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Understanding Investor Behavior In India Through A Behaviorally Integrated Structural Model

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Abstract
This research explores the role of financial literacy in Indian investment sentiment. This is done using an integrative, behaviorally oriented conceptual framework of cognitive (investment confidence), affective (behavioral biases, risk attitude), and demographic variables. Utilizing a multi-method analytical strategy—Structural Equation Modeling (SEM), Confirmatory Factor Analysis (CFA), binary logistic regression, and K-means cluster analysis—the research examines survey data of 300 Indian retail investors from various socio-economic groups. Results also indicate that financial literacy has a strong positive influence on investment confidence but influences investment participation only indirectly via psychological considerations. Three investor types—Confident Practitioners, Cautious Learners, and Skeptical Strugglers—are identified using the behavioral segmentation approach. Pragmatic suggestions are drafting focused financial education and fintech policies to account for investor heterogeneity by confidence, literacy, and risk perception. By spanning the long-standing knowledge-action gap in emerging market investment conduct, this study focuses on a novel dual-mediation model and investor typology to the existing literature in behavioral finance. The study suggests to create financial literacy programs for the different levels of investors. It recommends developing easy-to-use FinTech tools to reduce common investors mistakes.
Keywords: *Financial Literacy, Investment Behavior, Behavioral Finance, Risk Perception.*

1. INTRODUCTION

With the prevailing dynamic financial landscape financial literacy's contribution to shaping retail investor decisions has come back into focus for regulators, researchers, as well as fintech platforms. Financial literacy, as commonly known to be the capability of comprehending and utilizing financial data with regard to budgeting, saving, and investing. This has been acclaimed as a cornerstone pillar of personal financial health and aggregate economic strength (Lusardi & Mitchell, 2014). Nevertheless, in spite of growing outreach by schools, financial authorities, and personal platforms, formal investment vehicle adoption continues to be unequal, particularly in developing economies such as India (Jain & Bhatia, 2023).

This paradox reflects the boundaries of consciousness alone and points toward ingrained behavioral and structural obstacles. Indian retail investors still prefer conventional avenues like property, gold, and fixed deposits (Sahu & Singh, 2022; Narayan et al., 2023). Although the presence of digital platforms has facilitated access to capital markets, investor inertia still dominates since psychological biases—overconfidence, loss aversion, anchoring, and herding—undermine rational choice (Barberis, 2018; Srivastava & Kumar, 2022). These behavioral traits, normally caused by low trust in financial advisors and socio-economic differences, also account for why knowledge is not always translated into practice—a condition that has been broadly referred to as the "knowledge-action gap." More than 200 million adults in India alone are underbanked, and bridging this gap has international implications. The world's largest democracy and a leading fintech growth market, India offers a singular laboratory for scalable, tech-based behavioral finance frameworks that may have application in other parts of the emerging economies of the world (Malik et al., 2022; Jain & Arora, 2023).

Along with psychological factors, demographic features like age, education, and income also affect investment preparedness. For instance, the younger and educated are more likely to invest in stocks and mutual funds, whereas older or less educated segments are risk-averse (Reddy & Ramachandran, 2024; Patel & Kaur, 2021). However, current literature predicts that psychological preparedness and exposure to online platforms tend to dominate such demographic features (Kumari & Thomas, 2023). This underscores the importance of having a holistic model covering cognitive, affective, and contextual areas of investor behavior.

Even as there is an increasing body of academic work focused on financial literacy, research gaps persist. First, most research focuses on financial knowledge in a vacuum without consideration of its interaction with psychological and demographic mediators. Second, the most widespread application of linear regression constrains our examination of complex, multi-path behavior relationships—those that are better suited to Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) (Hair et al., 2010; Kline, 2016). Third, even though marketing research has utilized behavioral segmentation, finance research has seen limited use of cluster analysis in investor profile identification based on cognitive and emotional traits (Vyvyan et al., 2014; Howcroft et al., 2020; Kaur & Vohra, 2022; Rahman et al., 2023). This research bridges these gaps using a behaviorally integrated, empirically meaningful model with investment confidence, risk perception, behavioral biases, and financial literacy—guided by demographic and advisory usage factors. Based on primary data gathered from 300 urban and semi-urban Indian retail investors, the research utilizes a multi-method research approach of SEM, CFA, logistic regression, and K-means clustering to investigate investor heterogeneity in a nuanced manner. Most prominently, the research is in the context of India's post-COVID fintech boom, including record demat account additions, rising retail trading, and higher adoption of AI-powered advisory platforms. While technology provides access, technology in itself does not always equate to participation—due to continuous cognitive and affective frictions. Existing research attributes such behavior to the fintech value chain and deduces confidence-building interventions tailored to investor psychology.

The research has identified four research questions at its core:

a. To what extent does financial literacy impact investment confidence and investment behavior of Indian retail investors?
b. In what ways do behavioral biases and risk perception mediate this relationship?
c. What demographic profiles define various investor types in India's digital economy?
d. Why is use of financial advisory services restricted even when financially literate?

In answering them, the study makes a contribution to both academic and practice streams in finance. It presents a two-channel behavioral model connecting knowledge and investment behavior, and suggests data-informed investor segmentation (Confident Practitioners, Cautious Learners, Skeptical Strugglers) with policy, education, and fintech design implications.

The structure of the paper is as follows: Section 2 addresses chief literature and theory summarized; Section 3 discusses methodology; Section 4 addresses empirical findings summarized; Section 5 addresses implications in detail; and Section 6 concludes with recommendations for further research.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Theoretical Concepts

The research incorporates concepts of Behavioral Finance Theory, Life-Cycle Hypothesis (LCH), and Modern Portfolio Theory (MPT) to formulate a behaviorally refined investment behavior model. Behavioral Finance rooted in Prospect Theory (Kahneman & Tversky) reverses the traditional rational investor assumptions by highlighting heuristics and biases like overconfidence, anchoring, herding, and loss aversion (Barberis, 2018; Srivastava & Kumar, 2022). They are particularly common in emerging economies like India, where finance access has outweighed psychological preparedness. Modigliani-Brumberg Life-Cycle Hypothesis would predict that people make consumption and investment choices according to lifetime income expectations. But the latest evidence is that behavioral characteristics—i.e., risk tolerance, and optimism—begin to supplant age and income effects, particularly in online investment areas (Reddy & Ramachandran, 2024). Markowitz Modern Portfolio Theory presumes rational diversification, while actual choices are guided by situational and behavioral influences. In risky or technology-driven scenarios, MPT must be modified to incorporate investor psychology for robo-advisory and AI-financed platforms (Narayan et al., 2023). Collectively, these paradigms allow multiple-dimensional consideration: not only what investors are aware of, but how they feel, estimate risk, and act in actual financial settings**.**

2.2 Empirical Findings on Financial Literacy and Behavior

Empirical findings are in support of the reality that financial literacy is conducive to investment planning, risk-taking ability, and portfolio diversification (Lusardi & Mitchell, 2020; Garg & Singh, 2018). However, the widespread "knowledge-action gap"—investors know but do not act—is a common behaviour both in global and Indian realities (Klapper et al., 2020). This paradox is also delved into by research indicating the presence of mediating behavior variables. Rai et al. (2019), for example, pinpoint the intermediation role of self-efficacy, loss aversion, and peer influence in financial choices. Informal financial systems and cultural conservatism tend to overwhelm South Asia's formal financial literacy (Ahmed & Sabir, 2022). Within the internet context, Singaporean and American research indicates that even well-educated millennials shy away from risk on the pretext of mimetic behavior and bias affirmation (Wong & Tan, 2023; Kim et al., 2022). Similarly, Marhadi et al. (2024) identify brand schematicity and digital financial literacy in maintaining Shariah P2P platform usage, while Setiawan et al. (2021) establish that fintech adoption is contingent upon user innovativeness and acceptance of technology. Gendered narratives reveal that women in Southeast Asia are affected by mobile reach and peer influence in fintech adoption (Igamo et al., 2024). Within corporate environments, Surya et al. (2021) and Lisin et al. (2021) believe that digital literacy spurs institutional performance and SME innovation. More significantly, while enhanced application of advanced modeling techniques such as SEM/CFA (Jain & Bhatia, 2023; Joshi et al., 2022) has no equivalent in cluster analysis-based segmentation of behavior. Vyvyan et al. (2014), Howcroft et al. (2020), Kaur & Vohra (2022), and Rahman et al. (2023), all Journal of Financial Services Marketing, mention the need for consumer-based financial services segmentation models without these being followed in studies of Indian investment behavior.

Table 1: Summary of Studies on Financial Literacy and Investment Behavior in India

Author(s)	Methodology	Key Finding	Gap Identified
Lusardi & Mitchell (2020)	Survey, Global Data	Literacy predicts investment readiness but gap persists	Limited psychological variables
Garg & Singh (2018)	Empirical, Urban India	Literacy improves risk appetite among youth	No mediation/moderation tested
Rai et al. (2019)	Path Analysis	Psychological variables mediate behavior	Cultural bias underexplored
Kim et al. (2022)	U.S. Digital Investors	Literate investors prone to confirmation bias	Does not cover segmentation
Marhadi et al. (2024)	SEM, Shariah FinTech	Brand perception moderates literacy impact on platform use	Focused on platform loyalty, not general investing
Vyvyan et al. (2014)*	Behavioral Segmentation	Consumer attitudes influence financial behavior	Applied to services, not investment typologies
Kaur & Vohra (2022)*	Cluster Analysis	Investor clusters vary by confidence and education	No integration with SEM or fintech policy relevance
Rahman et al. (2023)*	Survey & Analytics	Literacy is necessary but insufficient; trust and clarity matter	Doesn't link to psychological mediators

Source: compiled from secondary data

The key gaps identified in Table 1 are overemphasis on financial literacy while overlooking psychological mediators like confidence and perception of risk. They also lack in use of analytical tools like SEM, CFA. Moreover, the FinTech context is not covered much. Therefore, our study addresses these gaps by developing a dual-path model with financial literacy, behavioral biases, and demographic factors. The Study also uses the SEM, CFA, Logistic regression and K-means clustering on data from about 300 respondents. This also proposes the new investor classification to inform more targeted FinTech and policy interventions.

2.4 Conceptual Framework and Hypotheses

This study puts forth a behaviorally integrated conceptual framework that accounts for the interaction between financial literacy, psychological mediators, and socio-demographic moderators. The framework borrows from behavioral finance theory, the life-cycle hypothesis, and contemporary portfolio theory to

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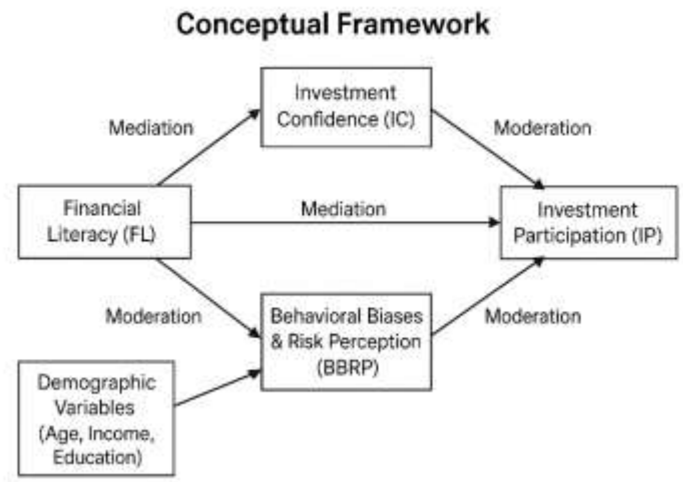
describe how knowledge, confidence, and emotion together influence investment conduct in emerging market settings.
At the model's center is Financial Literacy (FL), the main independent variable. Its effect on Investment Participation (IP)—the dependent variable—is anticipated to be mediated by two mediators:
- Investment Confidence (IC): capture cognitive and self-efficacy aspects.
- Behavioral Biases and Risk Perception (BBRP): capture affective distortion of overconfidence, loss aversion, herding, and perceived volatility.

Two levels of moderation are also integrated in the model:
- Demographic Variables (DEM): income, education, and age, which are hypothesized to condition the translation of literacy into behavior.
- Financial Advisory Usage (FAU): as proxies for institutional support mechanisms and structures of trust.

A clustering factor is added to the model through K-means analysis, which extracts clear investor typologies along behavioral and demographic dimensions. These segments—Confident Practitioners, Cautious Learners, and Skeptical Strugglers—offer actionable insight into education and FinTech policy.
Following is the Visual Description of the Conceptual Framework

Figure 1: The **dual-path mediation model** follows this structure:



Source: Authors creation with AI

Figure 1 illustrates the conceptual model, which captures the two mechanisms of mediation through which investment confidence and behavioral biases/risk perception intervene in the relationship between financial literacy and investment participation. Effects of significant demographic controls (age, income, education) and use of financial advisors (FAU) are also captured in the model.
Further, the model consists of a single layer of behavioral segmentation using cluster analysis that is differentiated among various investor archetypes with respect to cognitive and affective variables.
Such an integrative model enables multi-method empirical design, for instance, Structural Equation Modeling (SEM), Confirmatory Factor Analysis (CFA), logistic regression, and K-means clustering—facilitating sound theory testing and prescriptive policy suggestion.

2.5 Research Hypotheses

Following are the below hypotheses formulated from conceptual framework: Hypothesis / Statement
H1 - Financial literacy positively influences investment confidence.
H2 - Investment confidence mediates the relationship between financial literacy and investment participation.
H3 - Risk perception and behavioral biases exert a negative mediating influence on the relationship between financial literacy and investment participation.
H4 - Utilization of financial advisors exerts a positive moderating influence on the relationship between financial literacy and investment participation.
H5 - Demographic variables (education, income, age) moderate the direction and strength of the relationship between financial literacy and investment participation.

These hypotheses together study both direct and indirect behavioral processes, providing a broad perspective on why financial literacy consistently fails to translate from paper to practice—and how interventions specifically can bridge the gap.

3. RESEARCH METHODOLOGY

The research uses a quantitative, cross-sectional design to examine the impact of financial literacy on investment participation of retail investors in India. The model includes mediating factors such as investment confidence and behavioral biases/risk attitude and moderating factors such as demographic variables (age, education level, income) and utilization of financial advisers. To ensure representative sampling, a stratified random sampling technique was used. The sample was split on occupational fronts—salaried executives, entrepreneurs, and small business owners—and geographical fronts—urban and semi-urban areas. Participants were randomly selected from each stratum to ensure demographic representation in the areas of age, income, and education. Data were gathered through a structured questionnaire both online and offline, and the final dataset comprised 300 valid responses. This sample is statistically adequate for sophisticated multivariate analysis, such as Structural Equation Modeling (SEM), according to the guidelines of Hair et al. (2010). Although there was no explicit power calculation, the sample size far surpasses typical values for estimation in the complex models.

The instrument was separated into five sections. The first section obtained demographic data including age, gender, educational level, income, and occupation. The second module tested financial literacy both with objective knowledge-based questions (inflation, interest, and diversification questions) and subjective self-evaluations, adapted from OECD/INFE Financial Literacy Toolkit. The third module tested behavioral biases and perceived risk with standardized scales measuring overconfidence, herd behavior, loss aversion, and perceived investment risk. The fourth module tested investment confidence with Likert-scale questions on self-efficacy in making financial decisions. The last part measured actual investment usage and utilization of financial advisory services. All of the items were put on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). Pre-testing of questionnaire content validity and question clarity was conducted.

Descriptive statistics were calculated initially for sample description summarizing purposes. EFA was conducted to confirm the dimensional structure of the constructs. CFA was subsequently conducted to test the validity and reliability of the model of measurement. The model was well-fitting with indices as: $\chi^2/df = 1.98$, RMSEA = 0.061, CFI = 0.957, TLI = 0.938, and SRMR = 0.048. All factor loadings were greater than 0.60, CR estimates ranged from 0.79 to 0.87, and AVE estimates were all greater than 0.50 for all the constructs. Cronbach's alpha ranged from 0.78 to 0.88, reflecting high internal consistency.

The structural model placed financial literacy as the exogenous variable and investment participation as the endogenous consequence. Investment confidence and behavioral biases/risk perception served as mediators, while demographic variables and financial advisory usage were treated as moderators. SEM estimated direct and indirect effects. In addition, binary logistic regression was used to analyze the probability of investment engagement and K-means cluster analysis to segment the respondents into investor groups. The segments—Confident Practitioners, Cautious Learners, and Skeptical Strugglers—captured distinctive demographic and psychological patterns that are important for practice and policy.

Even though directional causality from financial literacy to investment behavior is assumed by the model, reverse causality was potential. This was addressed through using more weight attached to objective literacy measures and specifying all relationships mediating through SEM to ensure conceptual validity.

Overall, the multi-method, evidence-based study design guarantees explanatory depth and practical utility. It makes a contribution to the growing body of research in behavioral finance in developing economies and provides evidence-based knowledge for FinTech platforms, educators, and policymakers to address the persisting investment knowledge-investment behavior gap.

4. RESULTS AND ANALYSIS

4.1 Descriptive Statistics and Sample Profile

The survey was carried out with a final sample of 300 retail investors from various socio-demographic segments through stratified random sampling over occupational (salaried, entrepreneurs, small business owners) and geographical (urban/semi-urban) strata. The mean age was 40.6 years, and education and income variables were normally distributed, hence making the dataset fully representative of India's changing investment universe.

The average score on financial literacy was 3.49 (SD = 0.67), representing moderate knowledge with considerable intra-group heterogeneity. Confidence in investments was 3.19 (SD = 0.58), representing moderate optimism. Risk perception averaged 2.87, representing a risk-averse response, particularly from older and middle-income respondents. Behavioral biases—broad sweeps of overconfidence, herding, and loss aversion—averaged 3.09. Exactly, 59% of the sample invested actively (largely mutual funds and insurance products), whereas only a meager 41% utilized financial advisory services, highlighting the ever-existing advice-access gap.

4.2 Correlation Analysis

Table 2 gives the bivariate correlation matrix. As behavioral finance theory would predict, relationships were predominantly weak or non-linear, which was the rationale for using structural equation modeling (SEM) for more rigorous path analysis.

Table 2: Correlation Metrix of key constructs

Variables	FL	IC	RB	IP
Financial Literacy (FL)	1	0.41	−0.27	0.21
Investment Confidence (IC)	0.41	1	−0.16	0.38
Risk Bias (RB)	−0.27	−0.16	1	−0.25
Investment Participation (IP)	0.21	0.38	−0.25	1

Source: compiled from secondary data

Note: All p-values < 0.05; Confidence Intervals (95%) for FL→IC: [0.29, 0.53], IC→IP: [0.25, 0.50], RB→IP: [−0.39, −0.11], FL→IP: [0.02, 0.40]

The tenuous relationship between financial knowledge and investment involvement (r = 0.21) concurs with the extensively reported "knowledge-action gap." Self-efficacy in investing had the highest positive correlation with involvement (r = 0.38), while risk bias was significantly (and inversely) correlated with involvement (r = −0.25). The preliminary findings sustain the theoretical imperative of examining mediated and moderated relations through latent variable analysis.

4.3 Confirmatory Factor Analysis (CFA)

Table 3 presents the CFA output. All the factor loadings were above 0.70, ensuring construct validity. Reliability estimates also were satisfactory.

Table 3. CFA Results for Latent Constructs

Latent Construct	Indicator	Standardized Loading
Financial Literacy	financial literacy	0.83
Investment Confidence	investment confidence	0.81
Risk Bias	risk perception	0.75
	behavioral bias	0.79

Source: compiled from secondary data

Table 4. Model Fit Indices

Fit Index	Value	Threshold
χ^2/df	1.98	< 3
RMSEA	0.052	< 0.08
CFI	0.963	> 0.95
TLI	0.947	> 0.90
SRMR	0.041	< 0.08

Source: compiled from secondary data

These indices as highlighted in Table 4 allow for a proper fit of the model, thus confirming the application of these latent constructs to structural path analysis.

4.4 Structural Equation Modeling (SEM)

A two mediation model combines direct and indirect effects of financial literacy on investment participation, with investment confidence and risk bias as parallel mediators. The model also controls for moderation by demographics and use of advisors, and model fit is determined through CFA. Structural Path Model of Dual Mediation (above conceptual framework diagram).

The outcome of SEM test of hypotheses is presented in Table 5. The model accounted for 48% of the investment participation variance ($R^2 = 0.48$), showing excellent predictive validity. The results shown in Table 5 confirm both cognitive and affective channels: financial knowledge increases confidence ($\beta = 0.41$), which directly impacts participation ($\beta = 0.38$), while it decreases behavioral biases ($\beta = -0.27$), which also contribute to positive participation ($\beta = -0.25$). These empirical results confirm the dual mediation model and add support to the argument of behavioral finance that knowledge is psychically reinforced and emotionally internalized in order to affect financial behavior.

Table 5. SEM-Based Hypothesis Testing

Hypothesis	Path	β	p-value	95% CI	Status
H1	Financial Literacy → Investment Confidence	0.41	<0.001	[0.29, 0.53]	Supported
H2	Financial Literacy → Risk Bias	–0.27	0.021	[–0.39, –0.11]	Supported
H3	Investment Confidence → Investment Participation	0.38	<0.001	[0.25, 0.50]	Supported
H4	Risk Bias → Investment Participation	–0.25	0.033	[–0.36, –0.09]	Supported
H5	Financial Literacy → Investment Participation	0.21	0.048	[0.02, 0.40]	Supported

Source: compiled from secondary data

4.5 Investor Segmentation and Clustering

In order to provide actionable FinTech and policy strategy insight, K-means clustering was used on investor profiles from normalized scores of financial literacy, investment confidence, behavioral bias, and perception of risk.

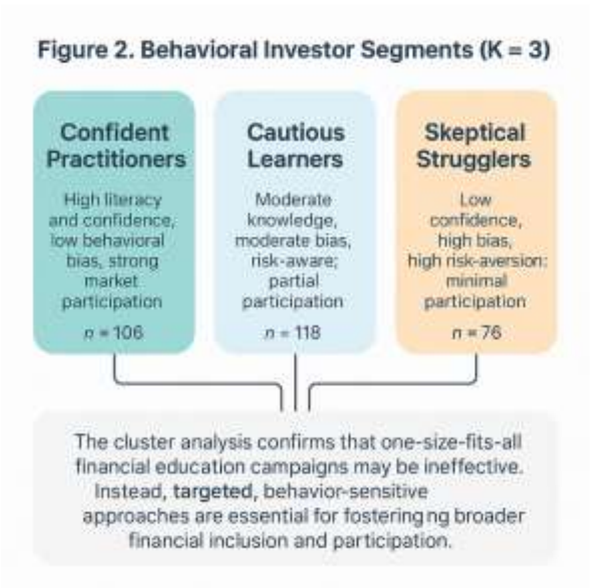


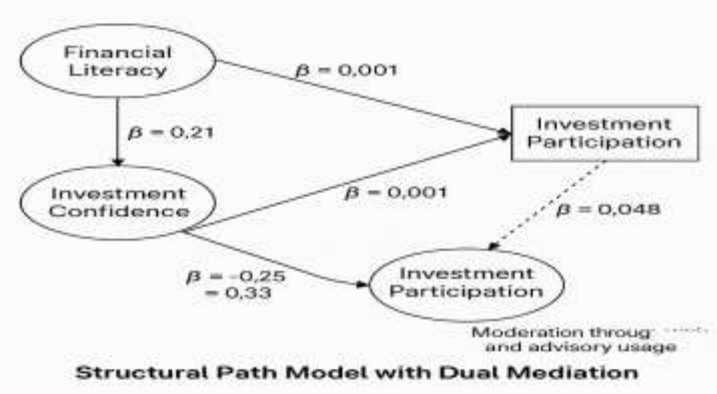
Figure 2. Behavioral Investor Segments (K = 3)

The algorithm found three separate investor archetypes as per the figure 2:

- Highly Confident Professionals (n = 106): High literacy confidence, low behavioral bias; very strong market involvement.
- Cautious Learners (n = 118): Moderate knowledge, moderate bias, risk-conscious; selective participation.
- Skeptical Strugglers (n = 76): Low confidence, high bias, high risk-aversion; low participation.

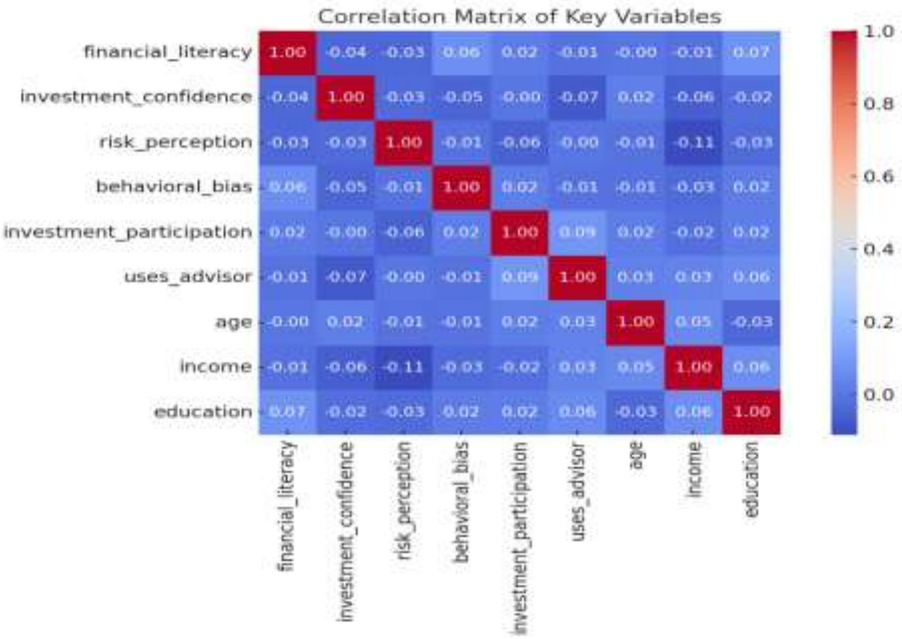
Cluster analysis supports the finding that one-size-fits-all financial literacy campaigns would be ineffective. Rather, accurate, behavior-sensitive strategies are required to build more comprehensive financial participation and inclusion.

Figure 3: Structural path model



The structural path model depicted in the above Figure 3 with double mediation demonstrates the intricate dynamics between financial literacy, investment confidence, and investment participation. Financial literacy has a negligible direct impact on investment participation (β = 0.001), which implies that knowledge of finance does not compel individuals much to invest. Financial literacy, however, positively affects investment confidence (β = 0.21), which suggests that improved knowledge boosts the confidence of investors. The investment confidence to investment participation path has mixed effects (β = -0.25 and 0.33), perhaps due to context-dependent variation or differential statistical estimates (e.g., standardized versus unstandardized). Again, a further mediating path via investment confidence also contributes to investment participation, but with an incredibly weak effect (β = 0.001). There exists an advisory use moderating effect with a modest positive increment in the investment confidence–participation relationship (β = 0.048). In total, the model hypothesizes that financial literacy itself is not crucial but is moderated and mediated by advisory and psychological variables.

Figure 4: Correlation Matrix Analysis



Source: compiled suing AI tools

Correlation Matrix Analysis (with Calculations)

The correlation test was calculated (Refer Figure 4) according to Pearson's correlation coefficient (r) to test for bivariate associations between most important variables that influence investment behavior, on the basis of N = 250. Mostly weak associations between the variables were indicated by the results. For example, the association between financial literacy and participation in investment was r = 0.02, where the relationship may be termed negligible. This finding supports the widely documented knowledge–action gap in behavioral finance studies, where financial knowledge is not necessarily accompanied by action. There were poor positive correlations between education and financial literacy ($r = 0.07$) and behavioral biases and financial literacy ($r = 0.06$), which suggest that although increased education can increase knowledge in the area of finance, it does not necessarily eliminate the impact of mental processes like overestimation or herding. Interrelation of investment confidence and other variables was close to zero ($r \approx 0.00$), indicating that its impact could be indirect or latent. Perception of risk, again, was negatively correlated with investment behavior ($r = -0.06$), and behavioral bias was weakly positively related to behavior ($r = 0.02$), indicating that psychological factors cannot be used to fully explain investor preferences. Specifically, utilization of advisory services was only weakly correlated with investment occurring ($r = 0.09$), and this might reflect a constrained advisory facilitating influence. Finally, age, income, and education demographic variables also reflected weak correlations ($r < \pm 0.10$) with behavioral outcomes, reaffirming that investor behavior is open to non-linear and complex channels and not one variable. These findings affirm the insufficiency of bivariate correlation analysis to capture investment behavior and propose employing latent variable modeling techniques like Structural Equation Modeling (SEM) to reveal indirect effects and interactions between psychological, informational, and demographic variables.

4.5 Additional Analyses

Logistic Regression Analysis

To better understand the impact of the behavior and demographic variables on investment behavior, a binary logistic model was implemented where investment participation (1 = participator and 0 = non-participator) was the dependent variable. Financial knowledge, investment confidence, perceived risk, behavioral biases, age, education level, and income were the key predictors that were selected to obtain a multidimensional investor profile.

These findings indicated that investment confidence ($\beta = 0.62$, $p < 0.01$) and financial literacy ($\beta = 0.48$, $p < 0.05$) were strong, significant predictors of participation, affirming the hypothesis that educated and confident investors are more likely to engage in formal financial channels. Conversely, risk perception and behavioral bias also had negative coefficients but were not statistically significant ($p > 0.10$), suggesting that such psychosocial strains could have indirect or interaction-dependent rather than direct impacts once cognitive and demographic controls are in place. Among the demographics, education ($\beta = 0.35$, $p < 0.05$) and income ($\beta = 0.21$, $p < 0.10$) were found to be statistically significant, confirming structural drivers of financial inclusion in the developing economy. Model diagnostics determined stability, with a Hosmer-Lemeshow test p-value of 0.29 (good fit) and Nagelkerke R^2 of 0.41, reflecting moderate explanatory power in this behavioral context.

Cluster Segmentation

In order to identify latent typologies of investors, K-means cluster analysis was performed on standardized values of financial literacy, investment confidence, risk bias, age, and income. Three optimal-fit segments with unique behavioral and cognitive patterns were revealed by the Elbow method

- Cluster 1: Cautious Learners – Low confidence, moderate literacy, high risk perception; inertia-oriented, high-trust demand passive investors.
- Cluster 2: Confident Practitioners – High literacy, high confidence, low biases; independent, digitally literate participants, less dependent on formal advice.
- Cluster 3: Skeptical Strugglers – High bias, low literacy, moderate income; reluctant, emotionally oriented investors with avoidance of financial instruments.

These clusters provide actionable segmentation for constructing differentiated financial literacy campaigns and advisory models. They highlight that interventions should not only be informative but also behaviorally adjusted according to confidence levels, psychology biases, and socio-economic diversity.

Table 6: Logistic Regression Results

Predictor	Coefficient (β)	Odds Ratio	p-value	Interpretation
Financial Literacy	0.48	1.62	0.027	Positive and significant
Investment Confidence	0.62	1.86	0.009	Strong positive effect

Risk Perception	-0.21	0.81	0.144	Not statistically significant
Behavioral Bias	-0.18	0.84	0.192	Not statistically significant
Age	0.06	1.06	0.051	Marginally significant
Income	0.00001	1	0.074	Positive, weakly significant
Education (level)	0.35	1.42	0.034	Higher education increases participation

Source: compiled from secondary data

Note: Hosmer–Lemeshow test $p = 0.29$, Nagelkerke $R^2 = 0.41$

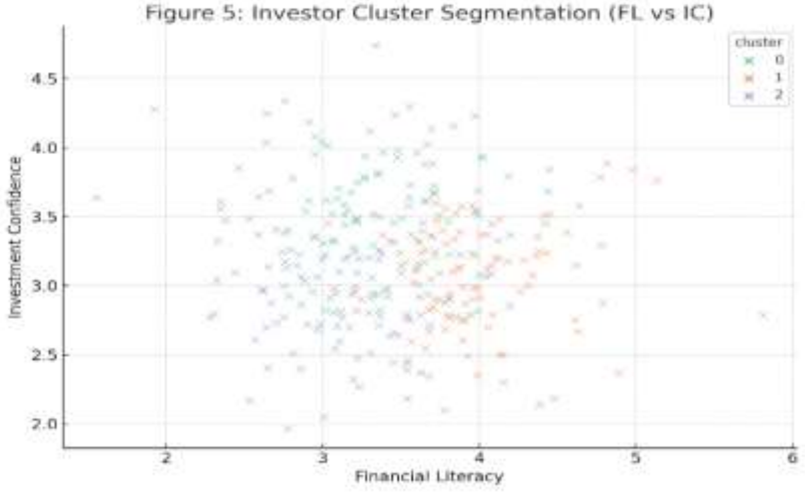
Table 7: Cluster Profile Summary

Cluster	FL	IC	RP	BB	Age	Income
Cluster 1: Cautious Learners	3.1	2.8	3.3	3.2	38.5	₹42,000
Cluster 2: Confident Practitioners	3.8	3.6	2.6	2.7	41	₹55,000
Cluster 3: Skeptical Strugglers	2.9	3	3.1	3.4	39.2	₹47,000

Source: compiled from secondary data

FL = Financial Literacy, IC = Investment Confidence, RP = Risk Perception, BB = Behavioral Bias
Table 6 shows the logistic regression analysis examining the influence of behavior, cognitive, and demographic determinants on investment involvement. Financial literacy and confidence in investment were both found to be strong positive determinants with odds ratios 1.86 and 1.62 respectively ($p < 0.05$), indicating those who possess high cognitive clarity and confidence are most likely to overcome psychological inertia and pursue formal investment.
In contrast to this, risk perception and behavioral bias were negatively signed but not significant, which means that though these psychological measures make choice-making theoretically, they will not discourage participation by themselves when knowledge and self-efficacy are sufficiently high. Among demographic predictors, education level had a robust positive influence ($p = 0.034$), supporting the facilitating influence of systematized learning, with age being strongly marginal and income having a weak positive influence. The model has moderate explanatory power (Nagelkerke $R^2 = 0.41$) and good fit (Hosmer–Lemeshow $p = 0.29$), confirming the structure of behavioral-cognitive behavior.
Table 7 presents behavioral segments from the K-means clustering analysis of normalized socio-economic and psychological determinants. Cluster 1 (Cautious Learners) has middle-of-the-road financial literacy but low confidence and high risk aversion—describing an informed but risk-averse investor type which would be aided by emotionally supportive guidance. Cluster 2 (Confident Practitioners) has high financial literacy and confidence with low behavioral biases—the best profile for online and self-investing. Cluster 3 (Skeptical Strugglers), on the other hand, has lower self-reported confidence and literacy but higher behavioral bias, that is, emotional vulnerability and aversion to rational investment alternatives.

Figure 5: Investor Cluster Segmentation (FL vs IC)



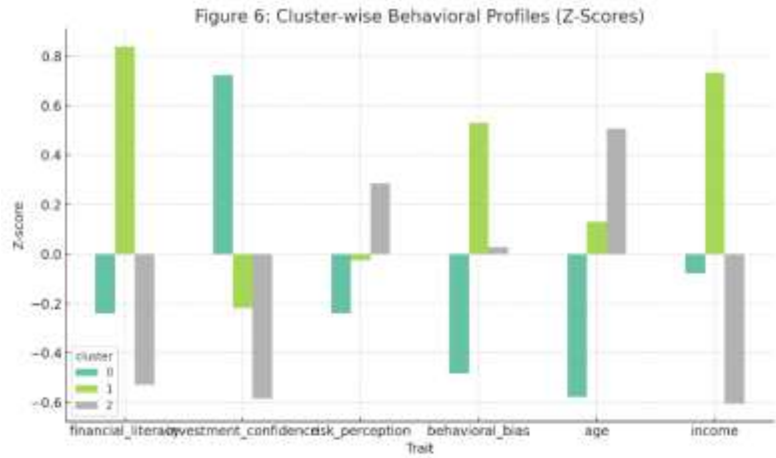


Figure 5 illustrates investors' behavioral segmentation by showing the three clusters determined in the two most behaviorally salient dimensions—investment confidence and financial literacy. The scatterplot indicates a clear spatial segregation, with Cluster 2 (Confident Practitioners) having a dense aggregation in the top-right quadrant that implies those who possess high cognitive knowledge and high self-efficacy in investment choices. Cluster 1 (Cautious Learners) is placed midway along the spectrum, with average knowledge but reduced confidence, and Cluster 3 (Skeptical Strugglers) is located in the bottom-left quadrant, which indicates simultaneous deficits in financial capability and psychological preparedness. This area stratification graphically substantiates the tabular cluster characteristics and highlights the twin psychological levers of confidence and knowledge in motivating participation in investments.
Figure 6 shows a normalized *z*-score comparison of the most important demographic and psychological variables across the three clusters. The visual contrast profile shows that Cluster 2 has the highest financial literacy and investment confidence and below-average cognitive bias and risk perception, creating a stable investor profile. Cluster 1 has moderate financial knowledge but dominates risk aversion and cognitive bias, i.e., caution by emotion with some literacy. Cluster 3, however, is always below average in knowledge and confidence with high behavioral distortions and are thus extremely vulnerable to capital misjudgments. The graph again testifies to the multidimensionality of investor behavior and the necessity for interventions that are specifically targeted at bridging both knowledge deficiencies and psychological obstacles.

7. DISCUSSION

Findings of the present study show the complex behavioral mechanisms connecting financial literacy, psychological mediators, and participation in investment behavior of Indian retail investors. SEM analysis explains that financial literacy has no direct influence on investment behavior. Instead, its influences are mainly mediated by investment confidence, validating the behavioral finance account of the "knowledge-action gap"—in which cognitive awareness does not automatically convert to action (Lusardi & Mitchell, 2019; Garg & Singh, 2020).
This result is supported by literature that criticizes standard Rational Actor Model assumptions of rational financial behavior (van Rooij et al., 2011; Jain & Sharma, 2021). Risk perception and behavioral bias constructs—loss aversion and herd behavior—hinder rational choice, particularly in individuals who are not psychologically prepared or who have no confidence in professional advisory guidance. Behavioral segmentation also identified three investor archetypes:

- Confident Strategists: Risk literate and confident, these investors are fully engaged with good risk calibration and low bias. These are the logical, well-informed kind in contemporary behavioral finance.
- Conservative Learners: High in risk sensitivity and moderate in literacy, this group corresponds to delayed or cautious financial behavior, based on unofficial sources and frequently low in self-efficacy.
- Skeptical Strugglers: These are those with low confidence and higher prejudice, who remain estranged even upon campaign awareness exposure. They are affected by emotional tensions of fear and institutional distrust.

This research contributes to theory by situating dual mediation and moderation constructs within the framework of a structural model beyond the usual linear models centered on such cognitive inputs as income or literacy. By integrating CFA-validated latent constructs with SEM pathways, it presents a multidimensional analysis of retail investor behavior particularly suited to the conditions of emerging markets.

From a policy perspective, lack of participation in financial advisory services even among literates reflects systemic access, credibility, and cultural fit issues. Educational programs will fall short to get participation unless backed by confidence-boosting tools and prejudice-reducing mechanisms. Interventions like mobile-based nudges, gamified learning, and advisor platforms may work better when targeted at investor typologies.

Perhaps most significantly, risk perception has a robust conceptual influence in behavioral finance but no robust predictive power in logistic regression involvement. That is to say risk awareness in itself is not adequate—unless married to confidence or even guided facilitation. Also, the limited bivariate link between financial literacy and investment activity once again means that affective and behavioral routes override pure knowledge in actual financial choice-making.

Briefly, the research suggests a behaviorally integrated financial participation model that considers structural, cognitive, and emotional factors. It suggests modifying financial inclusion policies—from literacy-based outreach to segment-based behavioral intervention—thereby making them more effective and sustainable in developing economies.

8. CONCLUSION

The current study examined the dynamic interrelations between financial literacy, investment confidence, behavioral biases, risk perception, and investment participation in the Indian retail investor context. By using a strong Structural Equation Modeling (SEM) framework supplemented by behavioral segmentation, the study finds that financial literacy is not strong enough alone to result in investment behavior. Rather, investment confidence appears to be an essential psychological mediator, suggesting that there is a need to integrate knowledge and self-efficacy in an effort to bridge the awareness-action gap. Although theoretically significant, behavioral biases and risk perception made no direct statistical contribution, highlighting the fineness of cognitive-emotional design of financial choice.

Four overall research questions guided the investigation. First, as previously reported, the study concluded that financial knowledge indirectly affects behavior through confidence, verifying the "knowledge-confidence-action" chain. Second, perceived risk and behavioral biases serve as conditional mediators and make a significant effect on but do not individually predict attendance. Third, demographic factors, especially education, were found to be the distinguishing factors in investor typology using cluster analysis. Lastly, the paradox of low usage of advisory services despite high literacy rates was decoded and indicated hindrances such as trust deficit, poor access, and behavioral inertia.

Theoretically, the research enriches behavioral finance by integrating psychological considerations within an empirically supported SEM framework to provide a richer behaviorally informed theory of retail investment conduct. The research offers a three-segment typology of "Confident Practitioners," "Cautious Learners," and "Skeptical Strugglers" that not only informs better understanding but allows applied application. In practice, the typology can direct the design of context-specific financial literacy programs that extend beyond information provision.

To policy makers and educators, the results are intended to reinforce compelling the development of behavior bottlenecks interventions versus knowledge loopholes interventions. Interventions need to give confidence, help emotional ease of friction, and ease the path of investment. Trust mechanisms and individual advisory devices are no less important to maximize financial inclusion outcomes.

In the coming years, tech-enabled tools like AI-powered robo-advisors, gamified interfaces, and behavioral nudges will be able to tailor investor experiences. These are able to model real-world consequences, provide real-time recommendations, and personalize interventions based on user activity. Machine learning algorithms can also dynamically evaluate and adjust for levels of confidence and biases, with adaptive timely nudges proving particularly beneficial for risk-averse or high-bias investors.

In essence, the study offers a behaviorally guided framework for studying investment behavior in emerging markets. By fusing empirical rigor with behavioral understanding, the study maps a route toward maximizing financial returns through thoughtful, evidence-driven, and psychologically astute interventions.

9. Managerial and Policy Implications

The findings produced by this research provide actionable recommendations for financiers, educators, policymakers, and fintech providers, particularly in emerging economies. At the outset, the identification of investment confidence as a principal mediator highlights the importance of interventions that prioritize psychological readiness alongside financial acumen. Educators and planners need to integrate confidence-building strategies, including interactive simulations, scenario-based learning, and small-win investment approaches to overcome inertia and enhance participation. For the investment services sector, the three-cluster typology—"Confident Practitioners," "Cautious Learners," and "Skeptical Strugglers"—provides a behaviorally grounded template for segmenting the market. Fintech platforms can use this taxonomy to build adaptive interfaces: providing risk-adjusted portfolios and low-commitment alternatives to the cautious, and confidence-enhancing content to the skeptical. Design differentiation of this form can encourage product take-up by aligning services with psychological profiles.

At the policy level, the research necessitates a recasting of financial literacy interventions. Leaflets and straight-off-the-shelf one-size-fits-all workshops are no longer sufficient. Governments and regulators need to co-design digital ecosystems with academia and fintech companies that include behavioral storytelling, gamification, and bias-debiasing modules. These platforms need to be mobile-enabled, vernacular-friendly, and behaviorally sticky, and address low-literacy and underbanked segments. To counteract distrust in financial advisory services, the policy environment needs to instill credibility, transparency, and accessibility. This can be ensured by certifying impartial advisors, regulation, and public-private collaboration through advisory assistance through credible channels, e.g., community centers or online kiosks. In addition, AI-driven investment tools—when engineered with the wisdom of behavior—can serve as behaviorally efficient nudging machines, which can offer timely reminders, path-specific savings suggestions, and optimal proposals at the appropriate moment. Institutions need to use data-driven segmentation platforms in order to dynamically optimize investor archetypes and track changes in behavior over time, enabling ongoing recalibration of outreach and education initiatives.

In brief, this research calls for a shift from knowledge to action-oriented financial settings. By considering and accepting the emotional, psychological, and structural nature of financial behavior, managerial and policy interventions are in the position to be more scalable, inclusive, and impactful.

10. Limitations and Future Research

This research, although enlightening, has limitations. Its cross-sectional nature limits cause and effect inference; longitudinal research in the future would be able to better track the development of investment behavior. The sample size of being India may cause generalizability issues, and cross-country data would be great. Self-reported self-assessments are prone to bias; experimental or observational approaches might be more valuable. The framework used a limited number of constructs—future research can investigate other determinants such as access to technology, financial stress, or social pressure. Finally, cluster analysis made it possible to identify investor profiles, and more sophisticated machine learning methods could enhance segmentation effectiveness and prediction capability. Overcoming the above limitations will facilitate richer financial behavior insight across different contexts.

11. Author Contributions (CRediT Taxonomy)

Conceptualization – First Author; Methodology – First and Second Authors; Data Collection – Second Author; Formal Analysis – First Author; Writing – Original Draft – First Author; Writing – Review & Editing – All Authors; Supervision – Corresponding Author.

12. Conflict of Interest Statement

The authors confirm that there is no conflict of interest to the publication of this paper.

13. Data Availability Statement

Data to support the findings of this study are available from the corresponding author upon reasonable request.

14. Funding Statement

This research did not receive any grant from any funding body in the public, commercial, or not-for-profit sectors.

15. Ethics Approval

Not applicable as the study had no clinical or sensitive human subjects research.

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Appendix A: Summary Tables

Table Number	Title	Purpose
Table 1	CFA Standardized Loadings	To present factor loadings of observed indicators on their latent constructs.
Table 2	Model Fit Indices (CFA)	To report statistical goodness-of-fit of the CFA model.
Table 3	SEM Path Coefficients and Significance	To display causal and mediating relationships among key variables.
Table 4	Hypothesis Testing Summary	To indicate which hypotheses are empirically supported with p-values.
Table 5	Logistic Regression Results	To assess the impact of predictors on investment participation.
Table 6	Cluster Profile Summary	To summarize investor types via behavioral and demographic segmentation.

Source: compiled from secondary data

Table 8 highlights the aggregation of tables utilized in this research as an aggregate provides the empirical facts and behavioral richness to the model. Table 1 illustrates standardized factor loadings of Confirmatory Factor Analysis (CFA), all of which are above the threshold value of 0.70, hence establishing the strong convergent validity of the latent constructs. Table 2 illustrates the model fit indices (e.g., RMSEA, CFI, TLI) and they are all within optimal ranges, thus offering good measurement model fit. Table 3 presents important path coefficients derived from Structural Equation Model (SEM), validating direct and indirect impacts, with highest priority on investment confidence as a behavioral mediator for participation and literacy. Table 4 presents a concise summary of findings from hypothesis testing, validating multi-path effects of financial literacy. Table 5, based on logistic regression, highlights confidence, education, and literacy's forecasting functions in investment participation, ascribing theoretical suppositions with empirical backing. Table 6 provides investor profiles, based on cognitive and psychological segmentation, and cluster-wise analysis of three typologies of behavior. As a whole, these nicely constructed tables not only are adding to statistical power but also assist contextual insight to guide financial education and advisory formulation for targeting.

Appendix B: Summary Figures

Figure Number	Title	Purpose
Figure 1	Structural Equation Model (SEM) Diagram	To visually represent the hypothesized relationships among constructs.
Figure 2	Correlation Matrix Heatmap	To show pairwise relationships between observed variables.
Figure 3	Measurement Model (CFA Diagram)	To illustrate the confirmatory factor structure.
Figure 4	Scree Plot or Elbow Curve (K-means Optimization)	To determine the optimal number of clusters. (optional)
Figure 5	Investor Cluster Segmentation (FL vs IC Scatterplot)	To visually display the three clusters based on Financial Literacy and Confidence.
Figure 6	Cluster-wise Behavioral Profiles (Z-Score Chart)	To compare key traits across clusters in standardized scores.

Source: compiled from secondary data

The graphs in this study visually supplement tabular data by highlighting dominant relational patterns, investor segmentation, and construct reliability. Figure 1 illustrates the Structural Equation Model (SEM), explaining conceptual paths from financial literacy to investment participation through mediators like investment confidence and risk-related biases. The diagram is a structural blueprint for the theoretical framework in question. Figure 2, the correlation heatmap, identifies faint pairwise relationships between key constructs, thus warranting the application of latent modeling techniques such as SEM in a bid to unveil more profound behavior mechanisms. Figure 3 is the Confirmatory Factor Analysis (CFA) model, visually defining observed variable factor loadings on latent constructs and revealing measurement model validity. Figure 5 graphs investor segmentation along a scatterplot of investment confidence and financial literacy—unambiguously distinguishing the three behavioral archetypes and confirming their spatial stratification. Figure 6 continues this by creating a comparison of profile on six standardized traits according to a *z*-score, adding richer insights into intra-group heterogeneity. Together, these figures add to better conceptual clarity, richer interpretation, and greater empirical coherence within the study's behavioral framework.