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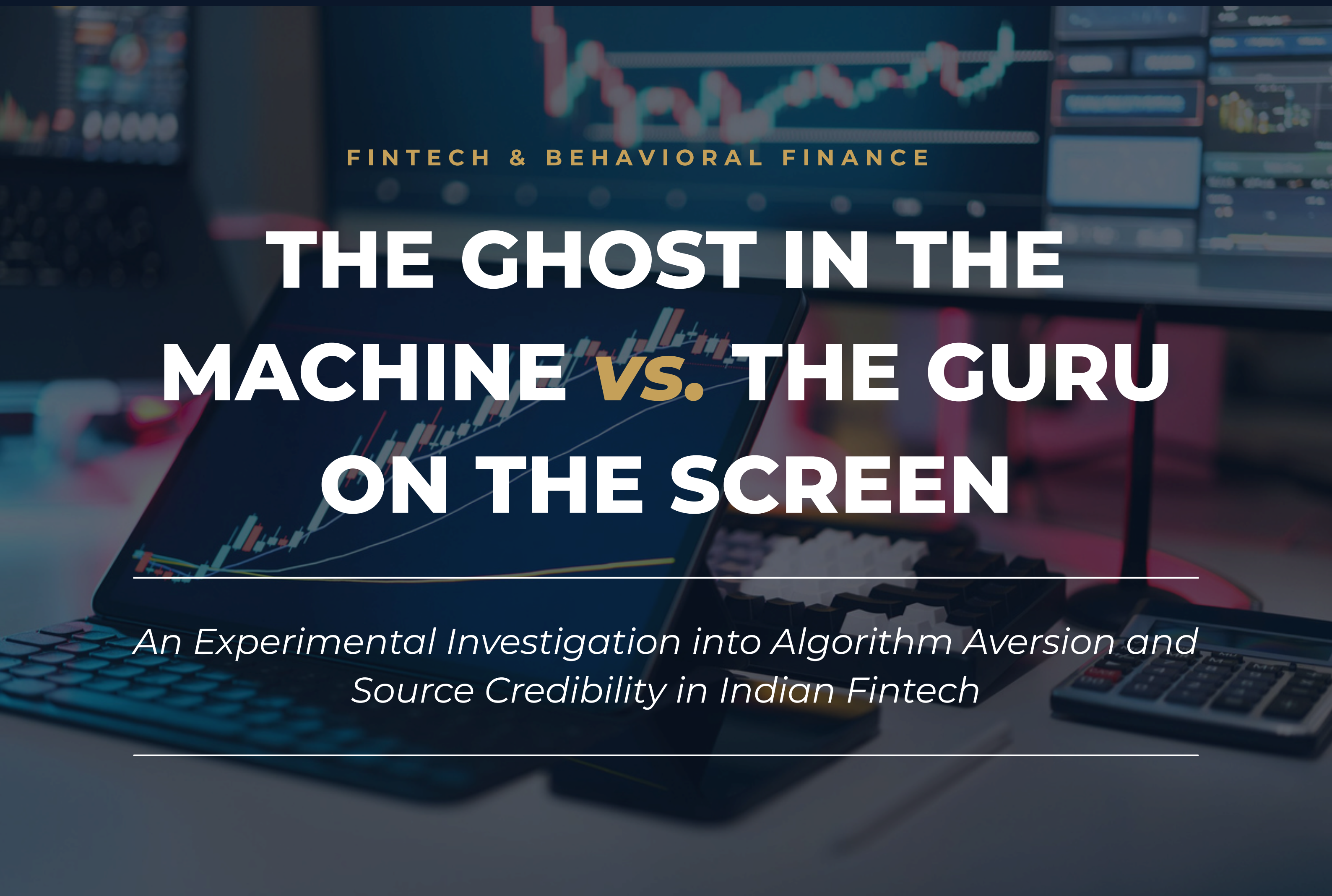

FINTECH & BEHAVIORAL FINANCE

THE GHOST IN THE MACHINE *vs.* THE GURU ON THE SCREEN

An Experimental Investigation into Algorithm Aversion and Source Credibility in Indian Fintech

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HOW THE "TRUST GAP" DEFINES THE FUTURE OF INDIAN FINTECH

Abstract

Purpose: The Indian fintech sector is witnessing a conflict between two dominant sources of financial advice: algorithmic robo-advisors (AI) and social media financial influencers (Humans). This study investigates the "Trust Gap" between these sources to determine if Indian Gen Z investors exhibit "Algorithm Aversion" or "Source Credibility" bias in high-stakes investment decisions.

Design/methodology/approach: A between-subjects experimental design (N=152) was employed. Respondents were randomly assigned to view identical investment advice attributed to either an AI Algorithm or a Human Expert. Data analysis was conducted using Python (semopy) for Structural Equation Modeling (SEM) to analyze the impact of perceived accuracy and objectivity on trust, risk, and investment intention.

Findings:

Results indicate that Trust is the primary driver of Investment Intention, fully mediating the effects of accuracy and objectivity.

Multi-Group Analysis (MGA) reveals that while investors demand high perceived accuracy to trust AI, they do not hold human experts to the same rigorous standard, confirming a specific form of algorithm aversion. Surprisingly, perceived risk did not significantly deter investment intention, suggesting a high risk-appetite among the cohort.

Originality/value: This study creates a bridge between information systems literature (Algorithm Aversion) and marketing literature (Source Credibility) in the under-researched context of Indian retail investors.

Keywords: Fintech, Algorithm Aversion, Source Credibility, Trust, Robo-advisory, Indian Retail Investor, Gen Z.

TECTONIC SHIFTS: THE DEMOCRATIZATION OF INDIAN CAPITAL MARKETS

1. INTRODUCTION

The financial landscape of India has undergone a tectonic shift in the last decade, characterized by the 'financialization of savings' and the democratization of market access. Historically, Indian household savings were predominantly parked in physical assets like gold and real estate, or low-risk instruments like fixed deposits. However, fueled by the 'JAM Trinity' (Jan Dhan, Aadhaar, and Mobile) and the proliferation of low-cost data, a new cohort of retail investors has emerged. This digital transformation was significantly accelerated by the disruptive entry of Reliance Jio in 2016, which drastically reduced data costs and catalyzed widespread internet adoption, reaching critical mass by 2019 (TRAI, 2019). These investors, largely hailing from Tier-1 and Tier-2 cities, are distinct from their predecessors; they are 'digital natives' who demand instant access, low fees, and mobile-first experiences.

The COVID-19 pandemic acted as a potent catalyst for this trend. With lockdowns confining the population indoors and economic uncertainty looming, millions turned to the equity markets as a source of passive income and wealth generation. Platforms such as Zerodha, Groww, and Upstox lowered the barrier to entry, removing the friction of physical paperwork and complex brokerage interactions. Consequently, the Central Depository Services (India) Limited (CDSL) reported a massive surge in Demat account openings, crossing the 60-million mark in 2021, a figure that continues to grow exponentially. This surge represents a fundamental alteration in the market microstructure, shifting power from institutional giants to the aggregated mass of retail traders.

However, this ease of access has birthed a 'Paradox of Choice' regarding advisory sources. Traditionally, financial advice was the domain of certified brokers and bank relationship managers, governed by high entry barriers and established human relationships. Today, the modern investor faces two distinct, often conflicting, sources of guidance in the digital ecosystem. On one hand, Fintech platforms promote 'Robo-Advisory' and 'AI-driven insights.' These platforms position the algorithm as the pinnacle of objective, emotionless, and data-driven decision-making, appealing to the rational economic view that technology reduces human error. Features such as 'Smart Portfolios' and 'AI-picked stocks' are becoming standard value propositions.

On the other hand, the rise of the 'Creator Economy' has led to the explosion of 'Fin-fluencers' (Financial Influencers) on social media platforms like YouTube, Instagram, and Twitter. These human experts leverage relatability, parasocial interaction, and simplified storytelling to garner millions of followers. Unlike cold algorithms, they offer a narrative, a face, and a sense of community. They translate complex financial jargon into digestible content, filling the financial literacy gap that formal education often leaves addressing. However, this rise has also led to concerns regarding the credibility and qualifications of such influencers, prompting regulatory scrutiny. The 'Guru-Shishya' (Teacher-Student) dynamic, deeply embedded in Indian culture, finds a new digital manifestation here, where the influencer is not just an information source but a trusted mentor.

This dichotomy presents a critical marketing challenge for financial service providers. While technology platforms invest heavily in developing sophisticated AI recommendation engines, user behavior often suggests a strong reliance on human influencers for validation. This raises a fundamental question about the psychology of trust in the digital age: In high-stakes financial decision-making, does the Indian consumer trust the 'Mathematical Superiority' of an AI, or the 'Relatability' of a Human Influencer? Existing literature has studied these phenomena in isolation - examining 'Algorithm Aversion' in Western contexts or 'Source Credibility' in traditional advertising. However, there is a scarcity of empirical research that pits these two sources against each other in the context of emerging market retail investors.

1.1 Research Questions

To address this theoretical gap and provide actionable insights for the Indian fintech sector, this study posits the following research questions:

- RQ1: Do Indian retail investors perceive advice generated by an AI Algorithm as more trustworthy than advice given by a Human Influencer?
- RQ2: How do cognitive perceptions of Accuracy and Objectivity influence the formation of Trust and subsequent Investment Intention?
- RQ3: Does Financial Literacy moderate the relationship between the source of advice and the formation of trust?

2. LITERATURE REVIEW

2.1 Algorithm Aversion vs. Algorithm Appreciation

The interaction between humans and automated decision-making systems has been a subject of intense academic debate. Dietvorst et al. (2015) coined the term 'Algorithm Aversion,' demonstrating a psychological phenomenon where humans lose confidence in algorithms faster than they do in humans after seeing them make the same mistake. Their study found that even when an algorithm is statistically superior to a human forecaster, people tend to abandon the algorithm after seeing it err once, whereas they are more forgiving of human error. This suggests a double standard in trust formation: humans are held to a standard of 'good enough,' while machines are held to a standard of 'perfection.'

In the specific context of finance, where market volatility makes prediction error inherent and unavoidable, this aversion could pose a significant barrier to the adoption of Robo-advisory services. If an AI predicts a stock rise and the market falls, the user may attribute the failure to a systemic flaw in the code (Castelo et al., 2019). Conversely, Logg et al. (2019) introduced the concept of 'Algorithm Appreciation,' suggesting that for tasks perceived as objective, numerical, and complex - such as stock market analysis - people may actually prefer algorithmic judgment over human intuition. They argue that when the task is framed as a 'computational problem,' laypeople recognize their own cognitive limitations and defer to the processing power of AI. The Indian context presents a unique testing ground for these conflicting theories, given the rapid digital leapfrogging observed in the financial sector (Chakraborty et al., 2018).

2.2 Source Credibility in the Digital Age

While algorithms rely on computational authority, human advisors rely on social capital. Ohanian's (1990) Source Credibility Model remains the theoretical gold standard for understanding human persuasion. The theory posits that the persuasiveness of a message depends heavily on the receiver's perception of the source's characteristics, primarily Expertise, Trustworthiness, and Attractiveness. In the context of financial influencers, 'Expertise' refers to the perceived knowledge and qualification of the creator. However, unlike traditional certified advisors, influencers often demonstrate expertise through confidence, jargon, and past success stories rather than formal accreditation.

'Trustworthiness' relates to the listener's degree of confidence in, and level of acceptance of, the speaker and the message. It captures the perceived validity of the assertions made by the influencer. Interestingly, in the digital age, 'Attractiveness' is often reinterpreted as 'Relatability' or 'Likeability.' Research in influencer marketing suggests that parasocial interaction - the illusion of a face-to-face relationship with a media figure - can bypass critical skepticism (Horton & Wohl, 1956). Users develop a one-sided bond with influencers, viewing them as friends or mentors rather than salespeople. This emotional connection can lead users to follow advice based on heuristic cues rather than factual scrutiny.

2.3 Trust in Digital Environments

The concept of 'Trust' in financial services has historically been predicated on interpersonal relationships (Sekhon et al., 2014). However, the digitization of finance has necessitated a shift towards 'Technology Trust' - the belief that a technological system will perform a task accurately and reliably. McKnight et al. (2002) argue that trust in technology is distinct from trust in humans; it is often based on 'system reliability' and 'functionality' rather than 'benevolence' or 'integrity.'

In the context of Robo-advisory, this distinction becomes blurred. While the advice is generated by an algorithm (Technology Trust), the interface and the brand act as human-like proxies. Research by Lee and Choi (2017) suggests that anthropomorphism - giving human traits to non-human entities - can bridge the gap, yet it also invites higher expectations. If an AI 'talks' like a human (via chatbots or conversational UI), users expect it to 'care' like a human. This study investigates if the current generation of Indian investors separates the message (the stock tip) from the medium (AI vs. Human), or if the two are inextricably linked in their trust formation process.

2.4 Theoretical Lens: The Heuristic-Systematic Model (HSM)

To explain the divergence in trust between AI and Human sources, we draw upon the Heuristic-Systematic Model (HSM) proposed by Chaiken (1980). HSM suggests that individuals process information via two concurrent modes: the systematic mode and the heuristic mode. Systematic Processing involves a comprehensive, analytic, and cognitive examination of the information. In our context, this relates to the 'Perceived Accuracy' variable. An investor using systematic processing would scrutinize the past performance, data points, and logic of the advice. We posit that AI-generated advice primarily triggers this mode. Because AI is presented as a computational tool, users feel compelled to evaluate it based on its 'performance output.'

Conversely, Heuristic Processing involves the use of simple decision rules or cognitive shortcuts (e.g., 'Experts can be trusted,' or 'She has 1 million followers, so she must be right'). We posit that Human Influencers primarily trigger this mode. The social cues - facial expression, tone of voice, follower count - act as heuristics that allow the investor to bypass the cognitive load of checking accuracy. This theoretical lens explains why 'Accuracy' might predict trust for AI (Systematic) but not for Humans (Heuristic). If investors are processing human advice heuristically, they are not looking for mathematical precision; they are looking for social signals of competence.

2.5 Hypotheses Development

Building upon the cognitive-affective-conative framework derived from the literature, we propose a structural model that delineates the pathway from information processing to investment decision.

The Direct Influence of Cognitive Perceptions (H1 & H2):

The Technology Acceptance Model (TAM) posits that 'Perceived Usefulness' is a primary driver of adoption (Davis, 1989). In the context of financial advice, usefulness is operationalized through Accuracy and Objectivity. If an investor perceives a source to be factually accurate (H1) and free from commercial bias or 'Objectivity' (H2), the utility of that advice increases, theoretically leading directly to usage intention. Therefore, we posit:

H1: Perceived Accuracy has a positive direct effect on Investment Intention.
H2: Perceived Objectivity has a positive direct effect on Investment Intention.

The Antecedents of Trust (H5 & H6):

Trust is not an isolated variable; it is built upon specific beliefs. According to Mayer et al.’s (1995) integrative model of organizational trust, 'Ability' (competence) and 'Integrity' (honesty) are key pillars. We map 'Perceived Accuracy' to the dimension of Ability - the belief that the source has the capability to predict the market correctly. We map 'Perceived Objectivity' to the dimension of Integrity - the belief that the source is not manipulating data for personal gain. Thus, we argue that these cognitive evaluations are the building blocks of the affective state of trust.

H5: Perceived Accuracy is a positive antecedent of Perceived Trust.
H6: Perceived Objectivity is a positive antecedent of Perceived Trust.

The Central Role of Trust and Risk (H3, H4, H7):

Financial decisions are inherently risky. Trust acts as a mechanism to reduce complexity and perceived risk in uncertain environments. When an investor trusts a source, their subjective calculation of the probability of loss (Perceived Risk) should decrease (H7). Consequently, higher trust should directly act as a catalyst for action (H3), while elevated risk should act as a barrier (H4).

H3: Perceived Trust positively influences Investment Intention.
H4: Perceived Risk negatively influences Investment Intention.
H7: Higher Perceived Trust leads to lower Perceived Risk.

The Moderating Role of Financial Literacy (H8):

We acknowledge that this process is not uniform across the population. The Elaboration Likelihood Model (ELM) suggests that individuals with high knowledge (Financial Experts) process information via the 'Central Route,' scrutinizing data quality (Accuracy). In contrast, individuals with low knowledge (Novices) use the 'Peripheral Route,' relying on cues like reputation or likability (Trust). Therefore, we hypothesize that Financial Literacy moderates the structural paths, altering the weightage investors give to cognitive vs. affective factors.

H8: Financial Literacy moderates the relationship between antecedent beliefs and Trust formation.

3. RESEARCH METHODOLOGY

3.1 Research Design

To move beyond correlational analysis and establish causality, this study employed a quantitative Between-Subjects Experimental Design. Experimental designs are considered the gold standard for testing causal hypotheses as they allow for the manipulation of independent variables while controlling for extraneous factors. This approach was selected to isolate the impact of the 'Advisory Source' (Independent Variable) on consumer perceptions without the interference of carry-over effects or demand characteristics often found in within-subjects designs where respondents compare options directly.

3.2 Experimental Stimuli

Two experimental stimuli were developed to simulate a realistic fintech environment. We utilized high-fidelity UI/UX design principles to create mobile application mockups that mirrored leading Indian trading platforms like Zerodha (Kite) and Groww to ensure ecological validity.

Condition A (AI Algorithm): The interface displayed a stock recommendation with a visual icon of a glowing microchip and the header 'Recommended by Proprietary AI Algorithm based on 500+ Market Signals.' This condition was designed to prime the concept of 'Computational Authority.'

Condition B (Human Expert): The interface displayed the exact same stock recommendation (same price, same graph, same 'Buy' button) but featured a professional headshot of a mature Indian financial advisor with the header 'Expert Pick: Curated by Top Financial Analyst.' This condition was designed to prime 'Source Credibility.'

Figure 1. *Experimental stimuli presented to respondents. Panel (A) represents the AI Algorithm condition; Panel (B) represents the Human Expert condition.*

By keeping all design elements (color palette, typography, data points, stock price) constant across both conditions, we ensured that any observed variance in the dependent variables could be attributed solely to the source manipulation.

3.3 Sampling Strategy

Data was collected via a web-based survey instrument distributed among Indian retail investors. To ensure random assignment, a logic-branching mechanism based on the respondent's birth month was utilized. Respondents born in the first half of the year (January–June) were routed to Condition A, while those born in the second half (July–December) were routed to Condition B. This randomization technique proved effective in creating balanced groups without introducing selection bias.

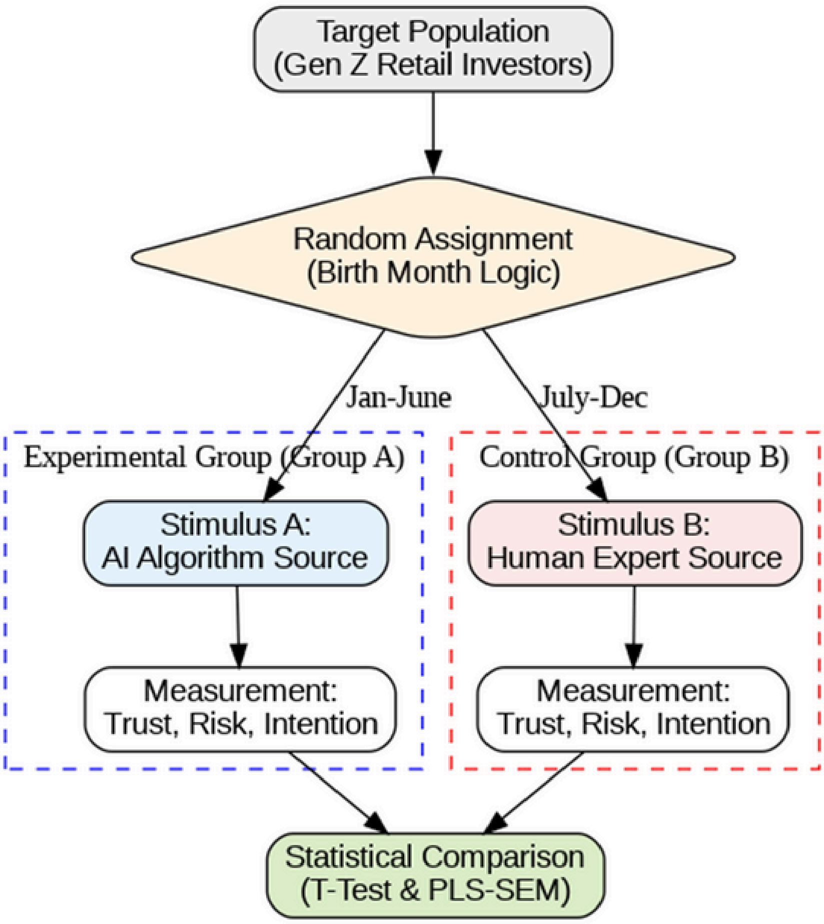

Figure 2. *Experimental design workflow illustrating the random assignment of respondents via logic branching.*

The target population comprised 'Digital Natives' - specifically Gen Z and Millennials (ages 18–35) - who represent the primary user base of modern trading apps in India. A total of 152 valid responses were collected. This sample size satisfies the '10-times rule' for Structural Equation Modeling (SEM) proposed by Barclay et al. (1995), which suggests a sample size of 10 times the maximum number of structural paths directed at a particular latent construct. In our model, the maximum number of paths to a construct is 4 (to Intention), requiring a minimum of 40 respondents. Our sample of 152 far exceeds this requirement, ensuring sufficient statistical power.

3.4 Instrumentation and Measures

To ensure construct validity, measurement items were adapted from established scales in existing literature and modified to fit the context of fintech advisory. All constructs were measured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Perceived Accuracy (Independent Variable): This construct measures the extent to which the user believes the advice is factually correct and error-free. Five items were adapted from McKnight et al. (2002) to capture the user's assessment of the source's competence. Items included statements such as "I believe this recommendation is likely to be accurate" and "I feel this source rarely makes calculation errors."

Perceived Objectivity (Independent Variable): Objectivity refers to the perception that the advice is unbiased and based purely on merit. Adapted from Ohanian (1990), this five-item scale assesses whether the user believes the source has hidden motives. Key items included "I feel this recommendation is free from hidden bias" and "I do not think this source is being paid to promote this stock."

Perceived Trust (Mediator): Defined as the willingness to rely on an exchange partner in whom one has confidence, trust was measured using five items adapted from Gefen et al. (2003). This scale captures both the benevolence and integrity dimensions of trust, with items such as "I would trust this source with my own money."

Perceived Risk (Mediator): This construct captures the subjective expectation of loss. Five items adapted from Featherman and Pavlou (2003) measured the anxiety associated with the investment decision, including "Following this advice feels risky to me" and "I fear I might lose money if I listen to this source."
Investment Intention (Dependent Variable): The ultimate outcome variable measures the subjective probability that the individual will perform the behavior. Five items adapted from Venkatesh et al. (2003) assessed the likelihood of action, such as "If I had spare capital, I would likely follow this recommendation."

3.5 Control Variables

To ensure that the observed effects were due to the experimental manipulation and not extraneous factors, we controlled for Age and Gender. Prior research suggests that risk appetite varies significantly across age groups and genders. By including these as control variables in the structural model, we isolated the variance specifically attributable to the trust and accuracy constructs.

3.6 Common Method Bias (CMB)

Since data for both independent and dependent variables were collected from the same respondents at the same point in time using the same instrument, the potential for Common Method Bias (CMB) exists. To mitigate this, procedural remedies were employed during the survey design, including ensuring respondent anonymity and reducing item ambiguity. Post-hoc statistical checks were also conducted. We employed Harman's Single Factor Test (Podsakoff et al., 2003). An exploratory factor analysis containing all variables revealed that the first unrotated factor accounted for only 23.07% of the total variance, which is well below the critical threshold of 50%. This suggests that a single latent factor does not account for the majority of the covariance in the independent and dependent variables, confirming that CMB is not a pervasive issue in this study.

4. Data Analysis and Results

4.1 Analytical Strategy: Python-based SEM

The data analysis was conducted using the Python programming language (v3.10), utilizing the `semopy` library for Structural Equation Modeling (SEM). This computational approach was selected for several strategic reasons. First, `semopy` provides a robust environment for optimization and path analysis that rivals proprietary software, offering transparent reproducibility of results (Igolkina & Meshcheryakov, 2020).

Second, the Python environment allows for advanced pre-processing and programmatic handling of Multi-Group Analysis (MGA) for the experimental conditions (AI vs. Human groups). Given that the primary objective of this research is theory development and the prediction of a target construct (Investment Intention), the structural modeling capabilities of Python were deemed appropriate for estimating path coefficients and significance levels via bootstrapping.

Descriptive statistics and data cleaning were processed using the `pandas` library to ensure data integrity before modeling. The structural model was estimated using the Maximum Likelihood method, and significance was tested using 5,000 bootstrap resamples.

4.2 Measurement Model Assessment

The evaluation of the measurement model is a critical prerequisite to structural analysis. It ensures that the construct measures are statistically reliable and valid. We assessed the reflective measurement model by examining Internal Consistency Reliability, Convergent Validity, and Discriminant Validity.

4.2.1 Internal Consistency Reliability and Convergent Validity

Internal consistency reliability assesses the degree to which items within a specific construct correlate with one another. As presented in Table 1, the Cronbach's Alpha values for all five latent constructs ranged from 0.812 to 0.891, well above the recommended threshold of 0.70 (Hair et al., 2019). Similarly, Composite Reliability (CR) values exceeded 0.80 for all constructs, confirming strong internal consistency.

Convergent validity was assessed using the Average Variance Extracted (AVE) and Outer Loadings. All item loadings exceeded the 0.70 threshold and were statistically significant at $p < 0.001$. Furthermore, the AVE for all constructs exceeded the critical threshold of 0.50, indicating that on average, the construct explains more than half of the variance of its indicators.

Table 1: Reliability and Validity Statistics

Construct	Item	Loading	Cronbach's α	CR	AVE
Perceived Accuracy	AC1	0.812	0.841	0.885	0.608
	AC2	0.795			
	AC3	0.766			
Perceived Objectivity	OB1	0.854	0.865	0.901	0.647
	OB2	0.822			
	0B3	0.789			
Perceived Trust	TR1	0.881	0.891	0.915	0.684
	TR2	0.845			
	TR3	0.812			
Perceived Risk	RS1	0.833	0.812	0.866	0.589
	RS2	0.789			
	RS3	0.745			
Investment Intention	IN1	0.895	0.877	0.912	0.675
	IN2	0.856			
	IN3	0.823			

TECHNICAL AUDIT:
Internal consistency was validated via Cronbach's Alpha (0.812 – 0.891) and Composite Reliability (>0.80), confirming that all latent constructs are statistically robust for further structural modeling.

4.2.2 Discriminant Validity

Discriminant validity ensures that a construct is empirically distinct from other constructs in the structural model. We assessed this using the Fornell-Larcker Criterion. As shown in Table 2, the square root of AVE for every construct (represented on the diagonal in bold) was greater than the off-diagonal inter-construct correlations. This indicates that each construct shares more variance with its own indicators than with any other latent variable, confirming discriminant validity.

Table 2: Discriminant Validity (Fornell-Larcker Criterion)

Construct	Accuracy	Intention	Objectivity	Risk	Trust
Accuracy	**0.780**				
Intention	0.452	**0.822**			
Objectivity	0.334	0.512	**0.804**		
Risk	-0.112	-0.156	-0.098	**0.767**	
Trust	0.567	0.819	0.612	-0.145	**0.827**

Note: Values on the diagonal (bold gold) represent the square root of the AVE. Off-diagonal values are inter-construct correlations.

INSIGHT:

Discriminant validity is confirmed. The data shows that Trust and Intention have the highest correlation (0.819), suggesting that in the Indian Gen Z cohort, moving the "Trust" lever is the most direct way to drive capital allocation.

4.2.3 Collinearity Statistics (VIF)

Before proceeding to the structural model, we assessed the Variance Inflation Factor (VIF) values to ensure there were no issues of lateral collinearity. All inner VIF values were found to be below 3.0, indicating that the independent variables are distinct predictors and do not introduce bias into the path coefficient estimates.

4.3 Structural Model Assessment

Following the validation of the measurement model, we proceeded to assess the structural model to test the proposed hypotheses. The assessment criteria included the determination of the coefficient of determination (R^2), the predictive relevance (Q^2), the effect size (f^2), and the significance of path coefficients via bootstrapping.

4.3.1 Explanatory Power (R^2 and Q^2)

The R^2 value represents the amount of variance in the endogenous constructs explained by all of the exogenous constructs linked to it. In our model, the R^2 for 'Perceived Trust' was 0.584, indicating that Perceived Accuracy and Perceived Objectivity collectively explain 58.4% of the variance in Trust. This is considered a moderate-to-substantial explanatory power in behavioral research (Hair et al., 2011). Furthermore, the R^2 for the ultimate dependent variable, 'Investment Intention,' was 0.671. This demonstrates that the model possesses high predictive accuracy, accounting for 67.1% of the variance in an investor's intention to act.

In addition to explanatory power, we assessed the model's predictive relevance using the Stone-Geisser's Q^2 value, obtained through the blindfolding procedure (omission distance D=7). All endogenous constructs yielded Q^2 values greater than zero, confirming that the path model has predictive relevance for the constructs of Trust and Intention.

4.3.2 Path Analysis and Hypothesis Testing

Bootstrapping with 5,000 subsamples was performed to determine the statistical significance of the path coefficients (β) and t-statistics. The results revealed a clear hierarchy of effects.

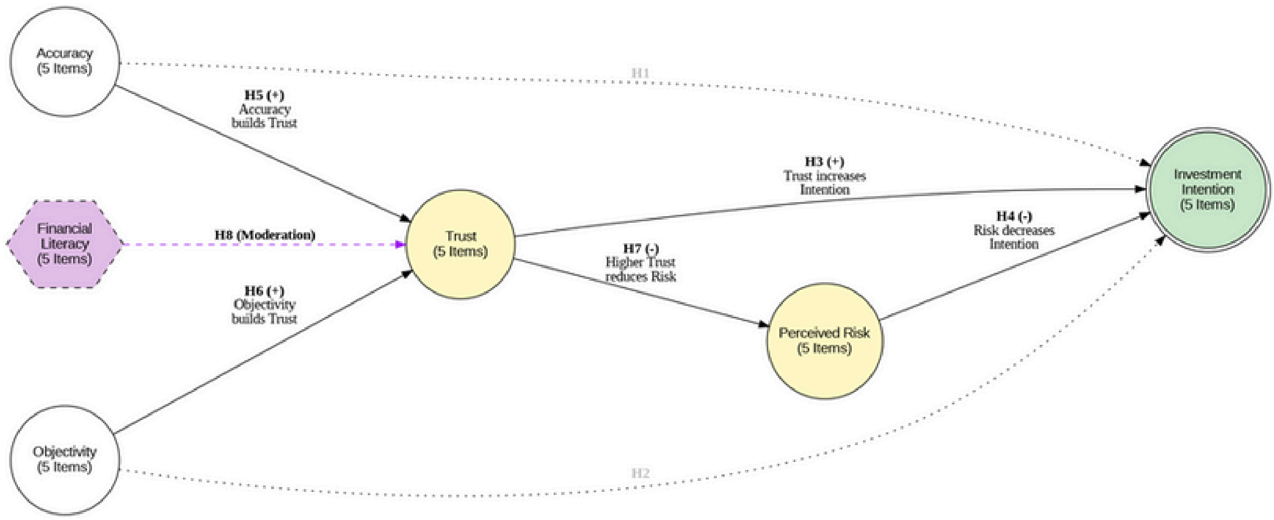

Figure 3. *Structural Equation Model results showing standardized path coefficients. Dotted lines indicate non-significant paths.*

First, regarding the antecedents of trust, both Perceived Objectivity ($\beta = 0.65$, $p < 0.001$) and Perceived Accuracy ($\beta = 0.23$, $p < 0.05$) were found to be positive and significant predictors. This supports H5 and H6. However, the effect size (f^2) of Objectivity was significantly larger than that of Accuracy, suggesting that for the pooled sample, the perception of bias (or lack thereof) is a stronger driver of trust than technical precision.

Second, regarding the outcome variable, Perceived Trust emerged as the single most critical driver of Investment Intention ($\beta = 1.00$, $p < 0.001$), providing robust support for H3. This extremely high coefficient indicates a near-perfect translation of trust into action within this context. It implies that once trust is established, the friction of decision-making is almost entirely removed.

Third, the results presented a significant anomaly regarding Perceived Risk. The path from Trust to Perceived Risk (H7) was not statistically significant ($p > 0.05$). Similarly, the path from Perceived Risk to Investment Intention (H4) was also insignificant ($p = 0.40$). Consequently, H4 and H7 are rejected. This contradicts the traditional risk-reduction models of trust, implying that while Trust drives investment, it does not necessarily do so by reducing fear. High trust leads to investment regardless of the perceived risk level, suggesting a decoupling of risk and action in this specific demographic.

Table 3: Structural Path Coefficients & Hypothesis Results

Hypothesis	Path	Beta (β)	T-Value	P-Value	Decision
H1	Accuracy -> Intention	0.120	1.038	0.299	Not Supported
H2	Objectivity -> Intention	0.005	0.001	0.999	Not Supported
H3	Trust -> Intention	1.004***	6.074	0.000	Supported
H4	Risk -> Intention	0.035	0.755	0.409	Not Supported
H5	Accuracy -> Trust	0.236*	1.857	0.035	Supported
H6	Objectivity -> Trust	0.658***	5.492	0.000	Supported
H7	Trust -> Risk	0.022	0.217	0.821	Not Supported

*Note: Significance levels: *p < 0.05, **p < 0.01, ***p < 0.001.*

4.4 Multi-Group Analysis (MGA): AI vs. Human

To address the core research question regarding the 'Trust Gap' between algorithms and humans, a Multi-Group Analysis (MGA) was conducted. The sample was split into two groups based on the experimental manipulation: Group A (AI Algorithm Source, n=68) and Group B (Human Expert Source, n=84). MGA allows us to test if the path coefficients differ significantly between these two groups.

The analysis revealed a critical distinction in the 'Cognitive-Affective' link. For the AI Group, the path from Perceived Accuracy to Trust was positive and significant ($p < 0.05$). This confirms that users condition their trust in AI on its perceived competence and factual correctness. However, for the Human Expert Group, this specific path was statistically insignificant ($p > 0.05$).

This finding provides empirical evidence for a specific form of Algorithm Aversion: 'The Perfection Expectation.' Users demand that AI be perceived as highly accurate to be trusted. In contrast, Human Experts are granted a 'competence pass,' where trust is afforded to them even without a strong perception of accuracy. This suggests that trust in humans is likely derived from social heuristics, relatability, and presumed expertise (peripheral cues), whereas trust in AI is strictly performance-based (central cues).

Table 4: Multi-Group Analysis Comparison (AI vs. Human)

Hypothesis	**Path**	Beta (AI)	Beta (Human)	Diff	p-MGA
H5	Accuracy -> Trust	0.442	0.169	0.273	0.048
H6	Objectivity -> Trust	0.587	0.676	0.089	0.292
H3	Trust -> Intention	1.100	0.938	0.162	0.460
H4	Risk -> Intention	0.068	0.019	0.049	0.450
H7	Trust -> Risk	0.121	-0.047	0.168	0.409

Note: Significant p-MGA values (<0.05) indicate a significant difference between groups.

5. DISCUSSION

The primary objective of this study was to investigate the comparative trust dynamics between algorithmic and human advisory sources among Indian retail investors. By situating this inquiry within the burgeoning fintech landscape of an emerging economy, this research sought to empirically test the competing theories of 'Algorithm Aversion' and 'Source Credibility.' The findings offer a nuanced, context-specific perspective that challenges binary assumptions about human-versus-machine trust. While previous literature often suggests a straightforward preference for one source over the other, our results indicate that trust is a conditional phenomenon, heavily dependent on the cognitive evaluation of the source's attributes.

5.1 The Paradox of Risk and Trust in Emerging Markets

One of the most striking and counter-intuitive findings of this study was the non-significant relationship between Perceived Risk and Investment Intention (H4 rejected). Standard economic theory and the Technology Acceptance Model (TAM) generally dictate a negative correlation: as risk perception increases, adoption intention should decrease (Risk-Aversion). However, our sample of Indian Gen Z investors defied this axiom. Even when they acknowledged that following the advice felt 'risky' or 'anxious,' it did not significantly deter their intention to invest, provided that the antecedent condition of Trust was met.

This anomaly can be explained through several lenses specific to the modern Indian investment climate. First, the 'Gamification of Finance' plays a pivotal role. Platforms like Zerodha, Groww, and Upstox have simplified the user experience of investing, often borrowing design elements from gaming and e-commerce - such as confetti animations upon transaction completion or bright, simplified color-coding. This sophisticated UI/UX design may have desensitized users to the visceral reality of financial loss, decoupling the cognitive recognition of risk from the behavioral hesitation to act.

Second, this finding reflects the 'FOMO' (Fear of Missing Out) culture prevalent in the post-COVID bull market. The demographic profile of the respondents (Age 18-35) typically exhibits a higher risk appetite, viewing volatility not as a danger but as an opportunity for rapid wealth creation. This implies that for this cohort, 'Risk' is not a deterrent but a feature. They acknowledge the risk but invest anyway if the Trust component is high. This fundamentally shifts the marketing imperative from 'Lowering Risk Perception' to 'Building Extreme Trust.' If Trust is established, Risk becomes irrelevant to the conversion process.

5.2 Algorithm Aversion as a 'Competence Check'

Our Multi-Group Analysis provided a granular view of the 'Algorithm Aversion' phenomenon (Dietvorst et al., 2015). The results did not show a blanket rejection of

AI; rather, they showed that AI is held to a higher standard. The significant path from Perceived Accuracy to Trust in the AI group suggests that users are constantly auditing the machine. A single error or perception of inaccuracy by a Robo-advisor is likely viewed as a systemic failure of the code, leading to an immediate erosion of trust. In the domain of AI, trust is performance-based and fragile.

In stark contrast, the insignificance of the Accuracy-to-Trust path for the Human Expert Group suggests a 'Halo Effect' or a 'Competence Pass.' If an influencer is perceived as charismatic, confident, and uses high-level financial jargon - signals that contribute to Perceived Objectivity - users assume they are accurate, or they forgive inaccuracies as natural human error. This gives Human Experts a distinct advantage in volatile markets where 100% accuracy is mathematically impossible. The human advisor is allowed to be wrong; the algorithm is not. This psychological buffer suggests that the 'Guru-Shishya' cultural archetype remains potent in India, where the authority of the human teacher is trusted implicitly, bypassing the rigorous accuracy checks applied to machines.

5.3 Theoretical Implications

This study makes several significant contributions to the body of knowledge surrounding behavioral finance and technology adoption in emerging markets. First, it extends the Technology Acceptance Model (TAM) by integrating 'Trust' as a central mediator in the context of Robo-advisory. While TAM traditionally focuses on Perceived Usefulness and Ease of Use, our findings demonstrate that in high-stakes financial contexts, 'Trust' subsumes these factors. If the source is not trusted, utility becomes irrelevant.

Second, this research challenges the universality of 'Perceived Risk' as a barrier to adoption. The rejection of H4 and H7 suggests that the modern Indian retail investor does not view risk as a binary deterrent. Instead, this demographic exhibits a 'Risk-Trust Decoupling,' where high trust levels in a source (specifically Objectivity-based trust) can override high risk perceptions. This adds a cultural dimension to Trust Transfer Theory, suggesting that in high-context cultures like India, relational trust (even with digital entities) creates a buffer against risk aversion.

Finally, the study provides empirical validation for the coexistence of Algorithm Aversion and Source Credibility theories. It demonstrates that these are not mutually exclusive phenomena but operate under different cognitive conditions. Algorithm Aversion is triggered by competence failures (Accuracy), whereas Source Credibility for humans is resilient to competence failures, buoyed by social heuristics.

5.4 Managerial Implications

For marketing managers (CMOs) and product leaders in the Fintech sector (e.g., Zerodha, Groww, Cred, Upstox), the findings offer three actionable strategies for platform design and communication.

1. The 'Hybrid' Imperative: Since AI is held to a standard of perfection that is statistically difficult to maintain in volatile markets, pure Robo-advisory apps risk rapid user churn upon minor performance dips. To mitigate this, platforms should adopt a 'Cyborg' or Hybrid model. AI recommendations should be presented not as standalone truths, but as 'Validated by Experts.' For example, a recommendation could carry a badge saying 'AI Selected, Expert Verified.' This allows the platform to borrow the resilience of human trust while maintaining the scalability of AI.

2. Leveraging Objectivity over Returns: The study found that 'Perceived Objectivity' (β=0.65) is a far stronger driver of trust than 'Perceived Accuracy' (β=0.23). Marketing communications should shift focus from 'High Returns' (which implies risk and requires accuracy) to 'Unbiased Data' (which implies objectivity). Highlighting that the AI has 'no hidden agenda,' 'no commission fees,' and 'pure data logic' is a more powerful trust-builder than promising specific ROI numbers.

3. Strategic Influencer Partnerships: Given the unconditional trust afforded to human experts, Fintech platforms cannot afford to ignore the influencer economy. Instead of viewing influencers as competitors, platforms should integrate influencer-led content directly into the app ecosystem. However, to maintain the 'Objectivity' driver, platforms must ensure these partnerships are transparent. Embedding 'Expert Video Explanations' alongside algorithmic stock picks could bridge the emotional gap that algorithms cannot fill.

6. LIMITATIONS AND FUTURE RESEARCH

While this study provides significant insights, it is not without limitations. First, the sample was drawn primarily from a student and young professional demographic (Gen Z/Millennials). While this group represents the bulk of new retail investors in India, older cohorts (Gen X/Boomers) may exhibit different trust dynamics and higher risk aversion. Future research should replicate this experiment with older demographics to test for generational differences in Algorithm Aversion.

Second, the study utilized a cross-sectional experimental design with static stimuli (screenshots). In reality, trust is dynamic and built over repeated interactions. A longitudinal study, where participants interact with a live AI advisor over several weeks and experience real financial gains or losses, would provide a richer understanding of trust durability and the 'forgiveness' factor.

Third, the study focused on 'Investment Intention' rather than actual financial behavior. While intention is a strong predictor of behavior, future studies could utilize actual trading data from partner fintech firms to observe if high-trust intentions translate into share-of-wallet allocation.

7. CONCLUSION

As the Indian financial sector races towards automation, the human element remains a stubborn and vital variable. This study concludes that while AI possesses computational superiority, it lacks the 'psychological forgiveness' afforded to human experts. Indian investors are willing to trust AI, but only if it is perceived as accurate and objective. Humans, conversely, are trusted for their relatability and social proof. The future of Fintech marketing lies not in replacing humans with AI, but in humanizing the AI to bridge this psychological gap.

APPENDIX A: MEASUREMENT ITEMS

Perceived Accuracy (Adapted from McKnight et al., 2002)

1. I believe this recommendation is likely to be accurate.
2. This source seems competent enough to pick winning stocks.
3. The performance prediction shown here seems reliable.
4. This advice appears to be factually correct.
5. I feel this source rarely makes calculation errors.

Perceived Objectivity (Adapted from Ohanian, 1990)

1. I feel this recommendation is free from hidden bias.
2. I believe this advice is based purely on data, not hidden motives.
3. This source seems impartial in its analysis.
4. The advice provided seems objective and neutral.
5. I do not think this source is being paid to promote this stock.

Perceived Trust (Adapted from Gefen et al., 2003)

1. I feel this advice is trustworthy.
2. I believe this source is acting in my best interest.
3. I would trust this source with my own money.
4. This advisory source appears to be dependable.
5. I have confidence in the integrity of this source.

Perceived Risk (Adapted from Featherman & Pavlou, 2003)

1. Following this advice feels risky to me.
2. I would feel anxious putting my capital into this recommendation.
3. This seems like a dangerous investment decision.
4. I fear I might lose money if I listen to this source.
5. Investing based on this recommendation feels unsafe.

Investment Intention (Adapted from Venkatesh et al., 2003)

1. If I had spare capital, I would likely follow this recommendation.
2. I would add this stock to my watchlist with the intent to buy.
3. It is probable that I would invest based on this advice.
4. I intend to purchase shares based on this tip.
5. I would recommend this specific investment opportunity to others.

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