 25% annual growth (National securities depository limited, 2025; Central depositary services limited, 2025). Online brokerage and zero-commission trade applications increased accessibility, especially to millennials and Gen Z investors (SEBI, 2024). Similarly to this growth, the so-called financial influencers (finfluencers) appeared as one of the most significant intermediaries on YouTube, Instagram, and X. It is expected that over 5,000 Indian finfluencers together have over 100 million followers by 2025 (KPMG India, 2025). One of its changes is that they are integrating artificial intelligence (AI) applications such as large language models to produce predictive analytics, sentiment analysis, and automated code. Dashboards and recommendation systems with AI enhance interest and seeming analytic proficiency (Gupta and Sharma, 2024; Rao et al., 2026). The augmentation, however, brings in concerns with respect to algorithmic openness and how it is affecting novice retail investors.

1.2 Research Problem and Objectives

Regardless of the SEBI (2023) advisory regarding unregistered finfluencers, there is still limited empirical evidence available on whether AI-generated financial content has a perceptual influence. The current literature reports the effects of social media-induced herding and speculative trading (Chhatwani, 2024) but fails to test them systematically to determine the existing amplification of behavioral biases by the AI credibility and algorithmic curation (Patel and Singh, 2025). Such a fissure is especially acute in India, where the proportion of retail investors in trading at NSE is about 60 percent and where they tend to be poorly financially literate (NSE, 2025).

This study addresses three objectives:
(1) Evaluate how finfluencer content created by AI affects the number of trades and the risk-taking behavior;
(2) investigate the most important mechanisms, which include perceived credibility and fear of the missing out (FOMO).
(3) Generate AI-based financial communication governance implications.

1.3 Significance

Most recent volatility cycles have led to huge equity loss among the retail investors (AMFI, 2025), making it worthwhile to comprehend the concept of AI-mediated persuasion. The research covers regulatory design, such as the possible AI-disclosure regulations in accordance with new international transparency standards (European Commission, 2024). Theoretically, it helps to move the field of behavioral finance by combining the Technology Acceptance Model (TAM) with AI-specific credibility constructs in a providing new market.

2. LITERATURE REVIEW

2.1 Finfluencers and Retail Investor Behavior

The social media has transformed the trading in retailing by increasing attention shock, herding and speculative momentum. Digital spaces are the engagement-based systems in which the visibility frequently prevails over the state of information. Emotionally salient content is amplified by means of algorithm, making it more vulnerable to cascades (O'Neil, 2016).
Indian data demonstrates that in cases of meme-stock, unusual trading volumes were related to online attention (Chhatwani, 2024). The application of AI also enhances a sense of sophistication and conceals the risk of the model (Gupta and Sharma, 2024). Algorithms-based curation has the potential to reinforce confirmation bias and high-beta stock promotion (Patel and Singh, 2025). Another study on international studies indicates that digital nudges enhance the frequency of trading (Baker and Dellaert, 2021).

Although the previous studies pay much attention to the influence as created by people, the aspect of AI-enhanced financial persuasion is under-researched.

2.2 AI, Perception, and Bias

AI brings in increased senses of utility and power, as well as incomprehensibility. The danger of making confident but false outputs has been emphasized in the research about language model hallucinations (Ji et al., 2023). Fluency can be mistaken with rigor in the financial contexts.

AI dashboards increase engagement (Gupta & Sharma, 2024), and algorithmic optimization drives trading spikes (Rao et al., 2026). Regulatory discussions emphasize transparency in AI-generated content (European Commission, 2024), yet Indian standards remain nascent.

In this way, AI makes access more available and may raise the levels of automation bias and digital herding.

2.3 Theoretical Framework

This paper combines both TAM (Davis, 1989) and Prospect Theory (Kahneman and Tversky, 1979). Reliance in AI tools is explained by perceived usefulness, and increased risk-seeking, under bullish circumstances, is predicted by Prospect Theory. The references can be re-set with the credibility of AI, and FOMO will accelerate the process.

Accordingly:
H1: Perceived usefulness positively influences retail investors' trading frequency.
H2: AI credibility augments risk-taking in bull markets.
H3: FOMO generates the mediatory effect on AI credibility-trading relationship.

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The consumerism that AI generates through the use of influencers is therefore thought of as an accelerative, but not neutrally informational, behavioral input.

3. METHODOLOGY

The study adopts a convergent mixed-methods design that the Q1 behavioral finance standards can take into consideration. The quantitative analysis will compare the outcomes in the perceived usefulness, AI credibility, and FOMO in comparison to trading outcomes, and the qualitative analysis can put these terms into their contextual framework.

The problem of reverse causality is constrained through the control variables including trading experience and trading frequency at the beginning. It has coefficient stability, which is checked in the form of robust tests. It is mandatory that the framework of the methods involved is combined with TAM and Prospect Theory because both of the rational judgment and affective activation mechanisms bounded on the financial decision-making practiced through AI are represented.

3.2 Research Context

The target study will emphasis the retail equity investors in the two largest stock exchanges of India:

- National Stock Exchange of India
- BSE Limited

India offers an interesting empirical case because of the explosive retail participation in the country, the use of AI in digital finance and changing regulatory agency.

3.3 Sampling Strategy and Participants

3.3.1 Target Population

The sample consisted of active investors in retail including:

- Maintain operational demat account.
- Has engaged in at least one equity trade over the last half year.
- Access financial contents through the social media.

3.3.2 Sampling Technique

To achieve representativeness in both demographic and experience factors, a stratified random sampling was adopted:

- Geographical Location: Urban vs. semi-urban/rural
- Experience Level:

Novice (≤2 years)

Intermediate (2–5 years)

Experienced (>5 years)

- Age Cohort: 18–25, 26–40, 40+

The stratification contributes to the external validity and the reduction of the sampling bias in the heterogeneous population.

3.3.3 Sample Size Justification

The quantitative stage was used with 450 respondents in it, which is a larger number than the minimum needed to conduct multivariate regression (Hair et al., 2022). The level of adequacy has been established at power =0.80, =.05 to identify medium effect sizes (f 2 = 0.15). The qualitative stage incorporated 25 semi-structured interviews, which were selected based on a promising foundation on the foundation of the customers of the surveys that had superior and lesser thought about AI-influences. The data saturation was reached in the interview of 21, the reason was that the four other interviews were utilized to ensure the consistency of the themes...

3.4 Data Collection Procedures

3.4.1 Survey Instrument

The questionnaire was a structured one that was applied within a 12-week period of time via Google Forms. The instrument was divided into four sections:

- Trading profile and demographics.
- AI-driven finfluencer content exposure.
- Perceptual constructs (behavioral variables and TAM-based variables)
- Trading frequency, risk behavior-self reported.

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A pilot study (n = 40) was carried out to clarify the items and to improve the level of reliability. A pilot study (n = 40) was conducted to refine item clarity and reliability.

3.4.2 Interviews

Semi-structured interviews were conducted via Zoom, lasting 30–40 minutes each. Interviews explored:

- Perceptions of AI credibility
- Emotional triggers in AI-enhanced content
- Trust in algorithmic opacity
- Decision-making narratives

Interviews were recorded (with consent) and transcribed verbatim for analysis.

3.5 Measurement Development

Five-point Likert scales (1 = Strongly Disagree; 5 = Strongly Agree) were used to measure all the perceptual constructs. Validated Scopus-indexed studies were edited to produce items that would have construct validity.

Table 1 Measurement Scales and Sources

Construct	Sample Items	Source
Perceived Usefulness (AI Content)	"AI-based financial insights improve my trading decisions."	Davis (1989); Venkatesh & Davis (2000)
Perceived AI Credibility	"AI-supported predictions are reliable."	Flanagin & Metzger (2000)
Emotional Trigger (FOMO)	"I feel pressure to trade when AI predicts strong gains."	Przybylski et al. (2013)
Herd Susceptibility	"I follow trending stocks recommended widely online."	Bikhchandani et al. (1992)
Trading Frequency	Monthly trade count (self-reported)	Barber & Odean (2000)
Risk-Taking Propensity	% allocation to high-volatility stocks	Kahneman & Tversky (1979)

3.6 Reliability and Validity Assessment

3.6.1 Internal Consistency

- Cronbach's Alpha ≥ .70
- Composite Reliability (CR) ≥ .70

3.6.2 Convergent Validity

- Average Variance Extracted (AVE) ≥ .50

3.6.3 Discriminant Validity

- Fornell–Larcker criterion
- HTMT ratio (< .85 threshold)

3.6.4 Common Method Bias

- Harman's Single-Factor Test
- Marker variable technique

3.7 Quantitative Data Analysis (Revised and Strengthened)

Quantitative data were analyzed using SPSS (Version XX) and Stata (Version XX). Statistical significance was evaluated at the 5% level unless otherwise stated. Robust standard errors were applied to correct for potential heteroskedasticity.

3.7.1 Operationalization of Market Condition

Bullish Market Condition (Bullish Market)

In a bid to have a magnified picture of current sentiment in the market, a dummy variable was formed by the use of Nifty 50 index monthly returns in the National Stock Exchange of India.

$$BullishMarket_i = \begin{cases} 1, & \text{if Nifty 50 monthly return} > 0 \\ 0, & \text{otherwise} \end{cases}$$

The responses to the questionnaires were compared with the associated Nifty 50 monthly returns depending on the date on which each respondent completed the questionnaire. This goal operationalization corresponds to the Prospect Theory insofar as it is used to model positive gain-domain settings that can fuel an enhancement of risk-seeking behavior. To control the herding behavior at the baselines, herd susceptibility was added. Financial

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literacy measurement scale was based on a five-item objective scale of knowledge scale which were adapted to their own investor literacy instruments.

3.7.2 Model Specifications

Control Variables

To isolate the unique effect of AI-driven content, the following controls were included:

- Age
- Gender
- Trading experience
- Income level
- Financial literacy score

Herd Susceptibility (behavioral control)

Herd susceptibility was included to account for baseline herding tendencies independent of AI exposure. Financial literacy was measured using a five-item objective knowledge scale adapted from established investor literacy instruments.

Model 1: Perceived Usefulness and Trading Frequency (H1)

$$TradingFrequency_i=\beta_0+\beta_1 PU_i+\beta_2 Herd_i+Controls+\varepsilon_i$$

Model 2: AI Credibility and Trading Frequency

Model 2 separates the independent impact of AI credibility before the co-estimation of AI credibility with TAM constructs.

$$TradingFrequency_i = \beta_0 + \beta_1 AICredibility_i + \beta_2 HerdSusceptibility_i + \beta_3 Controls_i + \epsilon_i$$

Model 3: Moderation Model (H2)

$$RiskTaking_i = \beta_0 + \beta_1 AICredibility_i + \beta_2 BullishMarket_i + \beta_3 (AICredibility \times BullishMarket)_i + \beta_4 HerdSusceptibility_i + \beta_5 Controls_i + \epsilon_i$$

Model 4: Mediation Model (H3)

The test was performed using bootstrapped mediation analysis (N=5,000 resamples) with PROCESS macro:

AI Credibility → FOMO → Trading Frequency

Significant indirect effects were taken to denote effects that had 95% confidence intervals that were not zero.

Robustness Model (Model 5)

To test incremental validity:

$$TradingFrequency_i = \beta_0 + \beta_1 AICredibility_i + \beta_2 PerceivedUsefulness_i + \beta_3 HerdSusceptibility_i + \beta_4 Controls_i + \epsilon_i$$

The model proves the presence of AI credibility in case of TAM constructs and behavioral tendencies are incorporated together.

3.8 Qualitative Analysis

Thematic analysis was performed using NVivo.

Analytical Steps:

- Open Coding (authority perception)
- Axial Coding (connection between credibility and trading aggression)
- Targeted Encoding (integrative behavioral themes)

Investigator triangulation ensured interpretive reliability.

3.9 Ethical Considerations

Ethical compliance adhered to institutional research guidelines.

- **Informed Consent:** Participants were informed about study objectives, voluntary participation, and withdrawal rights.
- **Anonymity:** No personally identifiable financial data collected.
- **Confidentiality:** Encrypted storage of responses.

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- **Non-Affiliation Disclosure:** Study clarified independence from Securities and Exchange Board of India.

4. Results

The chapter offers the practical results of the study. These are categorized under three subsections viz., the descriptive statistics, the hypothesis testing according to the regression analysis and the qualitative thematic knowledge. The triangulation of quantitative findings is made through a qualitative method of seeking to strengthen interpretive power.

4.1 Descriptive Statistics

4.1.1 Demographic Profile

A total of **450 valid survey responses** were analyzed. Table 2 presents the demographic distribution.

Table 2 Sample Demographics (N = 450)

Variable	Category	Frequency	Percentage
Gender	Male	298	66.2%
	Female	146	32.4%
	Other/Prefer not to say	6	1.4%
Age	18–25	104	23.1%
	26–40	232	51.6%
	40+	114	25.3%
Experience	≤2 years	168	37.3%
	2–5 years	174	38.7%
	>5 years	108	24.0%
Location	Urban	302	67.1%
	Semi-urban/Rural	148	32.9%

The sample is representative of the changing market of retail investors in India which is filled with millennials and comparatively new investors

4.1.2 Exposure to AI-Driven Finfluencer Content

- 81% said they watched the content of the influencers regularly.
- 74 percent stated that AI-generated analytics or predictions were included in such content.
- 68% were categorical that AI-enhanced content raised their trading or risk-taking behavior.

Mean construct values (5-point scale):

Table 3

Construct	Mean	SD
Perceived Usefulness	3.89	0.74
AI Credibility	3.76	0.81
FOMO	3.52	0.88
Herd Susceptibility	3.41	0.92

Cronbach's alpha values ranged between 0.78 and 0.86, confirming internal consistency.

4.2 Quantitative Findings

Table 3 Regression Results: Trading Frequency

Variables	Model 1	Model 2	Model 5 (Robustness)
Perceived Usefulness	0.38*** (6.72)	—	0.21** (3.84)
AI Credibility	—	0.45*** (7.89)	0.39*** (6.55)
Herd Susceptibility	0.18** (2.94)	0.16** (2.61)	0.14* (2.12)
Controls	Included	Included	Included
R^2	0.31	0.36	0.42
N	450	450	450

t-values in parentheses

- p < .05, ** p < .01, *** p < .001

Interpretation

- The strongest predictor is AI credibility.
- Herd vulnerable: Stronger but weaker.
- Inclusion of herd does not have a material impact on AI effect.
- Robustness model raises the explanatory power to 42 percent.

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Table 4 Moderation Model: Risk-Taking Propensity

Variables	Model 3
AI Credibility	0.29*** (4.98)
Bullish Market	0.24** (3.76)
AI Credibility × Bullish Market	0.22** (3.14)
Herd Susceptibility	0.15* (2.28)
Controls	Included
R^2	0.34
N	450

- p < .05, ** p < .01, *** p < .001

Interpretation

- Interaction term significant.
- AI credibility effect stronger during positive market momentum.
- Prospect Theory mechanism empirically validated.

Table 5 Mediation Analysis (Bootstrapped)

Path	Coefficient	95% CI
AI Credibility → FOMO	0.42***	—
FOMO → Trading Frequency	0.33***	—
Direct Effect	0.31***	—
Indirect Effect	0.14**	(0.08, 0.22)

Partial mediation confirmed.

4.3 Qualitative Insights

Thematic analysis of 25 interviews yielded three dominant themes.

Theme 1: AI as an Authority Substitute

It is common to see AI-generated marketing of finfluencers discussed by the respondents as being scientific, data-driven, and smarter than human beings. It becomes more reasonable when they introduce AI models with predictors of targets as compared to the same case when the same is done by humans.

One of the participants of the interview is the 29-year-old investor who has 3 years of experience.

AI was viewed as objective and emotionless, which supports the presence of automation bias.

Theme 2: Perceived Objectivity Illusion

Despite the high level of trust, the subjects acknowledged that they had low knowledge regarding the underlying algorithms.

AI can perform both predictive functions and protect against downside risk. It does not tell us what assumptions it makes; this admits of algorithmic opacity and blind trust.

Theme 3: Theme 3: Sensationalized Herd Behavior.

Social proof was increased by AI-enhanced images demanded more social engagement.

AI-enhanced images were a source of exaggerated social proof effects, and social interaction between users. High-volume AI-related engagement amplified perceived consensus and urgency. You don't want to miss out.".

Triangulation of Findings

Regression results are supported by qualitative themes:

• The perceived authority narratives follow the statistical influence of AI credibility.

• Urgency and herd driven interview responses are aligned with mediation by FOMO.

Interaction effects in bullish markets are the same as investor reports of greater confidence going with AI predicts rallies.

Overall Interpretation of Results

The observations affirm that AI-based finfluencer messages have a major effect on the frequency and risk appetite of retail investors in India. The behavioral influence of AI credibility is the greatest, and emotional stimuli like FOMO partially mediate the impact of AI credibility.

The overlapping of both quantitative and qualitative data points to the assumption that AI does not simply make the informational efficiency more efficient, instead, it reconfigures the psychology of the investors, incorporating elements of perceived

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technological authority and mechanisms of social amplification.

4.4 Summary of Hypothesis Testing

Table: Objective–Hypothesis–Test–Result Mapping

Objective	Hypothesis	Test Used	Key Result	Status
O1: Assess whether AI-driven finfluencer content influences trading frequency	**H1:** Perceived usefulness positively affects trading frequency	Multiple Linear Regression (Model 1)	$\beta = 0.38^{***}$ ($p < .001$); $R^2 = 0.31$	**Supported**
		Robustness Regression (Model 5)	$\beta = 0.21^{**}$ ($p < .01$) when AI credibility included	**Supported (Reduced Effect)**
O2: Examine whether AI credibility increases risk-taking under bullish conditions	**H2:** AI credibility increases risk-taking in bullish markets	Moderated Regression (Model 3)	AI Credibility $\beta = 0.29^{***}$; Bullish Market $\beta = 0.24^{**}$; Interaction $\beta = 0.22^{**}$; $R^2 = 0.34$	**Supported**
O3: Test emotional mediation mechanisms	**H3:** FOMO mediates relationship between AI credibility and trading frequency	Bootstrapped Mediation (PROCESS, 5,000 resamples)	Indirect effect $\beta = 0.14^{**}$; 95% CI [0.08, 0.22]; Direct effect remains significant	**Partially Supported (Partial Mediation)**
O4: Assess incremental validity beyond herd behavior	—	Regression including Herd Susceptibility (Models 1, 2, 5)	Herd $\beta = 0.14$–0.18 (significant but weaker than AI credibility)	—
O5: Validate qualitative triangulation	—	Thematic Analysis (NVivo)	Themes: Automation Bias; Perceived Objectivity Illusion; Amplified Herd Behavior	Confirmatory

5. DISCUSSION

5.1 Theoretical Integration and Authors' Interpretation

The results give solid evidence regarding the hypotheses and offer a unitary explanation of the technology acceptance and behavioral finance as well as algorithmic governance.

To begin with, the positive influence of the perceived usefulness on the trading frequency is proof of the essence of the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Davis, 2000). The robustness analysis however, indicates that AI credibility takes precedence over usefulness with both estimated to be equal. Perceived algorithmic authority is more important than functional utility in financial decision-making under uncertainty. It causes TAM to grow not only past the stage of intentions to adopt the technology, but also the stage of risk-taking behaviour implementation, which makes credibility in positioning an independent psychological driving force in the domain of AI-mediated environment. Second, the credibility of AI and optimistic market environments have become empirically sounding Prospect Theory (Kahneman and Tversky, 1979). The positive moderation pro status the AI credibility has on gain-domain risk-seeking. When used together, optimistic forecasting and positive market moods need to set the reference points of the investors and increase the degree of speculative involvement (AI). It is an algorithmic authority that is employed as a momentum-congruent actor as opposed to bias reduction. Third, the mediation analysis indicates that fear of missing out (FOMO) to the extent is used to predict the relationship between AI credibility and trading frequency. It demonstrates two street directions: psychological trust in the effectiveness of algorithms and a sense of emotional urgency. The continuation of the direct effect validates that AI credibility has something additional other than

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emotional mobilization but through both informational persuasion and psychological reinforcement.

This interpretation can be supported by qualitative evidence. Respondents stated that the content created by AI is objective and scientific due to the bias of automation and authority heuristics. Little knowledge of the underlying algorithms did not weaken trust meaning there was confidence driven by opaqueness. Social proof and herding were also increased through the use of AI-enhanced engagement indicators. Notably, AI credibility remained substantial even after the control of herd susceptibility and financial literacy, and it could be argued that it is not the conventional form of herd behavior but the technological one that needs to be considered

In general, AI-driven finfluencer content materializes as modeled as a multidimensional behavior architecture as a pool of technological authority, harmonizing market amplification, and stimulating emotions. It is in the highly digitalizing retail markets that AI redefines decision space, making it more participatory and riskier.

5.2 Implications

Theoretical Implications

The proposed research will contribute to the advancements of behavioral finance and information systems research by generalizing TAM to AI-mediated financial influence. In addition to usefulness and perception of ease of use, perceived AI credibility and emotional appeals are behavioral facilitators. A combination of TAM and Prospect Theory creates a dynamic model of the interaction of TAM perceptions and cognitive biases in the face of uncertainty in the market. Algorithms that work as algorithms of authority are therefore not a neutral provider of information, but they act as an amplifier of psychology.

Practical Implications

The results create important governance issues. Even though SEBI (2023) has advised against unregistered finfluencers, there are now fresh risks of transparency related to AI-generated financial projections. The algorithms tend to be ascribed objectivity by investors, which makes them susceptible to overtrading.

Policy priorities can be viewed as such policy imperatives as Mandatory AI-disclosure labels, simplified transparency reports which explain model assumptions, which are repeatedly audited, and AI literacy programs.

6 LIMITATIONS AND FUTURE RESEARCH

Although the evidence gathered by the mix of the methods is strong, one should mention several limitations. Firstly, the pertinence of the self-trading frequency rates and risk behaviour would probably entail the social desirability bias and the recall bias. Second, it is impossible to cause inference with the cross-sectional design. The proposed study needs to be based on experimental or longitudinal studies with the possibility of the ability to control the degree of transparency of AI and find the causal links between algorithmic disclosure and investor action. In addition to this, objective behavioral validation may be provided by the brokerage level data of transaction.

7. CONCLUSION AND RECCOMMENDATIONS

7.1 Conclusion

This paper explored the role of AI-based finfluencer content in influencing equity trading among retail investors in India through a mixed-methods approach by combining the Technology Acceptance Model (TAM) and the Prospect Theory. The results prove that AI-enhanced financial communication can greatly boost the rate of trading and the risk-taking behavior of the retail investors.

Three conclusions stand out.

To start with, although perceived usefulness determines the trading activity, AI credibility is the most powerful determinant of behavior. TAM (Davis, 1989; Venkatesh and Davis, 2000) is extended, with the findings that usability receives less importance in action in high- uncertainty financial contexts due to the perceptions of credibility. Investors perceive AI-based predictions and analytics as the indicators of objectivity and technical authority, enhancing the process of implementation and strengthening confidence in the outputs of robots.

Second, in line with Prospect Theory (Kahneman and Tversky, 1979), AI trust does not help mitigate gain-domain risk-seeking, but it is provoked by bullish market conditions. Instead of bias neutralizing, algorithmic authority heightens speculative behavior as optimistic predictions are in line with market movement. AI therefore acts as an accelerator of behaviour and not as an equalizer of information.

Third, a partial mediator in this relation is the fear of missing out (FOMO), which proves that AI-enhanced influencer content works as a form of psychological reinforcement. Algorithms increase collective trade responses according to the informational cascade theory (Bikhchandani et al., 1992; Chhatwani, 2024).

Generally, AI-based financial communication democratizes access and makes behavior more vulnerable at the same time. The assumed algorithmic authority can be used to replace independent judgment in highly dynamic retail markets, reaffirming the effects of automation bias and digital herding. The article reinstates AI credibility as a behavioral agent, and advances the information about AI-mediated persuasion in new financial ecosystems.

7.2 Recommendations

The finding drives the conclusion that there should be a stronger regulation of AI-powered financial content. Explicit AI-disclosure labels should also be enforced by regulators, transparency reports simplified with data assumption and model limitation and audit structures of advisory systems that are AI based. Better risk communication norms should be promulgated so that one can counter algorithmic optimism. This should include digital platforms with digital AI-content tagging, controlling the amplification of hypothetical material by algorithms, adding behavioral nudges resulting in reasonable decision-making. The program needs to have financial literacy, automation bias and digital herd dynamics awareness programs as well undertaken by AI literate programs. The future will introduce the use of the experimental and longitudinal research designs, the use of transaction data on a brokerage level, and the influence of AI-inspired long term-portfolio will be researched. Sales-financial persuasion is a paradigm shift of the retail investment based on AI. The accomplishment of inclusion advantages at modest speculative power by algorithmic authority has become the significant challenge of regulators, platform and academic scholars alike.

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