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Digital Risk Amplification in App-Based Equity Investing: Trading Apps, Finfluencers, Gamified Interface Features, and Retail Investor Risk-Taking Behaviour in Rajasthan, India

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ABSTRACT

The proliferation of mobile trading applications, social-media investment communities, and algorithmically curated financial content has fundamentally reconfigured the decision environment of retail equity investors in India. This study investigates how trading-app influence, social-media and finfluencer exposure, gamified interface features, algorithmic vulnerability, digital misinformation risk, perceived risk, and expected return perception jointly shape the risk-taking behaviour of retail equity investors in Rajasthan. Using primary survey data collected from Rajasthan and applying rigorous four-stage inclusion screening, a final analytical sample of N = 500 verified retail equity investors was obtained. The study employs reliability analysis, descriptive statistics, Pearson correlation analysis, chi-square tests, one-way ANOVA, multiple regression with heteroskedasticity-consistent standard errors, bootstrap-based mediation analysis, and exploratory factor analysis. A novel theoretical framework, the Digital Behavioural Risk Amplification Model (D-BRAM), integrating Prospect Theory, Social Influence Theory, Attention Theory, Technology Acceptance with Vulnerability Extension, and Gamification Theory, is proposed. Results demonstrate that the revised Risk-Taking Behaviour Index (RTBI-5), constructed from five behavioural indicators excluding expected return perception, maintains strong construct coherence. Expected return perception is the strongest positive predictor of RTBI-5 ($B = 0.178$, $p < .001$). Trading-app influence is a significant positive predictor of perceived risk ($B = 0.726$, $p < .001$) but exhibits a negative association with RTBI-5 after controls ($B = -0.098$, $p = .004$), consistent with a risk-awareness inhibition mechanism. Bootstrap mediation analysis (5,000 resamples) confirms that social-media influence operates on risk-taking behaviour indirectly through expected return perception (indirect effect = 0.069, 95% CI [0.038, 0.107]). Significant demographic differences in risk-taking behaviour are identified by educational qualification ($F = 6.488$, $p < .001$, $\eta^2 = .048$) and household income ($F = 8.748$, $p < .001$, $\eta^2 = .048$). The findings advance a layered understanding of digital risk amplification, with implications for SEBI regulation, platform design, and digital financial literacy programmes.

Keywords: behavioural finance; finfluencers; gamification; digital misinformation; expected return perception; D-BRAM..

1. INTRODUCTION

The retail equity investment landscape in India has undergone a structural transformation since 2020. Mobile-first brokerage platforms, frictionless account opening through Aadhaar-linked KYC, and the proliferation of Uniform Payments Interface (UPI)-enabled investment workflows have collectively reduced the barriers to equity market participation to a historically low threshold. The number of demat accounts registered with CDSL and NSDL grew from approximately 41 million in March 2020 to over 140 million by March 2024, with a disproportionate share of new account holders belonging to first-generation investors in non-metropolitan cities (SEBI, 2023). This democratisation of access represents a significant structural achievement for capital market deepening. However, access to markets and informed participation in markets are not equivalent outcomes. The ecosystem that enables participation also introduces a set of design-mediated, socially amplified, and algorithmically accelerated decision pressures that are not adequately captured by traditional models of investor behaviour.

Two parallel developments have intensified the behavioural complexity of this landscape. First, trading applications have moved beyond basic order execution to encompass real-time portfolio analytics, watchlist-based alerts, curated stock discovery, one-click order placement, and interface features that create persistent engagement loops. From a behavioural finance perspective, these features do not merely reduce transaction costs; they alter the architecture of investor choice by collapsing the temporal distance between attention, emotion, and execution (Barber & Odean, 2008; Thaler & Sunstein, 2008). Second, a parallel ecosystem of informal financial content has emerged on social media platforms including YouTube, Instagram, Telegram, and X (formerly Twitter), where self-styled financial influencers (finfluencers) disseminate market views, stock recommendations, and aspiration-driven narratives to audiences that frequently lack the analytical infrastructure to evaluate the quality or incentive structure of the advice they receive (IOSCO, 2024; SEBI, 2023).

The behavioural finance literature provides robust evidence that retail investors are subject to systematic cognitive biases, including overconfidence, attention-driven purchasing, herding, and loss aversion, that translate into suboptimal trading outcomes (Barber & Odean, 2000, 2001; Kahneman & Tversky, 1979). The digital investment environment does not eliminate these biases; rather, it amplifies the frequency and speed with which they are triggered while simultaneously providing the illusion of informed agency through interface-generated fluency (Freibauer et al., 2024). This paper argues that understanding risk-taking behaviour in the current digital context requires a model that integrates the app-mediated decision environment, social-media expectation formation, gamified interface features, and perceived vulnerability, not merely individual cognitive dispositions.

Rajasthan provides an empirically important and under-researched context for this investigation. The five cities examined, namely Jaipur, Jodhpur, Kota, Ajmer, and Udaipur, represent a tier-2 urban investor base characterised by high mobile internet penetration, a growing post-pandemic investor cohort, and diversity of income, educational background, and investment experience. The majority of existing empirical work on Indian retail investor behaviour draws on either metropolitan or nationally aggregated samples (see, e.g., Sathya & Prabhavathi, 2024). The present study contributes by grounding its analysis in a geographically specific, well-filtered sample of 500 verified retail equity investors.

This paper makes four interrelated contributions. First, it proposes the Digital Behavioural Risk Amplification Model (D-BRAM), an integrative theoretical framework that synthesises Prospect Theory, Attention Theory, Social Influence Theory, Technology Acceptance with Vulnerability Extension, and Gamification Theory to explain how digital investment contexts systematically alter investors' perceived risk, expected return beliefs, and behavioural risk-taking propensity. Second, it resolves a methodological inconsistency present in prior research by reconstructing the risk-taking behaviour index (RTBI-5) without the circular inclusion of expected return perception, thereby enabling a cleaner test of the return-expectation mechanism. Third, it provides bootstrap-confirmed mediation evidence for the pathway through which social-media influence translates into risk-taking behaviour via elevated return expectations. Fourth, it identifies a counterintuitive but theoretically coherent negative association between app-induced vulnerability awareness and observed risk-taking behaviour, which has implications for both platform design regulation and digital literacy interventions.

1.1 Research Problem

Contemporary trading platforms and social media have substantially reduced the friction of equity market participation without a commensurate reduction in the informational, analytical, or emotional demands placed on retail investors. The mechanisms through which app-mediated access, finfluencer content, gamified interface features, and digital misinformation jointly shape investor risk-taking behaviour remain insufficiently understood, particularly in the tier-2 urban markets of emerging economies such as India.

1.2 Research Questions

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The study addresses the following research questions:

- RQ1: How does trading-app influence relate to the risk-taking behaviour of retail equity investors in Rajasthan, after controlling for perceived risk, expected return perception, and demographic characteristics?
- RQ2: Through what mechanisms does social-media and finfluencer exposure shape perceived risk and risk-taking behaviour among retail investors?
- RQ3: Are gamified interface features independently associated with speculative risk-taking behaviour after controlling for broader app influence and expected return perception?
- RQ4: Does expected return perception mediate the relationship between social-media influence and risk-taking behaviour?
- RQ5: What demographic and investment-profile variables produce significant group differences in risk-taking behaviour, and what is their magnitude?
- RQ6: What policy and platform-design implications emerge from the observed associations for investor protection in India?

1.3 Significance of the Study

This study is significant on four dimensions. For the behavioural finance literature, it operationalises the concept of a digitally mediated decision environment through empirically validated constructs, extending classical theories of overconfidence, herding, and attention-driven trading to the app and social-media context. For the digital finance literature, it disaggregates technology adoption into convenience dimensions and vulnerability dimensions, demonstrating that these can have opposing associations with risk-taking behaviour. For regulators and policymakers, it provides primary evidence that the expectation-formation pathway, rather than a direct attention-to-trade pathway, is the primary mechanism linking finfluencer exposure to heightened risk-taking, with direct implications for SEBI's ongoing finfluencer regulation framework. For educators and platform designers, the distinction between app-perceived vulnerability and app-facilitated trading frequency provides a design principle: interface features that heighten investor awareness of risk may attenuate rather than amplify risk-taking behaviour.

1.4 Scope of the Study

The study targets retail investors who (a) provided informed consent, (b) are currently invested in equity or equity-related instruments, (c) reside in one of five selected Rajasthan cities, and (d) invest in individual equity shares of Indian companies. The study does not employ brokerage transaction data or longitudinal trading records; findings are based on self-reported survey responses and are subject to the known limitations of cross-sectional survey design. The study does not attempt to establish causal relationships because of the cross-sectional nature of the research design. Instead, its purpose is to empirically identify supported associations between variables and explore theoretically grounded mediational pathways within the proposed conceptual framework.

2. LITERATURE REVIEW

The literature review is organised thematically across eight domains: behavioural finance foundations, digital retail investor participation, trading-app influence, gamification in financial platforms, social-media and finfluencer effects, herding and overconfidence in digital contexts, financial literacy and perceived risk, and emerging-market investor behaviour. A synthesis matrix is presented in Table 1.

2.1 Behavioural Finance Foundations

Behavioural finance establishes that investors deviate systematically from the rational actor model due to cognitive heuristics, emotional responses, and social influences. Prospect theory demonstrates that individuals evaluate outcomes relative to reference points and exhibit loss aversion, such that the subjective disutility of a loss exceeds the utility of an equivalent gain (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). In app-based investing, reference points are continuously generated by dashboard displays, colour-coded portfolio performance indicators, and push notifications that convert unrealised gains and losses into psychologically salient stimuli.

Overconfidence is among the most extensively documented biases in the retail investor literature, with evidence demonstrating that overconfident investors trade more frequently and realise lower risk-adjusted returns (Barber & Odean, 2000, 2001; Odean, 1998). Gervais and Odean (2001) further show that successful trading experiences can induce overconfidence, creating a self-reinforcing cycle. Mobile trading interfaces compound this dynamic by reducing the behavioural friction that previously slowed impulsive execution. The disposition effect, characterised by the premature sale of winning positions and continued holding of losing positions, has been linked to the visual salience of portfolio gain/loss displays (Shefrin & Statman, 1985), precisely the design feature most prominent in contemporary trading applications.

Sensation-seeking and entertainment motivations have been identified as independent drivers of speculative trading behaviour among retail investors (Dorn & Sengmueller, 2009; Kumar, 2009). These motivations are particularly relevant in gamified digital environments where the process of trading may itself generate positive affect independent of financial outcomes.

2.2 Retail Investor Participation in Digital Equity Markets

The empirical literature on digital retail investor participation has evolved substantially since the onset of pandemic-period market participation. Welch (2022) demonstrates that Robinhood investors as a collective were neither uniformly irrational nor uniformly well-informed; their aggregate behaviour reflected attention-driven purchasing patterns consistent with the salience hypothesis. Barber et al. (2022) provide direct evidence that Robinhood platform features, including the app's curated stock popularity rankings, caused attention-induced buying that temporarily elevated prices and subsequently reversed, representing a net transfer of wealth from app users to other market participants.

Freibauer et al. (2024) establish that trading-app users constitute a behaviourally and demographically distinct segment from traditional online brokerage users, exhibiting higher trading frequency and greater sensitivity to platform-generated signals. This finding motivates the treatment of mobile-app investors as a distinct analytical population in the present study, as 81.54% of the Rajasthan sample reported a mobile application as their primary trading platform.

The tension between access benefits and behavioural costs is a recurrent theme in this literature. Digital platforms may lower participation barriers while simultaneously creating conditions for attention traps, salience-driven trading, and expectation distortion. The appropriate policy response is therefore not to restrict access but to redesign the information and incentive architecture within which access is exercised.

2.3 Trading-App Influence and Technology-Induced Vulnerability

Trading applications alter the decision environment through multiple mechanisms: the compression of stimulus-to-execution time through one-click order placement; the normalisation of frequent trading through activity-based notifications; the creation of portfolio salience through real-time display and colour-coded performance visualisation; and the provision of AI-generated stock suggestions that may carry unwarranted authority due to their algorithmic framing (Da et al., 2011; Thaler & Sunstein, 2008).

The present study operationalises technology influence through two theoretically motivated sub-constructs: trading-app influence (APP, items APP1–APP5), capturing convenience and frequency-enabling features, and algorithmic vulnerability (ALGOVUL, items ALG1–ALG5), capturing perceived disadvantage relative to institutional algorithms and AI-driven systems. This distinction is important because convenience and vulnerability are theoretically separable mechanisms that may produce opposing behavioural effects. The finding, discussed in the Results section, that APP negatively predicts RTBI-5 after controls, is consistent with the hypothesis that investors who are most aware of app-mediated vulnerability exercise greater behavioural restraint.

2.4 Gamification in Financial Platforms

Gamification is defined as the application of game-design elements to non-game contexts to promote motivation and engagement (Deterding et al., 2011; Huotari & Hamari, 2017). In financial platforms, gamification manifests through visual reward elements such as confetti animations triggered by completed trades, achievement badges for milestones such as first investment or portfolio diversification, streaks and leaderboards that create social comparison incentives, and simplified goal-progress visualisations that reduce the perceived complexity of investment decisions.

The financial consequences of hedonic gamification have been investigated in controlled settings. Chapkovski et al. (2022, forthcoming) report that gamified trading conditions increase trading volume, though they note significant self-selection effects among participants who prefer gamified environments. Hüller et al. (2023) find that consumers in gamified financial platform conditions exhibit elevated risk preferences relative to control conditions. Newall and Weiss-Cohen (2022) argue that investment applications designed around frequent engagement and simplified risk presentation may blur the functional and psychological boundary between investing and gambling. Yelagin (2024) extend these concerns to the regulatory domain, identifying specific interface elements that are associated with retail trading quality deterioration.

The present study implements gamified interface features (GAM) as a distinct construct comprising five items (GAM1–GAM5) that measure the mechanisms that produce behaviour in a mobile investment platform. Construct elements cover aspects of notification-driven engagement, real-time portfolio and market information, heightened investment interest, interface qualities, and investment experiences with a 'gamifying' element. Instead of concentrating solely on the aesthetic aspects of gamification, this operationalization reflects behavioral mechanisms most closely related to higher trading engagement and impulsive tendencies for decision-making, including greater emotional salience, more interactions with the platform, and less deliberative processing. This method is well in line with the literature of behavioural finance and digital platforms that explains that this interface design can affect investor behaviour through the attention capture and behavioural reinforcement mechanism, not just through entertaining game design features.

2.5 Social Media, Finfluencers, and Expectation Formation

The research literature on social-media effects on investor behaviour has progressed from early studies documenting the information content of online message boards (Antweiler & Frank, 2004; Chen et al., 2014) to more recent investigations of platform-specific phenomena, including Reddit-based community investing (Bradley et al., 2024; Long et al., 2023), finfluencer credibility and incentive structures (Hulla & Qi, 2024), and algorithmic content amplification effects on investor attention (Tardelli et al., 2020).

A critical insight emerging from this literature is that social-media influence on investor behaviour may operate less through the direct transmission of actionable information and more through the systematic recalibration of return expectations. Finfluencer content is characterised by survivorship-biased success narratives, low-base-rate exceptional outcomes presented as representative, and aspirational identity framing that positions high returns as normative rather than exceptional (Hulla & Qi, 2024; Sathya & Prabhavathi, 2024). When these narratives are encountered at scale and with high emotional salience, they may elevate investors' reference point for what constitutes a normal or achievable return, thereby making risk-taking behaviours appear more rational within the investor's subjective framework.

This expectation-mediated pathway, rather than a direct influence pathway, is the mechanism tested in the mediation analysis of the present study. The result, that SMI predicts risk-taking behaviour through ERR rather than directly, is consistent with this theoretical account and is elaborated in the Results and Discussion sections.

2.6 Herding Behaviour, Overconfidence, and Social Proof in Digital Contexts

Herd behaviour arises when investors update their beliefs based on the observed actions of others rather than on independent private information (Banerjee, 1992; Bikhchandani et al., 1992). In social-media investing environments, herding cues are rendered highly visible through engagement metrics, trending stock lists, viral post shares, and influencer viewership counts that function as proxies for informational credibility irrespective of actual content quality.

Hirshleifer (2020) identifies social transmission bias as a systematic distortion in which socially visible information, regardless of its actual informational value, receives disproportionate weight in belief updating.

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This mechanism is directly applicable to the finfluencer environment, where content visibility is determined by algorithmic amplification rather than analytical quality. The present study's SMI construct incorporates items measuring FOMO (fear of missing out), herd behaviour, viral trend following, and emotional social-media sentiment, reflecting the composite nature of social-media influence as both informational and normative.

2.7 Digital Misinformation and Investor Vulnerability

Digital financial misinformation encompasses not only factually incorrect claims but also selectively presented information, undisclosed promotional arrangements, misleading return representations, and content that exploits emotional decision triggers such as urgency, fear, and social proof. SEBI's 2023 consultation paper on unregistered finfluencers and IOSCO's 2024 finfluencer report both identify the proliferation of unregistered, incentivised financial content as a structural risk to retail investor protection.

The present study operationalises misinformation risk (MISINFO) through items addressing paid promotional content presented as independent advice, unverifiable return claims, panic-inducing social-media content, difficulty distinguishing advisory from promotional content, and herd behaviour driven by viral financial narratives. While MISINFO does not emerge as an independent predictor of perceived risk after controlling for APP and SMI, this reflects conceptual overlap within the digital-risk measurement domain rather than the irrelevance of misinformation to investor vulnerability.

2.8 Financial Literacy, Perceived Risk, and the Paradox of the Informed Vulnerable Investor

Financial literacy has been consistently associated with higher market participation, improved diversification, and more accurate risk assessment in the traditional finance literature (Fernandes et al., 2014; Lusardi & Mitchell, 2014; Van Rooij et al., 2011). The digital investment context, however, introduces a more complex relationship between knowledge and behaviour. A financially literate investor may correctly understand volatility, diversification, and risk-adjusted return, yet remain susceptible to interface-generated urgency, social-proof-driven herding, and algorithmic suggestion effects that operate below the level of conscious deliberation.

The positive association between perceived risk and RTBI-5 observed in the present study is consistent with prior findings that risk-aware investors may simultaneously hold higher behavioural risk exposure, reflecting the engagement paradox whereby investors who are most actively monitoring risky markets are also the most behaviourally active in those markets (Barber & Odean, 2008). This finding argues for a careful conceptual distinction between risk perception and risk aversion.

2.9 Emerging Market and Indian Investor Behaviour

The international behavioural finance literature is disproportionately based on data from the United States, Europe, and developed Asian markets. Indian retail investor behaviour is characterised by a distinctive combination of rapidly growing digital access, a young first-generation investor base, strong social-network investment norms, limited formal financial advisory access, and high exposure to vernacular social-media financial content. These contextual factors warrant caution in applying findings from other institutional environments to the Indian case.

The five Rajasthan cities studied encompass a range of economic profiles: Kota's large student and test-preparation economy; Jaipur's administrative, service, and tourism base; Jodhpur's regional trade and handicraft industries; and Ajmer and Udaipur's service and hospitality economies. These economic heterogeneities are relevant to the interpretation of income and occupation-based group differences in risk-taking behaviour.

2.10 Literature Review Matrix

Table 1 presents a structured thematic synthesis of the representative literature informing the present study.

Theme	Representative Studies	Core Insight	Relevance to D-BRAM

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Behavioural biases	Kahneman & Tversky (1979); Barber & Odean (2000, 2001); Odean (1998)	Loss aversion, overconfidence, and attention-driven trading produce systematic underperformance among retail investors.	Provides the foundational bias mechanisms that digital interfaces amplify through reduced friction and increased salience.
App-based investing	Barber et al. (2022); Welch (2022); Freibauer et al. (2024)	App features influence investor attention and trading patterns; app investors differ from traditional online investors.	Motivates separate APP and ALGOVUL constructs; supports RTBI-5 as a behavioural proxy.
Gamification	Chapkovski et al. (forthcoming); Hüller et al. (2023); Newall & Weiss-Cohen (2022); Yelagin (2024)	Gamified design increases trading volume and risk appetite; risk-investing boundary may be eroded.	Supports GAM construct; non-significant direct effect in this study disciplines overclaiming.
Social media & finfluencers	Bradley et al. (2024); Hulla & Qi (2024); Tardelli et al. (2020); Buz and de Melo (2024)	Social platforms can carry informative signals but also create expectation distortion, herding, and promotional confusion.	Motivates SMI and MISINFO constructs; supports the mediated pathway SMI → ERR → RTBI-5.
Herding & social transmission	Banerjee (1992); Hirshleifer (2020); Bikhchandani et al. (1992)	Social learning and visibility-based weighting of signals can produce systematic behavioural cascades.	Underpins FOMO and herd-behaviour items within SMI construct.
Financial literacy	Lusardi & Mitchell (2014); Fernandes et al. (2014); Van Rooij et al. (2011)	Financial literacy improves participation and diversification but does not consistently prevent behavioural errors in digital contexts.	Supports the paradox of the informed vulnerable investor; grounds digital financial literacy implications.
Technology acceptance	Davis (1989); Venkatesh et al. (2003, 2012)	Perceived usefulness and ease of use drive technology adoption but do not capture vulnerability dimensions.	Motivates the vulnerability extension in D-BRAM beyond standard TAM.
Indian retail investors	SEBI (2023); Sathya & Prabhavathi (2024); Subramanian & Prerana (2021)	Indian retail investors show high social-media dependence, limited formal advisory access, and post-pandemic digital onboarding patterns.	Grounds the study's empirical context and motivates the Rajasthan tier-2 city focus.

Note. D-BRAM = Digital Behavioural Risk Amplification Model.

2.11 Research Gap Synthesis

Three categories of research gap motivate the present study. The first is a construct integration gap: existing

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studies tend to investigate trading-app effects, social-media influence, or gamification independently. No single primary-data study from the Indian context has simultaneously examined app influence, social-media influence, gamified interface exposure, digital misinformation risk, perceived risk, expected return perception, and investor risk-taking behaviour within a unified empirical framework.

The second is a measurement gap: prior constructs of technology acceptance do not adequately capture vulnerability dimensions of app-based investing. Behavioural finance constructs do not operationalise the interface design environment. Social influence theory, gamification theory, and attention theory have not been jointly integrated with a vulnerability-extended technology acceptance framework. The D-BRAM framework proposed in Section 3 addresses this gap.

The third is a geographic and population gap: the tier-2 urban investor base of Rajasthan is largely absent from the Indian behavioural finance literature. Given that this population represents a large and rapidly growing segment of Indian equity market participants, the absence of empirical evidence from this context is a significant omission in the investor protection and financial literacy policy literature.

THEORETICAL FRAMEWORK: THE DIGITAL BEHAVIOURAL RISK AMPLIFICATION MODEL (D-BRAM)

The present study proposes the Digital Behavioural Risk Amplification Model (D-BRAM) as an integrative framework that synthesises five theoretical traditions to explain how digital investment environments systematically alter investors' perceived risk, expected return beliefs, and behavioural risk-taking propensity. D-BRAM is not a single-theory extension but a multi-level integration in which each theoretical component addresses a distinct mechanism in the digital investment decision process. Figure 1 presents the complete conceptual path model.

Figure 1. Digital Behavioural Risk Amplification Model (D-BRAM) — Conceptual Path Diagram

Digital Investment Context

Exogenous Digital Inputs:

Trading-App Influence (APP) → Perceived Risk (RISK) [H4: +] | RTBI-5 [H1: –, cautionary awareness]

Gamified Interface Features (GAM) → RTBI-5 [H3: +, tested; non-significant in controlled model]

Algorithmic Vulnerability (ALGOVUL) → Perceived Risk (RISK) [H4: partial]

Social-Media Influence (SMI) → Expected Return Perception (ERR) [H6a: +] → RTBI-5 [H6b: +]

Digital Misinformation Risk (MISINFO) → Perceived Risk (RISK) [H5: +, tested]

Cognitive-Evaluative Mediators:

Perceived Risk (RISK) → RTBI-5 [H4 outcome: +]

Expected Return Perception (ERR) → RTBI-5 [strongest predictor, + direct; mediates SMI effect]

Outcome: RTBI-5 (Risk-Taking Behaviour Index, 5-component)

Boundary Conditions: Age (negative), Income (positive), Education (positive) [H7]

Note. Arrows indicate hypothesised directional paths. Signs indicate expected direction of association based on theoretical grounding. Paths to RTBI-5 are tested in multiple regression models with HC3 standard errors. The mediation path SMI → ERR → RTBI-5 is tested via bootstrap analysis (5,000 resamples).

2.12 Prospect Theory and Reference-Point Construction in Digital Environments

Prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) provides the foundational framework for understanding how investors evaluate risk in the D-BRAM context. The theory proposes that subjective value is computed relative to a reference point and that the value function is concave for gains, convex for losses, and steeper in the loss domain (loss aversion). In app-based investing, reference points are not fixed by objective portfolio cost basis alone; they are continuously constructed and updated by dashboard visualisations, daily percentage change indicators, benchmark comparisons, and peer portfolio screenshots shared on social media. The practical consequence is that investors in digital environments may experience a higher frequency of psychologically salient gain and loss events relative to their actual financial position, potentially driving defensive or speculative responses that are disproportionate to objective changes in portfolio value.

2.13 Attention Theory and the Architecture of Digital Salience

Barber and Odean's (2008) attention hypothesis proposes that retail investors, facing bounded attention, disproportionately buy stocks that have captured their attention through news, large price movements, or high trading volume. Mobile trading applications extend this mechanism by creating persistent, programmable attention structures: users can configure watchlists, enable price-threshold alerts, subscribe to earnings notification feeds, and receive curated 'trending' stock lists that direct attention to specific securities without any deliberate information-seeking on the investor's part. Da et al. (2011) establish that attention, measured through Google search volume, predicts subsequent institutional and retail trading activity. In the D-BRAM framework, trading-app influence is operationalised as the primary attention-channel mechanism, with one-click execution as the mechanism that converts salient attention into a trade without the intervention of reflective deliberation.

2.14 Social Influence Theory and Finfluencer Authority

Social influence theory (Cialdini, 2001; Deutsch & Gerard, 1955) distinguishes between informational social influence, in which individuals update beliefs based on others' presumed superior knowledge, and normative social influence, in which individuals conform to observed behaviour to gain social approval or avoid exclusion. Finfluencer content operates through both mechanisms simultaneously: the influencer's financial success and apparent expertise activate informational influence, while community engagement metrics, follower counts, and peer testimonials activate normative influence. Importantly, neither mechanism requires that the influencer's information be accurate for behavioural influence to occur; only the perception of credibility and the visibility of community consensus are required. The D-BRAM framework incorporates social influence as the primary driver of expected return expectation updating, rather than as a direct predictor of trading behaviour, which is consistent with the mediation evidence reported in Section 10.

2.15 Technology Acceptance with Vulnerability Extension

The Technology Acceptance Model (Davis, 1989) and its Unified Theory extension (Venkatesh et al., 2003, 2012) explain technology adoption through perceived usefulness and perceived ease of use but do not address the possibility that technology adoption produces systematically adverse decision-making conditions. The D-BRAM framework extends TAM by adding a vulnerability dimension, operationalised through (APP and ALGOVUL) items related to algorithmic disadvantage, AI-driven recommendation opacity, cyber risk exposure, platform outage risk, and professional judgment displacement. This extension is theoretically motivated by the recognition that, in financial markets, the same interface features that facilitate access and reduce transactional friction may simultaneously reduce deliberative friction, expose investors to adversarial algorithmic counterparties, and create false impressions of informational parity that do not reflect the structural informational advantages of institutional market participants.

2.16 Gamification Theory and Engagement-Welfare Trade-offs

Gamification theory (Deterding et al., 2011; Hamari et al., 2014) differentiates between educational gamification, which uses engagement mechanics to promote learning and skill development, and hedonic gamification, which uses engagement mechanics to maximise platform interaction time, which may not coincide with user welfare. In financial platforms, the D-BRAM framework treats gamified interface features as a specific sub-mechanism within the broader technology influence pathway that may reduce deliberative friction and amplify emotional salience without commensurate improvements in informational quality or decision accuracy. The non-significant controlled association between GAM and RTBI-5 reported in this study is interpreted within the D-

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BRAM framework as evidence that gamification effects may be subsumed by the broader app-influence and expected-return pathways when all constructs are jointly modelled, rather than as evidence that gamification is behaviourally irrelevant.

3. HYPOTHESES

The following hypotheses are derived from the D-BRAM framework. Each hypothesis is stated in directional form and corresponds to a specific estimated path in the regression or mediation models.

Hyp.	Statement	Theoretical Basis
H1	Trading-app influence is significantly associated with retail investor risk-taking behaviour (RTBI-5).	Attention Theory (Barber & Odean, 2008); TAM-V Extension. Note: direction is tested, not assumed positive.
H2	Social-media and finfluencer influence is positively associated with perceived risk.	Social Influence Theory; Digital Misinformation literature (SEBI, 2023; IOSCO, 2024).
H3	Gamified interface features are positively associated with risk-taking behaviour (RTBI-5).	Gamification Theory (Chapkovski et al., forthcoming; Hüller et al., 2023).
H4	Technology-induced vulnerability (APP, GAM, ALGOVUL) is positively associated with perceived risk.	TAM-V Extension; Prospect Theory reference-point construction (Kahneman & Tversky, 1979).
H5	Digital misinformation risk is positively associated with perceived risk.	SEBI (2023); IOSCO (2024); Hirshleifer (2020) social transmission bias.
H6	Expected return perception mediates the relationship between social-media influence and risk-taking behaviour (RTBI-5), such that the indirect effect SMI → ERR → RTBI-5 is positive and significant.	Social Influence Theory; Prospect Theory; survivorship-bias in expectation formation (Hulla & Qi, 2024; Sathya & Prabhavathi, 2024).
H7	Demographic characteristics (age, income, education) are significantly associated with group differences in risk-taking behaviour (RTBI-5).	Life-cycle investment theory; human capital and risk tolerance literature (Dohmen et al., 2011).

4. RESEARCH METHODOLOGY

4.1 Research Design

This study employs a cross-sectional quantitative survey design. A structured questionnaire was administered to retail equity investors in five Rajasthan cities. The cross-sectional design enables the identification of associations among constructs and the testing of mediation pathways; it does not permit causal inference. This delimitation is acknowledged explicitly, and the interpretive language throughout the paper is constrained accordingly.

4.2 Sampling and Inclusion Criteria

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A four-stage purposive-stratified inclusion process was applied to ensure that the analytical sample comprised verified retail equity investors from the specified geographic context. The filtering stages and their yield are presented in Table 2.

Filtering Stage	Criterion	Remaining N
Stage 0: Raw survey responses	—	580
Stage 1: Informed consent	Consent = Yes	580
Stage 2: Active equity investor	Currently invested	574
Stage 3: Selected Rajasthan city resident	Jaipur, Jodhpur, Kota, Ajmer, or Udaipur	—
Stage 4: Individual equity-share investor	Invests in individual equity shares	500 (final)

Note. All four criteria were applied simultaneously at the final stage to yield the analytical sample of N = 500.
The achieved sample size of N = 500 exceeds the minimum requirement for reliable multiple regression analysis with ten predictors and one dependent variable at the recommended ratio of ten observations per predictor (Hair et al., 2019), and is sufficient for bootstrap mediation analysis, EFA with 31 items, and subgroup comparisons. City-level representation is near-equal: Ajmer (n = 100, 20.00%), Jaipur (n = 100, 20.00%), Jodhpur (n = 100, 20.00%), Udaipur (n = 100, 20.00%), and Kota (n = 100, 20.00%).

4.3 Questionnaire Structure and Construct Operationalisation

The questionnaire comprised the following sections: (1) informed consent; (2) demographic profile; (3) investment profile (RTBI); (4) app influence (APP1–APP5); (5) gamified interface features (GAM1–GAM5); (6) algorithmic vulnerability (ALG1–ALG5); (7) social-media and finfluencer influence (SMI1–SMI5); (8) digital misinformation risk (MIS1–MIS5); (9) perceived risk (RISK1–RISK4); and (10) expected return perception (ERR1–ERR5). All construct items employed a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Investment-profile and risk-taking behaviour items used ordinal response categories appropriate to each behavioural domain.

4.4 Construct Operationalisation and the Revised RTBI-5

Following the reviewer's recommendation and in response to a methodological concern regarding the circular inclusion of expected return perception (ERR) in both the outcome index and as a regression predictor, this study introduces the Revised Risk-Taking Behaviour Index (RTBI-5). RTBI-5 is computed as the equally weighted mean of five ordinal behavioural indicators: (1) monthly income proportion invested in equity, (2) trading/investment frequency, (3) investment horizon risk (shorter horizons scored higher), (4) primary investment purpose risk (wealth creation and short-term profit scored higher than retirement planning), and (5) instrument risk exposure (individual equities and derivatives scored higher than ETFs and mutual funds). Expected return perception is retained as a separate predictor variable in all regression and mediation models, enabling a clean test of the theoretical mechanism through which digital influences shape risk-taking behaviour.

The construct mapping used throughout the study is presented in Table 3.

Construct	Items	Operational Meaning	Scoring

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APP	APP1–APP5	Trading-app influence: convenience, accessibility, self-directed investing, frequency encouragement, and simplified execution	Mean of 5 items
GAM	GAM1–GAM5	Gamified interface features: notifications, real-time engagement, visual stimulation, and game-like investment experience	Mean of 5 items
ALGOVUL	ALG1–ALG5	Algorithmic and AI vulnerability: perceived disadvantage relative to institutional algorithms	Mean of 5 items
SMI	SMI1–SMI5	Social-media and finfluencer influence: information dependence, FOMO, herd behaviour, viral trends	Mean of 5 items
MISINFO	MIS1–MIS5	Digital misinformation risk: promotional opacity, unverifiable claims, panic amplification	Mean of 5 items
RISK	RISK1–RISK4	Perceived equity-market risk: volatility, risk of ruin, modern market complexity	Mean of 4 items
ERR	ERR1–ERR5	Expected return perception: belief in above-market returns influenced by social-media success narratives	Mean of 5 items
RTBI-5	**5 behavioural indicators**	**Revised Risk-Taking Behaviour Index: income % invested + frequency + horizon risk + purpose risk + instrument risk. ERR excluded to eliminate circularity.**	**Composite mean of 5 ordinal items**

Note. RTBI-5 replaces the original RTBI used in the preliminary analysis. ERR is excluded from RTBI-5 and treated as a separate independent variable to eliminate tautological overlap. All construct scores are mean scores computed across their constituent items, with higher scores indicating greater intensity of the construct.

4.5 Analytical Methods

The following statistical procedures were employed: (1) Cronbach's alpha reliability analysis for all constructs; (2) descriptive statistics and normality diagnostics; (3) Pearson correlation analysis with a full inter-construct correlation matrix; (4) chi-square tests for selected categorical associations; (5) one-way ANOVA with eta-squared effect sizes for demographic group differences in RTBI-5; (6) multiple regression analysis with heteroskedasticity-consistent (HC3) standard errors for RTBI-5 and perceived risk outcome models, including variance inflation factor (VIF) diagnostics for multicollinearity; (7) bootstrap-based mediation analysis (5,000 resamples, Hayes PROCESS Model 4) for the SMI → ERR → RTBI-5 pathway; and (8) exploratory factor analysis with Promax rotation and communality reporting for scale diagnostics. All analyses were conducted in SPSS 27 with PROCESS macro version
4.2 for mediation analysis. Common method bias was assessed using Harman's single-factor test.

4.6 Common Method Bias Assessment

Given that all constructs were measured using the same self-administered survey instrument, common method

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bias (CMB) is a potential confound. Harman's single-factor test was conducted by entering all construct measurement items into an unrotated principal component analysis. The first unrotated factor accounted for less than 50% of the total variance, which would indicate substantial CMB (Podsakoff et al., 2003). While this test does not provide definitive evidence against CMB, it suggests that common method variance is unlikely to account for the primary findings of this study.

5. RESULTS

5.1 Demographic and Investment Profile

The sample of N = 500 retail equity investors exhibits the following demographic composition: 69.6% male, 30.2% female, 0.2% other; the 26–35 age group is the largest (37.8%), reflecting the post-pandemic cohort of first-generation digital investors. Graduates constitute the largest educational category (34.6%), followed by undergraduates (27.40%) and postgraduates (24.2%). Annual household income is concentrated in the below-5 lakh (34.8%) and 5–10 lakh (38.6%) bands, consistent with the tier-2 city economic profile. Investment experience is dominated by the 2–5 year category (57.2%), indicating a predominantly post-pandemic cohort.

Investment behaviour profile: 81.6% of respondents use mobile applications as their primary trading platform, with Zerodha, Groww, and Angel One as the most frequently cited. Monthly trading frequency is the most common (29.8%), followed by weekly (28.4%). Wealth creation is the dominant stated investment purpose (64.8%). Short investment horizons (less than 6 months and 6 months to 1 year) account for 39.4% of the sample, indicating significant short-termism.

5.2 Reliability Analysis

Table 4 presents Cronbach's alpha coefficients for all constructs. All values exceed the threshold of α = .70 recommended for exploratory survey research (Nunnally, 1978). The App influence (APP: α = .893), algorithmic vulnerability (ALGOVUL: α = .885), and social-media influence (SMI: α = .900+) constructs demonstrate excellent reliability. Gamified interface features (GAM: α = .838) exhibit good internal consistency, while perceived risk (RISK: α > .70) and expected return perception (ERR: α > .70) meet the acceptable threshold.

Construct	No. of Items	Cronbach's α	Classification
APP	5	.893	Excellent
GAM	5	.838	Good
ALGOVUL	5	.885	Excellent
SMI	5	.901	Excellent
MISINFO	5	.912	Excellent
RISK	4	.781	Acceptable
ERR	5	.824	Good

Note. Classification follows Nunnally (1978): Acceptable ≥ .70; Good ≥ .80; Excellent ≥ .90.

5.3 Descriptive Statistics

All digital-risk constructs exhibit above-midpoint mean values (range: 3.60–3.97), with negative skewness indicating respondent concentration toward higher agreement categories. RTBI-5 has a moderate mean (M = 2.94, SD = 0.331), indicating moderate behavioural risk-taking with right-censoring at the higher end. Table 5 presents full descriptive statistics.

Construct	N	Mean	SD	Min	Max	Skew	Kurt	Note

APP	500	3.938	0.812	1.00	5.00	−1.72	3.16	
GAM	500	3.951	0.842	1.00	5.00	−1.59	2.69	
ALGOVUL	500	3.966	0.827	1.00	5.00	−1.56	2.40	
SMI	500	3.915	0.811	1.00	5.00	−1.47	1.87	
MISINFO	500	3.968	0.836	1.00	5.00	−1.48	1.86	
RISK	500	3.674	0.812	1.00	5.00	−1.09	1.60	
ERR	500	3.604	0.907	1.00	5.00	−0.93	0.58	Predictor only
RTBI-5	500	**2.941**	0.331	1.83	4.17	0.21	0.25	**Revised outcome**

Note. RTBI-5 excludes ERR components present in the original RTBI. Kurt. = excess kurtosis.

Correlation Analysis

Table 6 presents the Pearson inter-construct correlation matrix. RTBI-5's highest bivariate association is with ERR ($r = .36$, $p < .001$), followed by RISK ($r = .24$, $p < .001$), SMI ($r = .16$, $p < .001$), and MISINFO ($r = .15$, $p < .001$).

Notably, the correlation between RTBI-5 and ERR is lower than the correlation between the original RTBI and ERR ($r = .39$), consistent with the removal of the ERR component from the index. High inter-correlations among APP, GAM, and ALGOVUL ($r = .83$ to $.97$) confirm the multicollinearity concern documented by the VIF diagnostics in Section 6.6.

	APP	GAM	ALGOVUL	SMI	MISINFO	RISK	ERR	RTBI-5
APP	1.00	.97**	.86**	.77**	.75**	.69**	.57**	.11*
GAM		1.00	.83**	.74**	.73**	.64**	.53**	.10*
ALGOVUL			1.00	.76**	.75**	.66**	.61**	.12**
SMI				1.00	.97**	.63**	.62**	.16**
MISINFO					1.00	.61**	.58**	.15**
RISK						1.00	.57**	.24**
ERR							1.00	.36**
RTBI-5								1.00

*Note. ** p < .01, * p < .05 (two-tailed). High inter-correlations among APP, GAM, and ALGOVUL (.83–.97) were addressed through parsimonious model specification and VIF diagnostics.*

5.4 Chi-Square Tests

Chi-square tests examined categorical associations of theoretical relevance. City-level mobile-app platform adoption was significantly heterogeneous across cities ($\chi2 = 17.33$, $df = 4$, $p = .002$, Cramer's $V = .183$). High

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social-media influence was significantly associated with high RTBI-5 ($\chi2$ = 17.84, df = 1, p < .001, Cramer's V = .185), providing categorical support for the SMI–risk-taking association. Age group was not significantly associated with high trading frequency ($\chi2$ = 6.07, df = 4, p = .194), suggesting that age group alone does not explain high trading propensity in this sample.

5.5 ANOVA: Demographic Group Differences in RTBI-5

Table 7 presents one-way ANOVA results for RTBI-5 across demographic grouping variables. Statistically significant and practically meaningful group differences are found for educational qualification (F = 6.488, p < .001, $\eta2$ = .048) and annual household income (F = 8.748, p < .001, $\eta2$ = .048). The effect size of $\eta2$ = .048 for both variables indicates a small-to-moderate practical effect. No significant group differences are observed for gender, investment experience, or primary trading platform.

Grouping Variable	F	p	η2 (Effect Size)	Decision
City	2.142	.075	.016	ns
Age Group	2.304	.057	.018	ns
Gender	0.071	.790	< .001	ns
Educational Qualification	**6.488**	**< .001**	**.048**	**Significant**
Annual Household Income	**8.748**	**< .001**	**.048**	**Significant**
Investment Experience	1.298	.274	.007	ns
Primary Trading Platform	2.380	.069	.014	ns

Note. ns = not significant at p < .05. η2 = eta-squared effect size.

5.6 Multiple Regression Analysis

Two regression models predicting RTBI-5 were estimated, following the D-BRAM structure. Model 1 includes APP, SMI, RISK, ERR, and five demographic controls. Model 2 replaces APP with the sub-components GAM and ALGOVUL. All models use HC3 heteroskedasticity-consistent standard errors. Table 8 presents the model summaries and Table 9 presents the full coefficient tables with VIF statistics.

Model	N	R^2	Adj. R^2	F	Note
Model 1: RTBI-5 (APP, SMI, RISK, ERR + controls)	500	.198	.181	11.23**	Primary model; ERR excluded from RTBI-5
Model 2: RTBI-5 (GAM, ALGOVUL, SMI, RISK, ERR + controls)	500	.195	.177	10.86**	Tests sub-component gamification effect
Perceived Risk Model (APP, GAM, SMI, MISINFO, ERR + controls)	500	.555	.546	53.75**	Tests H4 and predictors of perceived risk

*Note. ** p < .001. Adjusted R^2 values are slightly lower than the original RTBI models due to the removal of ERR from the outcome index.*

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Table 9 presents the full coefficient table for RTBI-5 Model 1 with VIF diagnostics.

Predictor	B	SE(HC3)	t	p	CI LL	CI UL	Cohen's f^2	VIF
Constant	2.531	0.118	21.45	< .001	2.299	2.763	—	—
APP_score	**−0.098**	0.033	−2.97	**.003**	−0.163	−0.033	.018	7.84
SMI_score	−0.006	0.034	−0.18	.860	−0.073	0.061	.001	8.12
RISK_score	**0.071**	0.027	2.63	**.009**	0.018	0.124	.014	2.51
ERR_score	**0.178**	0.025	7.12	**< .001**	0.129	0.227	.101	2.38
age_ord	−0.043	0.015	−2.87	.004	−0.072	−0.014	.016	1.33
income_ord	0.041	0.020	2.05	.041	0.002	0.080	.008	1.47
experience_ord	−0.013	0.023	−0.57	.571	−0.058	0.032	.001	1.29
edu_ord	0.026	0.019	1.37	.172	−0.011	0.063	.004	1.41
male_dummy	0.009	0.036	0.25	.803	−0.061	0.079	< .001	1.19
mobile_dummy	−0.025	0.046	−0.54	.588	−0.115	0.065	< .001	1.24

Note. HC3 = heteroskedasticity-consistent standard errors (MacKinnon & White, 1985). All VIF values < 10, indicating that multicollinearity does not critically distort coefficient estimates. ERR is now a predictor-only variable, not a component of RTBI-5. Cohen's f^2 computed as: R^2-change-attributable / (1 − R^2-full-model), approximated from t-value. Boldface indicates p < .05.

The highest VIF values are observed for APP (VIF = 7.84) and SMI (VIF = 8.12), which is attributable to their relationships with GAM, ALGOVUL, and MISINFO. These values are below the conventional threshold of VIF = 10 (Hair et al., 2019) and below the more conservative threshold of VIF = 5 applied in some fields.
ERR is the strongest positive predictor of RTBI-5 (B = 0.178, p < .001, Cohen's f^2 = .101), the only predictor with a medium effect size in the model. APP is a significant negative predictor (B = −0.098, p = .003), consistent with a risk-awareness inhibition interpretation: investors who score higher on app-induced vulnerability awareness exhibit lower, not higher, behavioural risk-taking after controlling for perceived risk, expected returns, and demographic characteristics. RISK is a significant positive predictor (B = 0.071, p = .009), consistent with the interpretation that risk-aware and more behaviourally active investors co-occur in equity markets. Age is a significant negative predictor (B = −0.043, p = .004), and income a significant positive predictor (B = 0.041, p = .041).

5.7 Mediation Analysis: SMI → ERR → RTBI-5

Bootstrap mediation analysis was conducted using Hayes PROCESS macro Model 4 with 5,000 bootstrap resamples. Table 10 presents the mediation results.

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Path	Estimate	p	Boot CI LL	Boot CI UL	Note
a: SMI → ERR	0.401	< .001	0.336	0.466	H6a: ✓
b: ERR → RTBI-5 (controlling SMI)	0.178	< .001	0.129	0.227	H6b: ✓
c': SMI → RTBI-5 (direct, controlling ERR)	−0.006	.860	−0.073	0.061	ns
c: Total SMI → RTBI-5	0.066	.038	—	—	
Indirect effect a×b (SMI → ERR → RTBI-5)	**0.069**	—	**0.038**	**0.107**	**H6: ✓**

Note. Bootstrap confidence intervals based on 5,000 resamples (Hayes PROCESS v4.2, Model 4). CI = confidence interval. The indirect effect CI [0.038, 0.107] excludes zero, confirming mediation. Applying the Zhao et al. (2010) classification, the result constitutes indirect-only (full) mediation: the direct effect c' is non-significant while the indirect effect is significant. ns = not significant.

The mediation analysis confirms H6: social-media influence operates on risk-taking behaviour (RTBI-5) exclusively through expected return perception rather than through a direct pathway. The indirect effect of 0.069 accounts for 104.5% of the total effect (0.066), indicating that the suppressed direct effect is negligible after the ERR pathway is accounted for. This pattern is consistent with Zhao et al.'s (2010) full mediation criterion.

5.8 Exploratory Factor Analysis

EFA was conducted on 31 core items using principal axis factoring with Promax oblique rotation (allowing factors to correlate, appropriate given the high observed inter-construct correlations). KMO = .968 indicates excellent sampling adequacy. Bartlett's test of sphericity: $\chi 2(465) = 13{,}294.09$, $p < .001$, confirms that the correlation matrix is factorable. Four factors were retained on the basis of the scree plot and the criterion of eigenvalue > 1, collectively explaining 67.93% of the total variance. The four-factor solution corresponds conceptually to: Factor 1 (Technology and Vulnerability), Factor 2 (Social Media and Finfluencer Influence), Factor 3 (Risk Perception and Expected Return), and Factor 4 (Gamified Interface Features). Item-level factor loadings and communalities are available in Appendix D. The EFA is treated as a scale-diagnostic tool; confirmatory factor analysis or PLS-SEM with full measurement model estimation is recommended as a methodological extension in future work.

5.9 Hypothesis Testing Summary

H	Statement	Key Statistic	p	Decision
H1	App influence is significantly associated with RTBI-5.	B = −0.098	.003	Supported (negative direction)
H2	SMI is positively associated with perceived risk.	B = 0.120	.464	Not supported
H3	Gamified features are positively associated with RTBI-5.	B = −0.034	.326	Not supported
H4	Technology vulnerability positively predicts perceived risk.	APP: B = 0.726	< .001	Partially supported (APP

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				only)
H5	MISINFO is positively associated with perceived risk.	B = 0.033	.832	Not supported
H6	ERR mediates the SMI → RTBI-5 pathway.	Indirect = 0.069	CI [0.038, 0.107]	Supported
H7	Demographic factors significantly differentiate RTBI-5.	F = 6.49–8.75	< .001	Supported (education, income)

Note. H = Hypothesis. All tests conducted at α = .05. Effect sizes reported in Section 6.6 and 6.7.

6. DISCUSSION

6.1 The Expectation-Formation Pathway: Primary Mechanism of Digital Risk Amplification

The most consequential finding of this study is the confirmation of a full mediation pathway: social-media influence predicts RTBI-5 exclusively through expected return perception, with the direct pathway becoming non-significant once ERR is included in the model. This result advances a theoretically specific mechanism that complements but substantially refines the general claim that social media increases investor risk-taking. The D-BRAM framework proposes that digital environments do not primarily increase risk-taking by directly lowering inhibitory thresholds or generating irrational exuberance; rather, they operate by systematically recalibrating the distribution of returns that investors regard as achievable. When finfluencer narratives repeatedly present outlier outcomes, such as one hundred percent returns in one year, as normative rather than exceptional, they shift investors' subjective return distributions upward. Within an individually rational decision framework, a higher expected return makes risk-taking more acceptable, not because the risk has changed but because the perceived reward has increased. This is consistent with prospect theory's emphasis on reference-point dependence and with the social comparison literature demonstrating that visible peer success recalibrates individual aspiration levels (Hulla & Qi, 2024; Sathya & Prabhavathi, 2024).

6.2 The Risk-Awareness Inhibition Effect of App Influence

The significant negative association between trading-app influence (APP) and RTBI-5 in the controlled regression model (B = −0.098, p = .003) is counterintuitive relative to the simple democratisation narrative but consistent with a more theoretically nuanced account. Investors who score highly on the APP construct report high awareness of app-specific vulnerabilities: the encouragement of frequent trading, the reduction of deliberative time through one-click execution, and the emotional activation created by real-time portfolio displays. This heightened awareness of vulnerability may activate a reflective or defensive response that partially counteracts the impulsive trade facilitation that app design provides.

This finding is important for platform design regulation. It suggests that interface features designed to increase investor awareness of their own behavioural vulnerability, such as trading frequency dashboards, time-since-last-trade displays, or friction-introducing confirmation prompts for high-risk orders, may have measurable risk-inhibiting effects. The policy mechanism is not prohibition of convenient interface features but the co-design of awareness features that activate reflective rather than impulsive decision modes.

6.3 Non-Significant Effects: Gamification and Misinformation

The non-significant association between GAM and RTBI-5 in the controlled model does not imply that gamified features are irrelevant to investor behaviour. In the bivariate correlation analysis, GAM is positively correlated with RTBI-5 (r = .10, p < .05). The controlled non-significance reflects the absorption of the GAM effect by the broader APP construct (of which GAM is a sub-scale) and by ERR, which may itself be elevated by gamification-induced engagement. This pattern is consistent with the mediation interpretation: gamification may increase risk-taking behaviour indirectly through elevation of expected return perception rather than through a direct behavioural channel. Future experimental work with controlled gamification manipulations would be needed to isolate the gamification effect cleanly.

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The non-significant coefficient for MISINFO in the perceived risk model, after controlling for APP and SMI, reflects conceptual overlap among the digital-risk constructs rather than the irrelevance of misinformation. The correlation between SMI and MISINFO is r = .97, indicating that these constructs are nearly collinear in this sample, likely because respondents experience misinformation and social-media influence as constituents of the same digital information environment. Future work with more explicitly differentiated measurement of information accuracy, source credibility, and promotional disclosure would enable a cleaner test of the misinformation hypothesis.

6.4 Demographic Boundary Conditions

The significant positive association between income and RTBI-5 is consistent with the financial risk-tolerance literature and with the rational expectation that higher-income investors have greater capacity to absorb losses, reducing the psychological cost of holding volatile equity positions (Dohmen et al., 2011). The significant negative association between age and RTBI-5 is consistent with the life-cycle investment literature, which documents declining risk appetite with age as human capital decreases and the importance of capital preservation increases. The absence of a significant gender effect, in a sample that is 75% male, should be interpreted cautiously; the sample

composition severely limits statistical power to detect gender differences. Future work with gender-balanced sampling is needed before concluding that gender is not associated with RTBI-5 in this population.

6.5 Contextual Contribution: Rajasthan Tier-2 Cities

The geographical specificity of this study constitutes a substantive empirical contribution beyond descriptive novelty. The high mean scores on all digital-risk constructs (range 3.60–3.97) in a tier-2 city sample suggest that the digital investment infrastructure that enables risk-amplifying behaviours is not confined to metropolitan centres. The balanced city representation and the active post-pandemic investor profile of the sample further indicate that the mechanisms identified in this study are likely to be generalisable to comparable tier-2 equity market ecosystems in other Indian states, subject to replication.

7. THEORETICAL IMPLICATIONS

This study advances the behavioural finance literature by operationalising the digital decision environment as a behavioural architecture with measurable and theoretically differentiated mechanisms, rather than treating technology as a neutral access conduit. The D-BRAM framework extends Prospect Theory by identifying app interface features as systematic reference-point manipulators; extends Attention Theory by specifying notification and watchlist design as programmable attention structures; extends Social Influence Theory by introducing the expectation-formation pathway as the primary mechanism linking finfluencer exposure to risk-taking; extends Technology Acceptance by adding a vulnerability dimension that can have risk-attenuating effects opposite to the convenience dimension; and extends Gamification Theory by distinguishing its direct effect on risk-taking from its indirect effect through expectation elevation.

The confirmation of full mediation in the SMI → ERR → RTBI-5 pathway provides a theoretically precise and empirically grounded mechanism for future research and model development. The finding that expected return perception, not perceived risk, is the dominant positive predictor of RTBI-5 repositions the debate: the question for digital financial literacy is not primarily how to reduce risk perception but how to calibrate return expectations to reflect realistic distributional outcomes.

8. PRACTICAL IMPLICATIONS

For retail investors, the primary implication is the importance of testing stated return expectations against base-rate distributional evidence before increasing equity allocations. Social-media success narratives are subject to survivorship bias, promotional incentives, and self-presentation effects that systematically inflate the apparent frequency of exceptional outcomes.

For trading platform designers and operators, the negative APP–RTBI-5 relationship suggests that interface features that heighten investor awareness of their own behavioural vulnerability, such as trading frequency logs, cooling-off period prompts, and real-time comparison of trade timing with market outcomes, may have risk-

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reducing effects without reducing overall platform engagement. Platform design should aim to inform the reflective system rather than exclusively facilitate the impulsive one.

For financial educators, the study indicates that digital financial literacy must move beyond instrument-level knowledge to include source literacy (Who is this person? What are their incentives?), platform literacy (How is this interface designed to influence my behaviour?), and expectations literacy (How do I evaluate whether this stated return is representative or an outlier?). These dimensions are not addressed by conventional financial literacy programmes.

For financial advisors, the results suggest that a meaningful client intake question concerns not only asset allocation but also information hygiene: which platforms does the client use, which information sources do they follow, and what return expectations do those sources generate?

9. POLICY IMPLICATIONS

Table 11 presents structured policy recommendations derived directly from the empirical findings of this study.

Policy Domain	Recommended Action	Empirical Basis
Finfluencer Regulation	Require visible disclosure of registration status, sponsorships, referral arrangements, and content classification (education / opinion / advertisement / advice) for all financial content exceeding 10,000 views or followers.	SMI mean = 3.915; mediated pathway to RTBI-5 confirmed.
Return Claim Disclosure	Mandate plain-language risk labelling for return claims in social-media-linked financial marketing, including mandatory disclosure of the proportion of investors achieving the stated returns and the time horizon.	ERR is the strongest predictor of RTBI-5 (B = 0.178, f^2 = .101).
Platform Design Standards	Require platforms to disclose engagement features that encourage trading frequency. Introduce optional friction features: mandatory confirmation for high-frequency trading sequences, trading frequency dashboards visible on login, and cooling-off period prompts for investors who have traded more than a threshold number of times in a defined period.	APP negatively predicts RTBI-5 after controls; awareness may attenuate impulsive trading.
Gamification Controls	Discourage celebratory animations, achievement badges, and leaderboard features linked to trade execution or portfolio gains. Permit and encourage educational gamification that improves understanding of diversification, compound growth, and risk-adjusted return.	GAM construct theoretically supported; direct effect non-significant in controlled model.

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Investor Education	Integrate modules on return expectation calibration, source credibility evaluation, promotional content recognition, and social-proof bias into SEBI's investor education programmes and National Institute of Securities Markets (NISM) certification curricula.	ERR mediation and demographic differences by education ($F = 6.49$, $p < .001$).
Suitability and Onboarding	Strengthen suitability assessment at account opening for high-risk products (derivatives, thematic ETFs, IPO grey market) particularly for investors with investment experience of less than two years, income below five lakh per annum, and high social-media financial content consumption.	Income differences in RTBI-5 ($F = 8.748$, $p < .001$); 22.69% post-COVID investors in sample.
Tier-2 City Surveillance	Extend SEBI's investor grievance and surveillance infrastructure to tier-2 cities. Current investor protection mechanisms are concentrated in metropolitan markets and do not adequately reflect the growth of digital equity participation in cities such as those studied here.	N = 500 verified equity investors across five Rajasthan tier-2 cities.

Note. All policy recommendations are derived from the empirical findings of this study. They should be considered alongside SEBI's existing regulatory framework, IOSCO (2024), and the recommendations of the National Strategy for Financial Education (NSFE) 2020–25.

10.CONCLUSION

This study examined the mechanisms through which the digital investment environment shapes the risk-taking behaviour of retail equity investors in tier-2 Rajasthan cities, using a filtered primary-data sample of N = 500 verified individual equity investors from Jaipur, Jodhpur, Kota, Ajmer, and Udaipur. The study proposed and tested the Digital Behavioural Risk Amplification Model (D-BRAM), an integrative theoretical framework that synthesises Prospect Theory, Attention Theory, Social Influence Theory, Technology Acceptance with Vulnerability Extension, and Gamification Theory.

The primary empirical contribution is the confirmation of full mediation: social-media and finfluencer influence affects the revised Risk-Taking Behaviour Index (RTBI-5) exclusively through expected return perception, not directly. This finding reframes the policy debate about finfluencer risk from a content accuracy problem to an expectation calibration problem. The secondary contribution is the identification of a risk-awareness inhibition effect: trading-app influence is a significant positive predictor of perceived risk but a significant negative predictor of RTBI-5 after controls, suggesting that investors who are most aware of app-mediated behavioural vulnerabilities exercise greater behavioural restraint. A third contribution is the construction and validation of RTBI-5, which resolves the methodological circularity present in prior composite risk-index operationalisations by excluding expected return perception from the outcome variable.

Digital risk amplification in Indian retail equity markets is not a simple direct-effect phenomenon. It operates through layered, interacting mechanisms: apps amplify perceived risk while paradoxically constraining observed risk-taking; social media recalibrates return expectations that then drive behavioural risk-taking; demographic factors set the boundary conditions within which these mechanisms operate with differential intensity. This complexity argues against both regulatory alarmism and uncritical democratisation optimism, and in favour of evidence-based, mechanism-specific policy interventions of the kind outlined in Section 10.

11. LIMITATIONS

• The study is geographically restricted to five Rajasthan cities. Generalisation to other Indian states, metropolitan investors, or rural investors requires independent replication.

• All constructs are based on self-reported survey data, which are subject to social desirability bias, recall bias, and subjective interpretation of Likert items.

• The cross-sectional design permits the identification of associations and mediation pathways but does not support causal inference.

• RTBI-5 is a behavioural risk-taking proxy based on self-reported investment behaviour; it does not incorporate objective financial risk capacity measures such as net worth, liabilities, or actual portfolio composition.

• The GAM construct is derived from three technology items rather than a dedicated, validated gamification scale, limiting the specificity of gamification-related conclusions.

• Common method bias, while assessed via Harman's single-factor test, cannot be fully ruled out in a single-source survey design.

• The sample is 75% male, limiting the statistical power to detect gender-related differences in risk-taking behaviour.

FUTURE RESEARCH DIRECTIONS

Longitudinal panel data linking survey-measured constructs to actual trading records from brokerage accounts, to verify the self-reported RTBI-5 associations with objective trading outcomes.

• Experimental interface manipulation studies isolating specific gamification elements (badges, confetti, leaderboards, notification frequency) to establish causal effects on risk-taking behaviour.

• A pan-India comparative study contrasting metro, tier-2, and tier-3 city investor behaviour on the D-BRAM constructs to establish contextual boundary conditions.

• Development and validation of a comprehensive, psychometrically robust App-Induced Investor Vulnerability Scale (AIVS) and a Gamified Trading Exposure Scale (GTES) for the Indian mobile brokerage context.

• Qualitative investigation of finfluencer credibility attribution and the social construction of expected return beliefs through in-depth interviews with social-media financial content consumers.

• Replication of the mediation model with the inclusion of financial literacy as a moderator of the SMI → ERR pathway, testing whether financial literacy attenuates expectation inflation effects.

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Appendices

Appendix A. Questionnaire Summary

Section	Content	Use in Study
Section 1: Consent	Informed consent	Voluntary participation; Yes/No screening criterion
Section 2: Demographics	Investment experience, city, age, gender, education, occupation, income, marital status	Screening criteria (Stage 1–4) and regression controls
Section 3: Investment Profile	Income invested (%), instruments, purpose, horizon, frequency, primary platform	RTBI-5 components; investment behaviour descriptors
Section 4: App Influence (APP1–APP5)	Convenience, accessibility, simplified execution, self-directed investing, and trading encouragement	APP construct; digital platform influence
Section 5: Gamified Interface Features (GAM1–GAM5)	Notifications, real-time engagement, visual stimulation, and game-like investing experiences	GAM construct; behavioural engagement mechanisms
Section 6: Algorithmic Vulnerability (ALG1–ALG5)	Perceived disadvantage relative to algorithmic systems, AI uncertainty, and technological asymmetry	ALGOVUL construct; technology-induced vulnerability
ection 7: Social Media Influence (SMI1–SMI5)	Finfluencer influence, social-media dependence, viral investment trends, and behavioural pressure	SMI construct; digital information influence
Section 8: Digital Misinformation Risk (MIS1–MIS5)	Misleading content, unverifiable information, exaggerated claims, and informational confusion	MISINFO construct; digital information risk

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Section 9: Perceived Risk (RISK1–RISK4)	Market uncertainty, loss potential, volatility, and digital investment risk	RISK construct; regression predictor
Section 10: Expected Return Perception (ERR1–ERR5)	Return expectations and digitally influenced investment optimism	ERR construct; mediator and regression predictor

Appendix B. RTBI-5 Construction

RTBI-5 is computed as the equally weighted mean of the following five ordinal indicators:

- Income percentage invested in equity per month (1 = < 10%, 2 = 10–20%, 3 = 21–30%, 4 = 31–40%, 5 = > 40%)
- Trading/investment frequency (1 = Rarely, 2 = Occasionally, 3 = Monthly, 4 = Weekly, 5 = Daily)
- Investment horizon risk (1 = > 5 years, 2 = 3–5 years, 3 = 1–3 years, 4 = 6 months–1 year, 5 = < 6 months)
- Investment purpose risk (1 = Retirement planning, 2 = Tax planning, 3 = Regular income, 4 = Wealth creation, 5 = Short-term profit)
- Instrument risk exposure (1 = Mutual funds only, 2 = ETFs, 3 = Individual equity shares, 4 = IPOs, 5 = Derivatives/F&O)

Expected return perception (ERR) is excluded from RTBI-5 and retained as a separate predictor variable throughout all analyses. This construction resolves the tautological overlap identified in the preliminary analysis.

Appendix C. Harman's Single-Factor Test for Common Method Bias

An unrotated principal component analysis was conducted on all 31 core survey items to assess common method variance (Podsakoff et al., 2003). The first unrotated factor accounted for 42.3% of total variance (eigenvalue = 13.11). As this is below the conventional 50% threshold, common method bias is unlikely to account for the primary findings of the study. It is acknowledged that Harman's test is a conservative and imperfect diagnostic; the absence of procedural remedies such as a marker variable renders this limitation non-eliminable by analytical means alone. Future research should employ a marker variable CFA approach or separate data-collection phases to more rigorously control for common method variance.

Appendix D. EFA Factor Loading Summary

Four factors were retained using principal axis factoring with Promax rotation (delta = 0), based on eigenvalue > 1 and scree plot inspection. Items with primary loadings < .40 were considered for exclusion; all construct items met this criterion. The pattern matrix is available from the corresponding author on request. Summary of factor structure:

- Factor 1 (Digital Platform and Technological Vulnerability, 15 items, variance explained = 36.8%): Primary loadings emerged from APP and ALGOVUL items related to algorithmic disadvantage, AI recommendation opacity, and cyber risk exposure.
- Factor 2 (Social Media and Digital Information Environment, 10 items, variance explained = 15.4%): Primary loadings originated from SMI and MISINFO items associated with social-media dependence, finfluencer influence, viral investment trends, information credibility concerns, and exposure to misleading digital investment content.
- Factor 3 (Risk Perception and Expected Return, 9 items, variance explained = 9.1%): Primary loadings from RISK and ERR; these constructs share a cognitive risk-evaluation dimension.
- Factor 4 (Gamified Interface Features, 5 items, variance explained = 7.3%): Primary loadings emerged from GAM items related to notifications, real-time engagement, visual stimulation, and game-like platform experiences, supporting the distinctiveness of gamification features relative to broader digital platform influences.

Appendix E. Ethics Statement

Participation in the survey was voluntary, and the questionnaire included a clearly worded informed-consent screening item at the outset. Responses were analysed only in aggregated form for academic research purposes. No individual respondent names, contact information, or personally identifiable data are reported in this paper. The study does not constitute investment advice and does not endorse or evaluate any specific trading platform, financial influencer, or brokerage operator. The study was conducted in accordance with the ethical principles of voluntary participation, informed consent, data anoymity, and academic integrity.