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Big Five Personality Traits, Risk Tolerance, and Investment Decision Behaviour: Examining the Moderating Role of Digital Financial Literacy among Retail Investors in India

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Abstract

Investment decision behaviour among retail investors emerges from the interaction of stable personality dispositions, risk preferences, and competency-based moderators. This study investigates the direct effects of Big Five personality traits on investment decision behaviour, the role of risk tolerance as an intermediary mechanism, and the moderating function of digital financial literacy (DFL) within this integrated framework. Grounded in Behavioural Finance Theory, Prospect Theory, the Five-Factor Model of personality, and the Theory of Planned Behaviour, data were collected from 450 active retail investors in Mumbai and Navi Mumbai, India, using a structured 27-item, five-point Likert-scale questionnaire. Analyses included exploratory factor analysis (KMO = 0.842; variance explained = 72.6%), hierarchical multiple regression, and Hayes' PROCESS Macro (Model 1) with 5,000 bootstrapped iterations. Openness to experience ($\beta = 0.28$, $p < 0.001$) and neuroticism ($\beta = -0.21$, $p < 0.001$) emerged as principal personality predictors of investment behaviour. Risk tolerance was a robust proximal determinant ($\beta = 0.43$, $p < 0.001$). Critically, DFL significantly moderated both the risk tolerance–investment pathway ($\beta\_int = 0.18$, $p < 0.001$) and the personality–investment pathway ($\beta\_int = 0.14$, $p < 0.01$), establishing that digital competency amplifies the behavioural expression of psychological dispositions. The study positions DFL as a theoretically precise boundary condition in the personality–risk–investment nexus, contributing to behavioural finance theory while providing actionable guidance for fintech platforms, regulators, and investor education frameworks in India's digitising capital markets.

Keywords: Big Five personality traits; risk tolerance; investment decision behaviour; digital financial literacy; behavioural finance; moderation analysis; retail investors; India

JEL Classification: G11, G41, D91, M12

1. Introduction

India's retail investment landscape has been structurally transformed over the past decade through a convergence of regulatory reform, fintech proliferation, and post-pandemic investor mobilisation. The introduction of zero-commission digital brokerages, UPI-enabled investment platforms, and gamified mobile applications has dismantled barriers that once confined capital market participation to affluent, advisor-dependent investors. By 2024, India recorded over 151 million active demat accounts, with the National Stock Exchange documenting a compounded annual growth rate exceeding 28% in new retail investor registrations between 2020 and 2024 (SEBI, 2024). This transformation has repositioned millions of first-generation investors as self-directed participants in an increasingly complex digital ecosystem operating without the institutional guidance historically provided by financial intermediaries.

Yet the democratisation of market access has not uniformly translated into investment quality. Decades of behavioural finance scholarship demonstrate that financial decisions systematically deviate from neoclassical rationality, shaped instead by stable personality dispositions, emotional heuristics, and cognitive biases (Kahneman & Tversky, 1979; Thaler, 2015; De Bondt & Thaler, 1985). In India's context marked by high information asymmetry, nascent investor education infrastructure, and aggressive fintech marketing practices these behavioural distortions are amplified. SEBI (2023) has documented that a substantial proportion of first-generation digital investors lack foundational competencies required to interpret risk disclosures, evaluate portfolio performance, or align asset allocation with long-term financial objectives.

Among dispositional predictors, the Big Five personality framework comprising openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism provides a psychometrically robust, cross-culturally validated taxonomy for understanding individual differences in financial behaviour (McCrae & Costa, 1987; John & Srivastava, 1999). Prior research has linked these dimensions to investment-related outcomes including portfolio diversification, trading frequency, susceptibility to cognitive biases, and response to market volatility (Durand et al., 2013; Tauni et al., 2020). However, personality traits function as distal antecedents; their influence on investment behaviour is principally channelled through proximal mechanisms, most notably risk tolerance.

Risk tolerance the degree of financial uncertainty an investor willingly accepts in pursuit of expected returns constitutes the primary psychological bridge between dispositional traits and observable portfolio decisions (Grable & Lytton, 1999). High risk tolerance predicts equity-heavy allocations and active portfolio management, while risk aversion is associated with capital-preservation strategies (Hallahan et al., 2004; Nosic & Weber, 2010). Yet the translation of risk preferences into calibrated investment actions is far from automatic in digital environments characterised by information overload, algorithmic nudges, and platform-amplified market volatility. This translation capacity is increasingly encapsulated in the construct of digital financial literacy (DFL).

DFL extends classical financial literacy to encompass the knowledge, skills, and attitudes required to manage financial activities through digital channels including platform navigation, evaluation of algorithmic recommendations, cybersecurity risk identification, and critical processing of online financial information (OECD, 2020; Morgan & Trinh, 2019). Research consistently links higher DFL to superior portfolio outcomes and resilience against platform-induced biases (Akhtar et al., 2022; Shukla & Jain, 2021). Despite this evidence, DFL has predominantly been treated as an independent predictor or demographic control. Its role as a boundary condition one that modulates the strength and direction of the personality–risk–investment pathway remains empirically underspecified.

This study addresses this gap by developing and testing an integrated conceptual model in which DFL moderates both the risk tolerance–investment decision relationship and the direct personality–investment decision relationship. Drawing on data from 450 retail investors in Mumbai and Navi Mumbai, the research makes three specific contributions: it establishes DFL as a theoretically grounded boundary condition in the personality–risk–investment nexus; it extends behavioural finance theory to the digital investment context in an emerging market; and it provides actionable frameworks for investors, regulators, and fintech designers.

The remainder of the paper proceeds as follows. Section 2 synthesises the relevant literature. Section 3 presents the theoretical framework. Section 4 articulates research gaps and objectives. Section 5 develops the hypotheses. Section 6 describes the methodology. Section 7 reports results. Sections 8 and 9 discuss findings and implications. Section 10 addresses limitations and future research.

2. Literature Review

2.1 Big Five Personality Traits and Investment Decision Behaviour

The intersection of personality psychology and financial decision-making has attracted sustained scholarly interest since the consolidation of the Five-Factor Model as the dominant personality taxonomy (McCrae & Costa, 1987; Goldberg, 1990). Each of the five dimensions exerts theoretically coherent and empirically documented influences on investment-related cognition and behaviour.

Openness to experience, characterised by intellectual curiosity, tolerance for ambiguity, and appetite for novelty, is consistently associated with exploratory investment behaviour, willingness to adopt financial technologies, and preference for growth-oriented, diversified portfolios (Durand et al., 2013; Peng & Xiao, 2022). In digitally mediated investment environments, openness likely manifests as engagement with novel instruments, proactive use of analytical tools, and comfort with algorithmic advisory services. Conscientiousness reflecting self-regulation, discipline, and goal orientation is associated with systematic investment planning, long-term strategy adherence, and resistance to impulsive trading (Tekce et al., 2016; Peng & Xiao, 2022). Conscientious investors are more likely to conduct periodic portfolio reviews and implement evidence-based rebalancing strategies.

Extraversion, driven by reward sensitivity and social engagement, has been linked to overconfidence bias, elevated trading frequency, and reliance on social networks for investment cues (Barber & Odean, 2001; Tauni et al., 2020). While extraversion fosters active market participation, it also predisposes investors toward excessive turnover and herd-following, particularly on social investing platforms. Agreeableness characterised by trust, cooperativeness, and conflict avoidance is associated with deference to expert or peer recommendations, which in digital contexts may translate to uncritical reliance on algorithmic curation or crowd-sourced investment tips (Pan & Cai, 2022). Neuroticism, reflecting emotional instability and threat sensitivity, consistently emerges as the most potent negative predictor of investment quality: neurotic investors exhibit heightened loss aversion, panic-driven selling, and systematic avoidance of volatile instruments (Kaur et al., 2021; Gambetti & Giusberti, 2012). Meta-analytic evidence confirms neuroticism's adverse effect on risk-adjusted portfolio performance and long-term wealth accumulation (Dohmen et al., 2011).

Critically, personality traits function as distal rather than proximal antecedents of investment behaviour; their influence is mediated by psychological constructs principally risk tolerance and moderated by competency-based and situational factors. This interaction logic underpins the present study's examination of DFL as a boundary condition.

2.2 Risk Tolerance and Investment Behaviour

Risk tolerance is operationalised as the maximum degree of financial uncertainty an individual is willing to accept in pursuit of expected returns (Grable & Lytton, 1999). The Financial Risk Tolerance Scale established it as a multidimensional construct encompassing cognitive probability assessments, emotional comfort with uncertainty, and past risk-taking experience. Empirically, risk tolerance is a robust predictor of asset allocation: high risk tolerance predicts equity-heavy portfolios, engagement with derivatives, and international diversification, while risk aversion is associated with fixed-income concentration and capital-protected products (Hallahan et al., 2004; Nosic & Weber, 2010).

The psychological antecedents of risk tolerance are well-established. Neuroticism is inversely associated with risk tolerance through amplified threat perception and loss sensitivity; openness and extraversion predict higher risk tolerance via curiosity and reward sensitivity (Nicholson et al., 2005; Zuckerman, 1994). Financial knowledge, income, and investment experience also moderate risk tolerance, indicating contextual malleability around a trait-anchored baseline (Lusardi & Mitchell, 2014). However, a critical gap in this literature is its underspecification of the conditions under which risk preferences are faithfully enacted in behaviour a gap that DFL is well-positioned to address.

2.3 Digital Financial Literacy: Conceptualisation and Evidence

Digital financial literacy represents a consequential extension of traditional financial literacy, encompassing the competencies required to manage financial affairs effectively through digital channels (OECD, 2020; Morgan & Trinh, 2019). Core DFL competencies include navigating digital investment platforms, evaluating algorithmic and robo-advisory recommendations, identifying cybersecurity risks, and critically assessing the quality of online financial information. As financial intermediation shifts decisively toward digital interfaces, DFL has emerged as both a determinant of financial inclusion and a prerequisite for investment quality in platform-mediated markets.

Empirical evidence consistently links DFL to superior investment outcomes. Akhtar et al. (2022) found that digitally literate Indian equity investors exhibited lower overconfidence bias and more disciplined portfolio management. Shukla and Jain (2021) demonstrated that DFL positively predicts active investment management and product diversification among app-based investors. Grohmann et al. (2018), in a cross-country study, established financial literacy inclusive of digital dimensions as a significant predictor of formal financial market participation. Conversely, DFL deficits are associated with vulnerability to digital fraud and susceptibility to platform-induced impulsive trading (Potrich et al., 2022). Despite these findings, DFL's moderating function within established personality–risk–behaviour pathways remain empirically underspecified.

2.4 The Moderating Function of DFL

The theoretical logic for positioning DFL as a moderating boundary condition draws upon Simon's (1955) bounded rationality framework and Kahneman's (2011) dual-process theory. Decision-making under financial uncertainty is constrained by cognitive resources, attentional capacity, and situational complexity. DFL functions as an enabling competency resource that expands decision-making capacity, potentially compensating for personality-driven cognitive limitations (e.g., neuroticism-amplified anxiety) or amplifying adaptive dispositions (e.g., openness-driven diversification). When DFL is high, psychological risk preferences and personality dispositions are more faithfully translated into observable behaviour because the investor possesses the platform mastery and analytical literacy to close the intention–behaviour gap. When DFL is low, investment behaviour may decouple from underlying psychological states, as investors resort to heuristic, emotionally driven, or platform-mediated shortcuts.

Ghosh and Das (2023) found that financial literacy moderates behavioural biases' effects on Indian stock market participation, providing proximate empirical grounding for the proposed moderation logic. Potrich et al. (2022) demonstrated that the investment-enhancing effects of financial knowledge were amplified among investors with higher digital competencies. These findings, while not directly testing the personality × DFL interaction, establish the empirical plausibility of DFL as a moderator within the broader personality–risk–investment framework examined in this study.

3. Theoretical Framework

This study integrates four complementary theoretical frameworks that collectively account for the psychological, cognitive, and competency-based mechanisms underlying retail investment decision behaviour.

3.1 Behavioural Finance Theory

Behavioural finance challenges the neoclassical assumption of fully rational, utility-maximising investors by integrating psychological insights into the analysis of financial decisions (De Bondt & Thaler, 1985; Shefrin & Statman, 1985). The theory posits that systematic cognitive biases, affective influences, and social heuristics produce predictable deviations from optimal financial decision-making. In digital investment environments where algorithmic nudges, real-time data streams, and gamified interfaces amplify cognitive load behavioural finance provides a foundational lens for understanding how personality traits and digital competencies interact to produce calibrated or distorted investment outcomes.

3.2 Prospect Theory

Kahneman and Tversky's (1979) Prospect Theory articulates a psychologically realistic model of decision-making under risk through two core propositions: loss aversion (losses are weighted approximately twice as heavily as equivalent gains) and probability weighting (systematic misestimation of outcome likelihoods at the tails of probability distributions). These principles directly inform how personality traits modulate risk perception. Neurotic investors, characterised by heightened threat sensitivity, exhibit amplified loss aversion; open investors may discount low-probability risks in favour of exploratory, gain-oriented investment. Prospect Theory thus provides the micro-foundational logic underpinning risk tolerance's mediating role in the personality–investment pathway.

3.3 Five-Factor Model of Personality

The Five-Factor Model (FFM) classifies human personality across five broad, heritable, and cross-culturally stable dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism (McCrae & Costa, 1987; Goldberg, 1990; John et al., 2008). In financial contexts, these traits function as dispositional anchors shaping information processing, risk calibration, and the translation of investment intentions into observable action. The FFM's robust psychometric properties, extensive cross-cultural validation, and demonstrated predictive utility across economic domains make it the most appropriate personality framework for examining trait-based heterogeneity in retail investment behaviour.

3.4 Theory of Planned Behaviour

Ajzen's (1991) Theory of Planned Behaviour (TPB) posits that behaviour is determined by intentions, which are in turn shaped by attitudes toward the behaviour, subjective norms, and perceived behavioural control (PBC). In investment contexts, personality dimensions shape risk attitudes; social networks and platform communities influence subjective norms; and DFL directly enhances PBC by increasing platform mastery, analytical confidence, and the capacity for informed decision execution. TPB thus provides structural rationale for modelling DFL as a moderator that strengthens or attenuates the intention–behaviour translation, particularly when personality-driven dispositions must be enacted within complex digital decision environments.

Conceptual Model. The integrated framework specifies the following relationships: Big Five personality traits directly influence investment decision behaviour (H1) and risk tolerance (H2); risk tolerance directly predicts investment decision behaviour (H3); and DFL moderates both the risk tolerance–investment decision (H4) and personality traits–investment decision (H5) pathways. Risk tolerance serves as a psychological bridge between distal trait dispositions and proximal investment actions; DFL functions as a boundary condition determining the fidelity of both translation pathways.

4. Research Gap and Objectives

4.1 Identified Research Gaps

A systematic review of extant literature reveals three substantive gaps motivating this study:

Gap 1 Contextual underrepresentation: Despite growing empirical interest in personality–investment linkages, the Indian retail investor context characterised by collectivist cultural values, rapid first-generation digital market entry, and an evolving regulatory architecture remains underrepresented. The transferability of findings from Western or East Asian contexts to India's distinctive investment ecosystem is theoretically and empirically uncertain.

Gap 2 DFL as moderator: Digital financial literacy is predominantly examined as an independent predictor or demographic control in investment behaviour research. Its theoretical and empirical function as a boundary condition one that alters the magnitude and nature of personality–investment and risk–investment relationships has not been rigorously tested within an integrated framework.

Gap 3 Pathway decoupling in digital contexts: The transition to self-directed digital investing substantially elevates the cognitive and informational demands placed on individual investors. Whether DFL compensates for, amplifies, or interacts differentially with trait-driven risk calibration in platform-mediated investment environments constitutes an empirically uncharted but theoretically consequential question.

4.2 Research Objectives

The study pursues the following five objectives:

O1: To examine the direct influence of Big Five personality traits on investment decision behaviour among retail investors in Mumbai and Navi Mumbai.

O2: To investigate the relationships between Big Five personality traits and individual risk tolerance levels.

O3: To assess the direct effect of risk tolerance on investment decision behaviour.

O4: To evaluate the moderating role of DFL in the relationship between risk tolerance and investment decision behaviour.

O5: To assess the moderating role of DFL in the direct relationship between Big Five personality traits and investment decision behaviour.

5. Hypotheses Development

H1: Big Five Personality Traits and Investment Decision Behaviour

Trait activation theory posits that stable personality dispositions are expressed in behaviourally relevant contexts when environmental cues are congruent with trait-related tendencies (Tett & Burnett, 2003). In investment contexts, openness promotes exploratory asset selection; conscientiousness supports disciplined strategy adherence; extraversion drives active trading and social information reliance; agreeableness fosters consensus-following; and neuroticism amplifies loss aversion and avoidance behaviour (Durand et al., 2013; Tauni et al., 2020; Kaur et al., 2021).

H1: Big Five personality traits significantly influence investment decision behaviour among retail investors.

H2: Big Five Personality Traits and Risk Tolerance

Risk tolerance is a dispositional construct shaped by emotional regulation capacity, threat perception, and reward sensitivity (Grable & Lytton, 1999). Neuroticism is consistently and negatively associated with risk tolerance through heightened loss sensitivity and anxiety (Nicholson et al., 2005); openness and extraversion predict higher risk tolerance through curiosity-driven information seeking and reward responsiveness (Zuckerman, 1994; Dohmen et al., 2011).

H2: Big Five personality traits significantly predict risk tolerance levels, with neuroticism negatively and openness and extraversion positively associated with risk tolerance.

H3: Risk Tolerance and Investment Decision Behaviour

Risk tolerance is the most established proximal predictor of asset allocation in personal finance research. Higher risk tolerance consistently predicts equity-heavy allocations, portfolio diversification, and willingness to engage with volatile instruments (Hallahan et al., 2004; Nosic & Weber, 2010).

H3: Risk tolerance significantly and positively predicts investment decision behaviour.

H4: DFL as Moderator of Risk Tolerance → Investment Decisions

DFL provides investors with the platform competencies and analytical resources required to convert risk preferences into calibrated portfolio allocations. High DFL enables efficient access to risk-appropriate instruments, interpretation of volatility metrics, and utilisation of digital advisory tools, thereby aligning actual behaviour with underlying risk appetite. Low DFL may produce misalignment between preferences and actions due to platform complexity and decision overload (Lusardi & Mitchell, 2014; Akhtar et al., 2022).

H4: Digital financial literacy positively moderates the relationship between risk tolerance and investment decision behaviour, such that this relationship is stronger at higher levels of DFL.

H5: DFL as Moderator of Personality → Investment Decisions

DFL amplifies adaptive personality dispositions or attenuates maladaptive ones through provision of cognitive resources and analytical scaffolding. For open investors, high DFL enables informed diversification; for neurotic investors, DFL provides risk management tools that mitigate anxiety-driven reactivity; for extraverted investors, DFL imposes analytical discipline that moderates impulsive overtrading (Ghosh & Das, 2023; Potrich et al., 2022).

H5: Digital financial literacy positively moderates the relationship between Big Five personality traits and investment decision behaviour, such that the personality–investment relationship is stronger at higher levels of DFL.

Table 1: Summary of Research Hypotheses

Hypothesis	Relationship	Type
H1	Personality traits → Investment decision behaviour	Direct
H2	Personality traits → Risk tolerance	Direct
H3	Risk tolerance → Investment decision behaviour	Direct
H4	DFL moderates Risk Tolerance → Investment Decisions	Moderation
H5	DFL moderates Personality → Investment Decisions	Moderation

Note. *DFL = Digital Financial Literacy.*

6. Research Methodology

6.1 Research Design

The study adopts a quantitative, descriptive-cum-analytical research design grounded in positivist epistemological assumptions (Hair et al., 2019). Descriptive analysis profiles respondent characteristics and construct distributions, while analytical techniques hierarchical regression and moderation analysis test hypothesised structural relationships. The cross-sectional design, standard in behavioural finance survey research, is acknowledged as precluding strict causal inference; this limitation is addressed in the limitations section.

6.2 Population and Sampling

The target population comprises active retail investors in Mumbai and Navi Mumbai, a region accounting for approximately 23% of India's active demat accounts (NSE, 2024). This setting was selected for its status as India's most financially and digitally mature investor ecosystem, providing optimal heterogeneity in personality-driven investment styles and DFL levels across diverse investor segments.

Sample size was determined using Krejcie and Morgan's (1970) table, prescribing a minimum of 384 respondents for populations exceeding 100,000 at a 5% margin of error (95% confidence interval). The achieved sample ($N = 450$) provides adequate statistical power for multivariate analyses including hierarchical regression with interaction terms (Hair et al., 2019). A non-probability combination of purposive, convenience, and snowball sampling was employed: initial recruitment occurred through digital investment communities, brokerage networks, and professional finance associations, with subsequent referral-based expansion. Eligibility criteria required respondents to be active investors with at least one investment made in the preceding 12 months and documented experience using a digital investment platform.

6.3 Measurement Instrument

A structured, self-administered questionnaire comprising 27 items on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree) was developed. Four construct sections were included:

Personality Traits (10 items): Adapted from John and Srivastava's (1999) Big Five Inventory, with two items per dimension. The use of two-item subscales is acknowledged as a methodological constraint; this approach was adopted given survey length limitations and is explicitly flagged as a limitation warranting replication with the full BFI (John et al., 2008) or NEO-PI-R.

Risk Tolerance (5 items): Adapted from Grable and Lytton's (1999) Financial Risk Tolerance Scale, a widely validated instrument with established convergent and predictive validity in personal finance research.

Digital Financial Literacy (6 items): Developed based on the OECD's (2020) DFL measurement framework, capturing platform navigation proficiency, algorithmic evaluation competency, cybersecurity awareness, and critical online financial information processing.

Investment Decision Behaviour (6 items): Self-constructed items measuring investment regularity, portfolio diversification, use of analytical approaches, periodic portfolio review, risk-level selection behaviour, and digital platform reliance.

The instrument underwent expert content validity review by a five-member panel of finance and psychology scholars, followed by a 30-respondent pilot test for clarity assessment and preliminary psychometric evaluation. Minor item revisions were incorporated based on pilot feedback. Full deployment occurred over three months using both digital (Google Forms) and print channels.

6.4 Statistical Analysis Strategy

All analyses were conducted using IBM SPSS Statistics (v26) and Hayes' PROCESS Macro (v4.1). The analytical sequence included: (1) Reliability testing via Cronbach's alpha (threshold $\alpha \geq 0.70$; Nunnally, 1978); (2) Construct validity via exploratory factor analysis (EFA) using principal axis factoring with Varimax rotation, assessed through KMO (≥ 0.70) and Bartlett's Test of Sphericity; (3) Bivariate Pearson correlation with multicollinearity diagnostics ($VIF < 5.0$); (4) Hierarchical multiple regression for H1–H3; (5) Moderation analysis using PROCESS

Macro Model 1, with mean-centred predictors, interaction terms, and 5,000 bootstrapped confidence intervals (Aiken & West, 1991).

7. Results

7.1 Demographic Profile

The sample (N = 450) exhibited a balanced gender distribution (50.4% male; 49.6% female). Age groups included: below 25 years (18.7%), 25–35 years (20.7%), 36–45 years (23.8%), 46–60 years (19.8%), and above 60 years (17.1%). Educational qualifications ranged from undergraduate (25.8%), graduate (26.0%), postgraduate (20.2%) to professional degrees (28.0%). Household income levels spanned below ₹3 Lakhs per annum (27.6%), ₹3–6 Lakhs (22.9%), ₹6–10 Lakhs (22.6%), and above ₹10 Lakhs (26.9%). Occupational categories included salaried employees (23.1%), self-employed individuals (26.9%), business owners (26.4%), and students (23.6%). Investment experience ranged from less than one year (25.1%), one to three years (27.6%), three to five years (22.0%), to more than five years (25.3%). This demographic heterogeneity supports the representativeness and external validity of findings across investor segments.

7.2 Reliability and Validity Analysis

Internal consistency was assessed using Cronbach's alpha across all eight construct scales (Table 2). All constructs exceeded the 0.70 threshold, ranging from $\alpha = 0.76$ (Agreeableness) to $\alpha = 0.88$ (Investment Decision Behaviour). The overall instrument reliability was $\alpha = 0.91$, confirming satisfactory composite internal consistency.

Table 2: Reliability Statistics — Cronbach's Alpha Coefficients

Construct	No. of Items	Cronbach's Alpha (α)
Openness to Experience	2	0.78
Conscientiousness	2	0.81
Extraversion	2	0.79
Agreeableness	2	0.76
Neuroticism	2	0.83
Risk Tolerance	5	0.86
Digital Financial Literacy	6	0.84
Investment Decision Behaviour	6	0.88
Overall Scale	27	0.91

Note. *All alpha values exceed the 0.70 threshold (Nunnally, 1978). Two-item personality subscales are noted as a methodological limitation; interpretation should be approached with appropriate caution.*

Construct validity was evaluated through EFA with Varimax rotation. The KMO measure was 0.842 (exceeding the ≥ 0.70 threshold), and Bartlett's Test of Sphericity was significant ($\chi^2 = 4{,}587.32$, df = 351, $p < 0.001$), confirming the suitability of the correlation matrix for factor analysis. Eight factors with eigenvalues > 1.0 were extracted, cumulatively explaining 72.6% of total variance above the 60% adequacy threshold (Hair et al., 2019). All items loaded on their intended constructs with primary loadings ≥ 0.50 and cross-loadings < 0.40, confirming the hypothesised eight-factor measurement structure.

7.3 Correlation Analysis

Pearson correlation coefficients among all study constructs are presented in Table 3. Openness ($r = 0.31$), Extraversion ($r = 0.27$), and Conscientiousness ($r = 0.22$) positively correlated with Investment Decision Behaviour (all $p < 0.01$), while Neuroticism was negatively correlated ($r = -0.25$, $p < 0.01$). Risk Tolerance demonstrated the strongest bivariate relationship with Investment Decision Behaviour ($r = 0.42$, $p < 0.01$). DFL positively correlated with both Investment Decision Behaviour ($r = 0.38$, $p < 0.01$) and Risk Tolerance ($r = 0.29$, $p < 0.01$). All VIF values ranged from 1.04 to 1.18, well below the 5.0 multicollinearity threshold.

Table 3: Pearson Correlation Matrix (N = 450)

Variable	1	2	3	4	5	6	7	8
1. Openness	1							
2. Conscientiousness	0.18**	1						
3. Extraversion	0.24**	0.15**	1					
4. Agreeableness	0.11*	0.09	0.13**	1				
5. Neuroticism	−0.08	−0.06	−0.21**	−0.10*	1			
6. Risk Tolerance	0.33**	0.22**	0.30**	0.05	−0.35**	1		
7. DFL	0.27**	0.19**	0.18**	0.08	−0.23**	0.29**	1	
8. Inv. Decision	0.31**	0.22**	0.27**	0.07	−0.25**	0.42**	0.38**	1

Note. *DFL = Digital Financial Literacy. **p < 0.01 (two-tailed); *p < 0.05 (two-tailed). VIF range: 1.04–1.18.*

7.4 Regression Analysis (H1, H2, H3)

Results for H1 (Table 4): The personality-predicting-investment-behaviour model was significant, $F(5, 444) = 18.42$, $p < 0.001$, $R^2 = 0.172$, Adjusted $R^2 = 0.163$. Openness was the strongest predictor ($\beta = 0.28$, $p < 0.001$), followed by Neuroticism ($\beta = -0.21$, $p < 0.001$) and Extraversion ($\beta = 0.16$, $p < 0.01$). Conscientiousness contributed a modest but significant effect ($\beta = 0.12$, $p = 0.036$). Agreeableness was non-significant ($\beta = 0.03$, $p = 0.577$). H1 is supported.

For H2 (personality predicting risk tolerance): $F(5, 444) = 22.67$, $p < 0.001$, $R^2 = 0.203$, Adjusted $R^2 = 0.194$. Neuroticism was the dominant negative predictor ($\beta = -0.32$, $p < 0.001$), with Openness ($\beta = 0.24$, $p < 0.001$) and Extraversion ($\beta = 0.18$, $p < 0.001$) as significant positive predictors. H2 is supported. For H3, simple regression confirmed risk tolerance as a robust investment behaviour predictor, $F(1, 448) = 104.39$, $p < 0.001$, $R^2 = 0.189$, $\beta = 0.43$, $p < 0.001$. H3 is strongly supported.

Table 4: Multiple Regression Results — H1 (Dependent Variable: Investment Decision Behaviour)

Predictor	β	SE	t-value	p-value	VIF
(Constant)	1.82	0.234	7.78	< 0.001	—
Openness to Experience	0.28	0.055	5.12	< 0.001	1.12
Conscientiousness	0.12	0.057	2.10	0.036	1.08
Extraversion	0.16	0.054	3.01	0.003	1.15
Agreeableness	0.03	0.054	0.56	0.577	1.04
Neuroticism	−0.21	0.053	−3.89	< 0.001	1.18

Note. *$R^2 = 0.172$; Adjusted $R^2 = 0.163$; $F(5, 444) = 18.42$, $p < 0.001$. β = standardised regression coefficient; SE = standard error; VIF = Variance Inflation Factor. H2 model: $R^2 = 0.203$, $F(5, 444) = 22.67$, $p < 0.001$. H3 model: $R^2 = 0.189$, $F(1, 448) = 104.39$, $p < 0.001$, $\beta = 0.43$.*

7.5 Moderation Analysis (H4 and H5)

Hayes' PROCESS Macro (Model 1) with 5,000 bootstrapped iterations was used to test H4 and H5. Results are presented in Table 5.

For H4, the Risk Tolerance × DFL interaction was significant ($\beta = 0.18$, $t = 3.45$, $p < 0.001$, 95% CI [0.077, 0.283]), explaining an incremental 3.8% variance ($\Delta R^2 = 0.038$). Conditional effects confirmed that the RT–investment relationship was substantially stronger at high DFL (+1 SD: $\beta = 0.52$, $p < 0.001$) than at low DFL (−1 SD: $\beta = 0.24$, $p < 0.05$). H4 is supported.

For H5, the Personality × DFL interaction was significant ($\beta = 0.14$, $t = 2.68$, $p = 0.008$, 95% CI [0.038, 0.242]), explaining an incremental 2.4% variance ($\Delta R^2 = 0.024$). Personality's effect on investment decisions was more pronounced at high DFL ($\beta = 0.36$, $p < 0.001$) compared to low DFL ($\beta = 0.15$, $p = 0.042$). H5 is supported.

Table 5: Moderation Analysis Results (Hayes' PROCESS Macro, Model 1; N = 450)

Predictor	β	SE	t	p	95% CI
Panel A — H4: DV = Investment Decision Behaviour					
Risk Tolerance (centred)	0.39	0.042	9.29	< 0.001	[0.307, 0.473]
DFL (centred)	0.34	0.046	7.39	< 0.001	[0.250, 0.430]
RT × DFL Interaction	0.18	0.052	3.45	< 0.001	[0.077, 0.283]
Panel B — H5: DV = Investment Decision Behaviour					
Composite Personality (centred)	0.25	0.038	6.58	< 0.001	[0.175, 0.325]
DFL (centred)	0.28	0.041	6.83	< 0.001	[0.199, 0.361]
Personality × DFL Interaction	0.14	0.052	2.68	0.008	[0.038, 0.242]

Note. *Panel A: $R^2 = 0.287$, $F(3, 446) = 59.88$, $p < 0.001$; ΔR^2 for interaction = 0.038. Panel B: $R^2 = 0.261$, $F(3, 446) = 52.14$, $p < 0.001$; ΔR^2 for interaction = 0.024. CIs based on 5,000 bootstrapped samples. Composite personality score = unit-weighted mean of Big Five dimensions (neuroticism reverse-coded). DFL = Digital Financial Literacy; RT = Risk Tolerance.*

Table 6: Summary of Hypothesis Testing

H	Relationship	Key Statistic	Decision
H1	Personality traits → Investment decisions	β = 0.28 (Openness), p < 0.001	Supported
H2	Personality traits → Risk tolerance	β = −0.32 (Neuroticism), p < 0.001	Supported
H3	Risk tolerance → Investment decisions	β = 0.43, p < 0.001	Supported
H4	DFL moderates RT → Investment decisions	β_int = 0.18, p < 0.001	Supported
H5	DFL moderates Personality → Investment decisions	β_int = 0.14, p < 0.01	Supported

Note. *All five hypotheses are empirically supported at conventional significance levels.*

8. Discussion

The empirical results present a theoretically coherent and practically significant account of how personality dispositions, risk preferences, and digital competencies jointly shape retail investment behaviour. The following discussion is organised around the study's five hypotheses and their broader theoretical ramifications.

8.1 Personality Traits as Predictors of Investment Behaviour and Risk Tolerance

The confirmation of significant personality effects on investment behaviour (H1, $R^2 = 0.172$) reaffirms and extends behavioural finance scholarship by demonstrating that stable trait dispositions persist as meaningful investment predictors even within algorithmically mediated digital environments. Openness to experience's prominence (β = 0.28) is consistent with Durand et al. (2013) and Peng and Xiao (2022), who document that intellectually curious, ambiguity-tolerant investors actively pursue novel instruments and diversified allocations. In India's fintech context, this likely manifest as disproportionate engagement with emerging products mutual fund schemes, international ETFs, and Sovereign Gold Bonds alongside greater willingness to trial robo-advisory platforms.

Neuroticism's significant negative effect (β = −0.21) corroborates Kaur et al. (2021) and aligns with Prospect Theory's loss aversion principle: emotionally unstable investors, driven by threat sensitivity, systematically underparticipate in volatile asset classes. This has particular practical urgency in India, where a substantial first-generation retail investor cohort may exhibit anxiety-amplified risk aversion that curtails long-term wealth creation despite unprecedented platform accessibility.

Agreeableness's non-significance ($\beta = 0.03$, $p = 0.577$) provides an illuminating contextual contrast. In advisor-mediated investment contexts, agreeableness facilitates consensus-following through interpersonal compliance. In self-directed digital platforms, however, the interpersonal dynamics that activate agreeableness-based behaviour advisor guidance, peer pressure, social recommendation are algorithmically mediated or absent, attenuating this trait's direct behavioural influence in digital-first investment environments.

The personality–risk tolerance model (H2, $R^2 = 0.203$) confirms that dispositional factors account for a theoretically meaningful proportion of variance in investors' risk profiles. Neuroticism's dominance as the strongest negative predictor ($\beta = -0.32$) is grounded in psychobiological accounts of emotional reactivity and aligns with neuroimaging evidence linking high neuroticism to elevated amygdala response to financial loss cues (Nicholson et al., 2005). Openness and extraversion's positive contributions ($\beta = 0.24$ and 0.18 respectively) confirm that reward sensitivity and curiosity predispose investors toward uncertainty acceptance a disposition that, when combined with high DFL, produces systematic and well-informed risk-taking rather than impulsive speculation.

8.2 Risk Tolerance as Proximal Predictor and the Amplifying Role of DFL

The robust risk tolerance–investment behaviour relationship (H3, $\beta = 0.43$) reaffirms risk tolerance's established status as the primary proximal determinant of asset allocation, with a standardised coefficient exceeding all direct personality effects (Hallahan et al., 2004; Nosic & Weber, 2010). That this effect is substantially amplified by DFL (H4) constitutes the study's most critical empirical finding: the interaction term ($\beta = 0.18$) demonstrates that at high DFL levels, the RT→investment coefficient nearly doubles (0.52 vs. 0.24). This finding extends Lusardi and Mitchell (2014) by demonstrating that DFL does not merely add incrementally to investment behaviour prediction but structurally conditions how underlying risk preferences are expressed in action precisely the boundary condition function that existing research has not yet documented for DFL.

The Personality × DFL interaction (H5, $\beta = 0.14$) reveals that digital literacy differentially amplifies trait-consistent investment behaviour across personality profiles. Open investors with high DFL leverage analytical dashboards and product comparison tools to translate intellectual curiosity into well-diversified, evidence-informed allocations. Conscientious investors use DFL-enabled automation features systematic investment plans, automated rebalancing, goal-based investing tools to sustain disciplined long-term strategies. Neurotic investors with high DFL do not eliminate anxiety-driven caution but channel it constructively through volatility filters, risk-adjusted return metrics, and advisory guardrails, transforming emotionally reactive tendencies into defensible, data-supported decisions.

Collectively, these moderation findings challenge the assumption that digital investment platforms homogenise investor behaviour by standardizing decision environments. Rather, DFL amplifies trait-consistent decision quality without eliminating fundamental personality-driven heterogeneity a nuanced finding with important implications for both platform design and regulatory policy.

9. Implications

9.1 Theoretical Implications

This study makes three primary theoretical contributions. First, by establishing DFL as a boundary condition in the personality–risk–investment nexus, the research advances behavioural finance theory beyond its predominantly Western, pre-digital empirical foundation. The finding that DFL structurally conditions rather than merely adds to the personality–investment and risk tolerance–investment pathways provides novel theoretical architecture for understanding investment behaviour in platform-mediated markets.

Second, the study extends Ajzen's (1991) Theory of Planned Behaviour by empirically demonstrating that DFL functions as a precise operationalisation of perceived behavioural control in investment contexts, closing the intention–behaviour gap that personality-driven dispositions alone cannot bridge. This contribution provides a more theoretically specified account of how digital competency shapes financial decision execution.

Third, the documentation of trait-differentiated moderation effects where DFL amplifies both adaptive dispositions (e.g., openness-driven diversification) and the constructive channelling of maladaptive ones (e.g., neuroticism-driven caution toward analytical tools) advances personality × environment interaction theory in financial domains. The findings underscore that digital investment environments are not neutral; they differentially amplify or attenuate trait-based investment tendencies as a function of investor competency.

9.2 Practical Implications

For Retail Investors

Investors should develop structured self-awareness regarding their personality profiles and their implications for risk-taking, decision reactivity, and platform usage patterns. Recognising that openness may drive productive exploration, while neuroticism may trigger premature exits during temporary market corrections, can enable more deliberate, metacognitive investment processes. Most actionably, investors should treat DFL development through platform-specific educational modules, investment simulators, and financial literacy programmes as a priority behavioural intervention, rather than a peripheral skill. The evidence indicates that DFL is the most accessible lever for ensuring that risk preferences are faithfully enacted in portfolio decisions.

For Policymakers and Financial Regulators

The finding that DFL significantly moderates investment behaviour pathways mandates an evolution in financial protection policy. SEBI's investor awareness campaigns and the Reserve Bank of India's financial literacy framework should integrate platform-specific DFL competency assessment as a regulatory priority, particularly for retail investors accessing high-risk digital products (e.g., Futures & Options, leveraged ETFs). DFL-gated product access modelled on the NISM certification framework represents a proportional investor protection mechanism consistent with the study's evidence. Financial literacy programmes must shift from generic content delivery to personality-sensitive, platform-specific interventions that directly address trait-based vulnerabilities.

For Fintech Platforms

Digital investment platforms can operationalize these findings through psychometrically grounded user experience design. Embedding validated Big Five and DFL assessments during investor onboarding would enable dynamic, trait-calibrated interface customization: simplified dashboards and automated risk buffers for high-neuroticism investors; advanced analytical tools for high-openness users; and trading frequency guardrails for highly extraverted profiles. Gamified DFL literacy modules, micro-certifications, and interactive risk simulators can systematically elevate platform-wide competency, converting personality-driven behavioural heterogeneity into informed, calibrated market participation.

10. Limitations and Future Research Directions

10.1 Limitations

Several methodological constraints warrant transparent acknowledgement. First, the cross-sectional design precludes causal inference; longitudinal tracking of investors across varied market conditions would yield considerably stronger evidence of trait–behaviour dynamics over time. Second, convenience and snowball sampling constrain generalization to tier-II/III cities and non-digitally engaged investors. Third, two-item personality subscales, while pragmatically adopted, may inadequately capture the full bandwidth of each Big Five dimension; future research should employ the full 44-item BFI or NEO-PI-R. Fourth, self-reported investment behaviour is susceptible to social desirability bias and retrospective rationalization; integration of objective transaction data or platform analytics would substantially enhance internal validity. Fifth, the composite personality score used in H5 conflates distinct trait effects; trait-specific moderation tests for each of the five dimensions would yield richer, more actionable insights.

10.2 Future Research Directions

Future investigations should employ longitudinal designs to examine how DFL moderates' personality–behaviour pathways across bull, bear, and high-volatility market conditions. Multi-city comparative studies contrasting metros and tier-II cities would illuminate urban–rural digital divides in investment decision quality. Non-linear moderation models (e.g., piecewise regression, quadratic terms) could identify DFL threshold effects where digital competency transitions from skill-enabling to overconfidence-inducing at very high levels. Mixed-method designs combining survey data with platform clickstream analytics and semi-structured interviews would deepen understanding of the mechanistic processes through which DFL shapes investment execution. Extending the framework to incorporate additional moderators institutional trust, platform gamification intensity, social media sentiment, and algorithmic recommendation transparency would further advance a comprehensive digital behavioural finance model.

11. Conclusion

This study demonstrates that retail investment behaviour is the product of a structured interplay between stable personality dispositions, risk preferences, and digital competencies, rather than any single psychological or situational factor. Analysing data from 450 active retail investors in Mumbai and Navi Mumbai, the findings confirm that openness and neuroticism are the principal Big Five predictors of investment behaviour, risk tolerance serves as a robust psychological bridge between traits and portfolio decisions, and digital financial literacy critically moderates both the risk tolerance–investment and personality–investment pathways amplifying the translation of psychological dispositions into calibrated investment actions.

The study's most theoretically significant contribution lies in establishing DFL as a boundary condition in the personality–risk–investment nexus. The near-doubling of the risk tolerance–investment coefficient at high DFL levels reveals the profound extent to which digital competency determines whether psychological risk preferences are faithfully enacted or systematically distorted in platform-mediated investment environments. These finding challenges prevailing assumptions about digital platform homogeneity and situates DFL at the centre of a new theoretical architecture for understanding investment behaviour in emerging digital markets.

For India's rapidly expanding retail investor base projected to exceed 200 million active accounts within the current decade the practical stakes of this research are substantial. Risk profiling alone is insufficient as an investor protection mechanism without complementary DFL development. Fintech platforms that embed personality-responsive design and competency-building features will not merely differentiate commercially; they will catalyse more informed, sustainable, and equitable capital market participation. As digital investment ecosystems continue to evolve, the integration of personality-aware design, DFL-responsive regulation, and competency-based investor empowerment will be indispensable for ensuring that market democratisation translates into genuine financial wellbeing.

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