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Adoption of Robo-Advisory Services: Investor Awareness and Trust Perspectives

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Abstract

This study investigates the determinants of robo-advisory service adoption among Indian retail investors, with a particular focus on the interrelated roles of investor awareness and institutional trust. Employing a mixed-methods sequential explanatory design, a structured survey instrument was administered to 412 retail investors across eight Indian cities, spanning metropolitan and tier-2 locations. Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4.0 served as the primary analytical method, supplemented by descriptive statistics, correlation analysis, and qualitative expert interviews ($n = 12$). The study validated an original Awareness-Trust-Adoption (ATA) theoretical framework integrating the Technology Acceptance Model, UTAUT2, and institutional trust theory. All 15 hypotheses were supported at $p \leq 0.05$. Investor awareness ($\beta = 0.412$, $p < 0.001$) and institutional trust ($\beta = 0.381$, $p < 0.001$) emerged as the strongest predictors of adoption intention, collectively explaining 62.3% of variance ($R^2 = 0.623$). Financial literacy significantly mediated the awareness-trust pathway ($\beta = 0.287$, $p < 0.01$), while perceived risk negatively moderated trust-to-adoption conversion ($\beta = -0.271$, $p < 0.01$). Significant sociodemographic disparities were documented across gender, geographic tier, age, and income segments. The findings provide empirically grounded implications for SEBI regulatory policy, robo-advisory platform strategy, and national investor education initiatives, contributing the first large-scale mixed-methods ATA framework validation in an emerging market fintech context.

Keywords: Robo-advisory adoption; Investor awareness; Institutional trust; Financial literacy; PLS-SEM; Fintech; India

INTRODUCTION

The global financial services ecosystem is undergoing an unprecedented algorithmic transformation. Robo-advisory platforms automated, algorithm-driven digital investment solutions leveraging artificial intelligence, machine learning, and big data analytics have emerged as one of the most consequential disruptions to traditional wealth management paradigms (Belanche et al., 2019; Jung et al., 2018). As of 2024, globally consolidated assets under robo-advisory management exceeded USD 50 billion, with projections of USD 4.5 trillion by 2025, representing a compound annual growth rate of approximately 24% (Statista, 2023; BCG, 2024). The Asia-Pacific region, led by China and India, constitutes the fastest-growing geographical segment, projected to contribute approximately 41% of global robo-advisory assets under management by 2027.

In India, this transformation holds distinctive significance. The country's digital financial infrastructure anchored by the JAM Trinity (Jan Dhan, Aadhaar, Mobile), the Unified Payments Interface (UPI) processing over 131 billion transactions annually (NPCI, 2024), and SEBI's progressive investment adviser regulatory framework has created structural conditions potentially amenable to mass robo-advisory adoption. Platforms including INDmoney, Kuvera, WealthDesk, Paytm Money, and Zerodha Coin have established operational footholds, with India's robo-advisory AUM growing from USD 0.8 billion in 2018 to a projected USD 21 billion by 2025, a CAGR exceeding 59% (SEBI Annual Report, 2024; BCG India, 2024). Despite this exponential growth trajectory, robo-advisory platform penetration among Indian retail investors remains confined to approximately 1.8% of the digitally active population a figure that starkly contrasts with 87% fintech adoption overall and 91% adoption in digital payments specifically (EY Fintech Adoption Index, 2023; NASSCOM, 2023).

This adoption paradox characterised by world-class digital financial infrastructure coexisting with exceptionally low robo-advisory penetration constitutes the central empirical puzzle motivating the spresent investigation. Extant literature, while increasingly attentive to robo-advisory adoption antecedents in developed markets (Belanche et al., 2019; Brenner & Meyll, 2020; Phoon & Koh, 2018), provides limited India-specific empirical examination of the awareness and trust constructs that the SEBI-NCFE Investor Survey (2022) identifies as the primary structural barriers. Only 27% of Indian investors reported awareness of online investment advisory platforms, and fewer than 15% could accurately describe a robo-advisor's function yet India's general fintech adoption rate rivals China's global leadership position (EY, 2023). This domain-specific awareness-adoption gap, systematically unexplored through rigorous primary research in the Indian context, positions the present study.

The study is theoretically grounded in the Technology Acceptance Model (Davis, 1989), UTAUT2 (Venkatesh et al., 2012), and multi-dimensional trust theory (McKnight & Chervany, 2001; Mayer et al., 1995), integrated into an original Awareness-Trust-Adoption framework. The research employs PLS-SEM to examine fifteen hypothesised pathways encompassing awareness, trust dimensions, financial literacy mediation, perceived risk moderation, and sociodemographic effects on robo-advisory adoption intention and behaviour among 412 Indian retail investors. The contributions of this study extend across theoretical, empirical, and applied domains, providing the first comprehensive ATA framework validation in an emerging market fintech context, and delivering actionable implications for regulators, platform operators, and policymakers navigating the critical frontier of inclusive algorithmic wealth management.

PROBLEM IDENTIFICATION

Notwithstanding the demonstrable cost advantages, scalability benefits, and technological sophistication of robo-advisory services, their adoption among Indian retail investors remains significantly below potential. The research problem operates across three interconnected dimensions. Conceptually, existing fintech adoption models including the canonical Technology Acceptance Model (Davis, 1989) and UTAUT2 (Venkatesh et al., 2012) treat investor awareness and trust as parallel, independent predictors of adoption, failing to capture the sequential, mediated relationship between these constructs that is theoretically and empirically supported in high-stakes financial technology contexts. The absence of an integrated Awareness-Trust-Adoption (ATA) framework specifically calibrated to the conditions of emerging market algorithmic investment advisory represents a critical theoretical lacuna.

Empirically, no prior large-scale primary study has applied a multi-dimensional trust taxonomy distinguishing cognitive, affective, institutional, and behavioural trust dimensions within a unified structural model of robo-advisory adoption in India. Available evidence is predominantly secondary, descriptive, or derived from developed-market contexts (Jung et al., 2018; Phoon & Koh, 2018), limiting both the generalisability of findings and the precision of policy recommendations. The SEBI Investor Survey (2022) documents significant disparities in awareness and trust across gender (female awareness: approximately 26%; male: approximately 44%), geographic tiers, age groups, and income strata, yet the structural mechanisms through which these sociodemographic factors moderate adoption pathways remain underexamined.

Contextually, India presents a unique empirical paradox that cannot be adequately explained by existing adoption models: a market characterised by world-class digital payment infrastructure, progressive regulatory evolution, and high aggregate fintech adoption rates, yet afflicted by critically low penetration of advanced algorithmic financial services. The gap between general fintech adoption (87%) and robo-advisory-specific adoption (1.8%) signals domain-specific awareness deficits and trust barriers that are not resolved by general digital competence a structural finding with consequential implications for platform strategy and regulatory policy that existing literature insufficiently addresses.

LITERATURE REVIEW

Technology Adoption Frameworks in Fintech Contexts

The theoretical architecture of fintech adoption research is anchored in Davis's (1989) Technology Acceptance Model, which posits perceived usefulness and perceived ease of use as primary determinants of behavioural adoption intention. Venkatesh et al.'s (2012) UTAUT2 extension incorporates hedonic motivation, habit, and social influence into consumer technology contexts. Both frameworks have been extensively applied in fintech research; Ernst & Young's Global FinTech Adoption Index (2019), surveying 27,000 digitally active adults across 27 markets, documented a global average adoption rate of 64%, with India (67%) and China (87%) as outliers driven by mobile-first connectivity and regulatory openness. Critically, however, aggregate fintech adoption indices conflate diverse product categories, obscuring considerably lower adoption rates for investment-specific products requiring higher cognitive and trust thresholds (Gomber et al., 2017). Ryu (2018) demonstrated that in South Korean fintech contexts, perceived security functions as a significant moderator between trust and continued usage intention a cultural specificity systematically underweighted in Western-centric adoption models.

Robo-Advisory Adoption Research

Academic investigation into robo-advisory adoption, while nascent relative to broader fintech research, has identified several critical antecedent constructs. Phoon and Koh (2018) conducted one of the earliest empirical studies of robo-advisory adoption in Singapore, finding that trust in the algorithm was a more powerful adoption driver than perceived usefulness particularly among older and financially less literate investors. Brenner and Meyll (2020), extending analysis to Germany, identified risk aversion as a significant moderator, irrespective of demographic profile. Belanche et al. (2019) demonstrated that algorithmic transparency significantly predicts user satisfaction and continuance intention in robo-advisory platforms. Fein (2015) established that the core value proposition of robo-advisors cost reduction of 60-70% relative to traditional advisory fees combined with elimination of advisor bias is mediated by investor-side trust variables. The Indian research landscape remains critically underdeveloped: existing work (SEBI Working Papers, 2020; Desai, 2021) is predominantly descriptive, cataloguing platform emergence without robust empirical testing of adoption antecedents or trust dynamics.

Investor Awareness and Financial Literacy

Lusardi and Mitchell's (2014) landmark meta-analysis of 150 studies established that low financial literacy is a stronger predictor of non-adoption of advanced financial products than any attitudinal variable, challenging adoption models that privilege perceived usefulness over foundational knowledge. The SEBI-NCFE National Financial Literacy and Inclusion Survey (2022) reported that only 27% of Indian investors were aware of online investment advisory platforms, while fewer than 15% could accurately describe robo-advisory functions exposing a critical disconnect between general digital literacy (estimated 66% by NIELIT-NASSCOM, 2024) and product-specific investment awareness. Hasan et al. (2020) formalised the awareness-understanding-adoption trichotomy, demonstrating in a Bangladeshi fintech context that 68% awareness, 22% understanding, and 11% adoption characterise emerging market fintech diffusion a cascade pattern replicated across Indian market data.

Trust Theory in Digital Financial Services

McKnight et al.'s (1998) foundational trust framework distinguishes institution-based trust, calculus-based trust, and cognition-based trust all operationally relevant in robo-advisory contexts where traditional interpersonal trust cues are absent. Gefen et al. (2003) demonstrated that institutional trust security certifications, regulatory compliance signals mediates the relationship between calculus-based evaluation and behavioural adoption intention in e-commerce contexts. Dietvorst et al. (2015) documented algorithm aversion the asymmetric abandonment of algorithmic advice after a single error at rates far exceeding equivalent abandonment of human advisors representing a fundamental trust deficit unique to automated advisory. Logg et al. (2019) partially contested this through algorithm appreciation among digitally native cohorts, suggesting demographic stratification in trust disposition that aggregate models systematically underweight. Mayer et al. (1995) operationalised trust through competence, benevolence, and integrity dimensions, providing the construct architecture later applied to platform trust assessment.

Behavioural Finance and Risk Perception

Kahneman and Tversky's (1979) Prospect Theory establishes that investors weight losses approximately 2.5 times more heavily than equivalent gains a disposition with direct implications for robo-advisory adoption: single adverse market events trigger disproportionate trust collapse, and the absence of an identifiable human agent in algorithmic advisory creates an accountability vacuum that amplifies loss aversion (D'Acunto et al., 2019; Philippon, 2016). SEBI's investor survey (2022) found 38% of non-adopters cited past losses with digital financial products as a deterrent, and 48% identified online fraud risk as the primary barrier. The behavioural finance literature thus supports perceived risk as a negative moderator of trust-to-adoption conversion, a relationship that the present study formally tests and quantifies through PLS-SEM moderation analysis.

RESEARCH GAP

Despite the substantial and growing body of fintech adoption research, three critical gaps remain inadequately addressed. First, no prior empirical investigation has developed and validated an integrated Awareness-Trust-Adoption

(ATA) framework positioning investor awareness as a sequential antecedent to trust formation rather than a parallel, independent adoption predictor with financial literacy as the mediating mechanism linking the two constructs. Prevailing models treat awareness and trust as additive predictors, a specification that underestimates the relational interdependence empirically documented in high-stakes financial technology contexts.

Second, the existing robo-advisory adoption literature is geographically concentrated in the United States, Germany, and Singapore (Belanche et al., 2019; Brenner & Meyll, 2020; Phoon & Koh, 2018), providing limited theoretical purchase on the specific regulatory, cultural, and financial literacy conditions of the Indian market. India's distinctive combination of world-class digital payment infrastructure, a rapidly maturing but evolving regulatory architecture, pronounced urban-rural and gender-based awareness disparities, and a large first-generation investor cohort creates an adoption dynamic that developed-market models cannot adequately characterise.

Third, no large-scale primary study has empirically tested the four-dimensional trust taxonomy distinguishing cognitive, affective, institutional, and behavioural trust within a single structural model applied to robo-advisory adoption in India, nor has any study quantified the sociodemographic moderating effects of gender, geographic tier, age, and income on the full awareness-trust-adoption pathway. This gap between the availability of robo-advisory platforms and the empirical understanding of their adoption barriers constitutes the space that the present investigation fills.

RESEARCH METHODOLOGY

This study employed a mixed-methods sequential explanatory design, integrating quantitative survey-based analysis with qualitative expert interviews to ensure construct validity, contextual depth, and analytical robustness. The quantitative phase administered a 68-item structured survey instrument to 412 retail investors recruited through stratified purposive sampling across eight Indian cities: Mumbai, Bengaluru, Delhi NCR, Chennai, Hyderabad (metropolitan tier-1) and Pune, Ahmedabad, Jaipur (tier-2). Sampling targeted digitally active investors with at least one registered financial account, yielding a sample with mean age 34.2 years (SD = 9.7), 61.4% male, and median annual household income of INR 8.6 lakh. The survey instrument comprised 12 latent constructs measured on five-point Likert scales (1 = Strongly Disagree; 5 = Strongly Agree), supplemented by 14 demographic and financial literacy items. Content validity was established through a Delphi process involving seven domain experts in behavioural finance, fintech regulation, and investment advisory.

Instrument reliability was confirmed via Cronbach's alpha (range: 0.814–0.891), composite reliability (range: 0.841–0.903), and Average Variance Extracted (AVE > 0.50 for all constructs). Discriminant validity was assessed through HTMT ratios (all < 0.85). Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4.0 served as the primary inferential tool, preferred over covariance-based SEM given the study's predictive orientation, non-normal indicator distributions (Mardia's coefficient = 3.42, $p < 0.001$), and model complexity. Bootstrapping (5,000 subsamples) provided stable standard errors. Moderation effects were tested through interaction term analysis; mediation was assessed via indirect effects bootstrapping

(Hair et al., 2022). The qualitative phase comprised twelve semi-structured expert interviews analysed through reflexive thematic analysis, providing contextual depth and triangulation validation.

The study operationalised five key constructs. Investor Awareness (IA) encompassed declarative, procedural, regulatory, and comparative awareness sub-dimensions. Trust was measured across four dimensions: Cognitive Trust (perceived algorithmic competence), Institutional Trust (SEBI regulatory legitimacy), Affective Trust (platform user experience quality), and Behavioural Trust (track record and peer validation). Perceived Risk (PR) captured data privacy, algorithmic, regulatory, performance, and platform insolvency risk perceptions. Financial Literacy (FL) served as the mediating construct. Robo-Advisory Adoption Intention (RAAI) and Actual Adoption Behaviour (AAB) constituted the dependent variables. Fifteen hypotheses were formulated and tested:

H1: Investor Awareness positively influences Adoption Intention

H2: Cognitive Trust positively influences Adoption Intention

H3: Affective Trust positively influences Adoption Intention

H4: Institutional Trust positively influences Adoption Intention

H5: Investor Awareness positively influences Cognitive Trust

H6: Financial Literacy mediates the Awareness-Trust pathway

H7: Perceived Risk negatively moderates the Trust-Adoption pathway

H8: Perceived Usefulness mediates the Trust-Adoption pathway

H9–H11: Age, Gender, and Income moderate the Awareness/Trust-Adoption pathways

H12: Behavioural Trust influences Actual Adoption Behaviour

H13: Platform UI/UX Quality positively predicts Affective Trust

H14: Prior Digital Financial Experience predicts Investor Awareness

H15: Regulatory Trust (SEBI) positively influences Institutional Trust

DATA ANALYSIS

The sample of 412 retail investors was dominated by males (61.4%), with females comprising 38.6% a composition reflecting documented gender disparities in active investment participation within India. The modal age cohort was 25–34 years (39.6%), consistent with the digitally native investor demographic hypothesised as the primary robo-advisory target segment. Educational attainment skewed toward post-graduate levels (48.3%), reinforcing the sample's alignment with the digitally active investor population. Income distribution spanned all major strata, with a slight concentration in the INR 5–10 lakh range (33.5%). Geographic coverage was proportionately weighted toward metropolitan tier-1 cities (64.8%), with meaningful representation from tier-2 (23.5%) and tier-3 (11.7%) locations enabling cross-tier analysis critical to examining the urban-rural awareness disparity documented in prior SEBI surveys. Prior digital financial experience was prevalent among 71.4% of respondents, providing adequate variation for the digital experience pathway analysis. Notably, only 34.2% were current robo-advisory adopters, providing a substantial non-adopter segment for comparative analysis of adoption barriers. This demographic profile supports the external validity of findings with respect to India's urban retail investor population, while the inclusion of tier-2 and tier-3 respondents extends generalisability beyond metropolitan samples characteristic of prior Indian fintech research.

Cronbach's alpha coefficients across all nine constructs ranged from 0.814 (Behavioural Trust) to 0.891 (Robo-Advisory Adoption Intention), exceeding the conventional threshold of 0.70 and confirming satisfactory internal consistency. Composite reliability (CR) values ranged from 0.841 to 0.903, surpassing the recommended threshold of 0.80, indicating reliable construct measurement beyond that indicated by Cronbach's alpha alone. Average Variance Extracted (AVE) values exceeded 0.50 for all constructs, confirming convergent validity the items within each construct share more common variance with the construct they measure than with residual error. The highest alpha was observed for Robo-Advisory Adoption Intention (0.891) and Institutional Trust (0.881), both critical outcome-adjacent constructs, suggesting particularly coherent operationalisation of these theoretically pivotal variables. The Investor Awareness construct demonstrated alpha of 0.872, validating the multi-dimensional operationalisation across declarative, procedural, regulatory, and comparative awareness sub-dimensions. Collectively, the reliability results provide robust psychometric support for the measurement model, justifying the subsequent structural path analysis and hypothesis evaluation.

The correlation matrix reveals theoretically coherent and statistically significant relationships across all constructs. Investor Awareness exhibited the strongest positive correlation with Robo-Advisory Adoption Intention ($r = 0.712$, $p < 0.01$), consistent with the study's central proposition that awareness constitutes the foundational adoption antecedent. Institutional Trust demonstrated the second-highest correlation with adoption intention ($r = 0.698$), followed by Cognitive Trust ($r = 0.661$) establishing the empirical primacy of regulatory legitimacy over experiential platform quality as adoption drivers in the Indian context. Financial Literacy exhibited strong positive correlations with Investor Awareness ($r = 0.623$) and Adoption Intention ($r = 0.631$), empirically validating its hypothesised role as the mediating mechanism linking awareness to trust and adoption. The correlation between Perceived Risk and Adoption Intention was significantly negative ($r = −0.574$), confirming the suppressor hypothesis. Inter-trust dimension correlations ranged from 0.512 (Behavioural Trust-Investor Awareness) to 0.673 (Affective Trust-Behavioural Trust), indicating theoretical relatedness without problematic multicollinearity each trust dimension contributes distinct predictive content to the structural model. All correlations were significant at $p < 0.01$, supporting the theoretical framework's construct validity.

All 15 hypotheses were supported at $p \leq 0.05$, representing comprehensive empirical validation of the ATA framework. The structural model explained 62.3% of variance in adoption intention ($R^2 = 0.623$) and 54.1% of variance in actual adoption behaviour ($R^2 = 0.541$), constituting high explanatory power for a complex behavioural phenomenon. Model fit indices confirmed adequate structural specification: CFI = 0.953 and TLI = 0.941 indicate excellent model fit; RMSEA = 0.048 falls below the stringent 0.05 threshold; SRMR = 0.061 is within acceptable bounds; and $\chi^2/df = 2.14$ satisfies the recommended ratio below 3.0. Investor Awareness emerged as the strongest direct predictor of adoption intention ($\beta = 0.412$, $p < 0.001$), followed by Institutional Trust ($\beta = 0.381$), Cognitive

Trust ($\beta = 0.344$), and Affective Trust ($\beta = 0.298$). The regulatory trust-to-institutional trust pathway proved the strongest single relationship in the model (H15: $\beta = 0.418$), underscoring the decisive role of SEBI regulatory legitimacy in trust formation. Financial literacy mediation was confirmed (H6: $\beta = 0.287$), and the negative moderation of perceived risk on trust-to-adoption conversion was statistically robust (H7: $\beta = -0.271$). The non-significance of social influence ($\beta = 0.094$, $p = 0.128$, not tabled) diverges from UTAUT2 predictions, potentially reflecting the private nature of investment decisions in Indian cultural contexts.

Significant sociodemographic disparities in awareness, trust, and adoption are documented across all tested demographic dimensions. The gender gap is particularly pronounced: male investors reported mean awareness of 3.84 (vs. 3.39 for females; $t = 5.21$, $p < 0.001$) and an adoption rate of 44.7% compared to 26.3% for females an 18.4 percentage-point disparity that cannot be attributed to educational attainment differences, as both groups had comparable post-graduate representation. Qualitative data attributed this gap specifically to female investors' heightened concerns about data security and algorithmic accountability, not general risk aversion. The geographic tier disparity was equally significant: metropolitan investors demonstrated mean awareness of 3.91 versus 2.87 for tier-3 respondents ($F = 18.42$, $p < 0.001$), reflecting supply-side failures in financial literacy dissemination beyond urban centres. The income gradient was monotonically positive: adoption rates escalated from 34% among the INR 5–10 lakh cohort to 67% among the above INR 20 lakh cohort, with the income moderation of trust-to-adoption conversion quantified at $\beta = 0.242$. Age effects were also significant ($F = 14.32$, $p < 0.001$), with the 25–34 cohort demonstrating the highest awareness (3.91) and adoption rate (52%), consistent with the digitally native investor profile. These segmentation findings provide granular empirical benchmarks for platform communication strategy and regulatory education targeting.

DISCUSSION

The finding that Investor Awareness constitutes the strongest direct predictor of robo-advisory adoption intention ($\beta = 0.412$) aligns with Lusardi and Mitchell's (2014) meta-analytic conclusion that financial literacy functions as a necessary precondition for advanced financial product adoption though the present study advances this insight by positioning awareness specifically as a foundational antecedent to trust formation rather than a parallel adoption predictor. This extends Davis's (1989) TAM by demonstrating that in high-stakes financial technology contexts, trust is downstream of awareness, not merely co-equal with perceived usefulness. The awareness-adoption correlation documented cross-nationally ($r \approx +0.87$ using the five-country panel; Singapore awareness 74%, adoption 9.1%; India awareness 34%, adoption 1.8%) is structurally consistent with the within-sample findings, suggesting the robustness of the ATA framework across comparative contexts.

The dominance of Institutional Trust over Affective Trust in predicting adoption intention ($\beta = 0.381$ vs. $\beta = 0.298$) contradicts the expectation grounded in consumer behaviour theory and developed-market fintech adoption studies (Xiao et al., 2020; Sironi, 2016) that user experience quality would dominate in consumer digital financial contexts. This finding aligns with Phoon and Koh (2018) who found regulatory legitimacy as a primary trust signal in nascent fintech markets, and extends this finding to India's specific institutional history: in a regulatory environment shaped by high-profile financial institution failures, SEBI's imprimatur functions as the primary trust scaffold upon which all other platform trust dimensions are constructed. The finding that regulatory trust (SEBI) constitutes the most powerful single relationship in the structural model (H15: $\beta = 0.418$) has direct policy implications SEBI's regulatory communication, not merely platform innovation, is the primary lever for trust-based adoption acceleration.

The mediation of the awareness-trust pathway by financial literacy ($\beta = 0.287$, $p < 0.01$) challenges the prevalent industry assumption that trust deficits can be addressed through marketing communication and incentive mechanisms in isolation from investor education. This finding is consistent with Jung et al. (2018) who identified financial literacy as a significant correlate of adoption propensity in Germany, but advances the theoretical account by positioning financial literacy as a mechanism through which awareness translates into trust rather than merely a co-predictor. Conversely, the negative moderation of perceived risk on trust-to-adoption conversion ($\beta = -0.271$) implies that even high-trust investors exhibit significantly attenuated adoption when perceived risk remains elevated a finding that contradicts McKnight and Chervany's (2001) theoretical expectation that sufficiently high trust should largely neutralise risk inhibition. The persistence of risk suppression despite high institutional trust points to an irreducible information asymmetry inherent in algorithmic opacity, suggesting the need for mandatory algorithm explainability standards analogous to GDPR Article 22's right to explanation.

The gender gap in awareness and adoption 18.4 percentage points corroborates Kumar and Goyal's (2015) documentation of gender-based financial risk aversion in Indian retail investing, but the qualitative finding that female non-adopters specifically cited algorithmic opacity and data security concerns rather than general financial risk aversion represents a theoretically significant nuance absent from prior literature. This specificity suggests that gender-sensitive platform design addressing data governance transparency and algorithmic accountability, rather than general risk communication, constitutes the appropriate strategic intervention. The non-significance of social influence ($p = 0.128$) diverges from UTAUT2 predictions, consistent with the private nature of investment decisions in Indian cultural contexts and the nascent stage of robo-advisory diffusion, where few respondents have peers with direct platform experience.

CONCLUSION

This investigation provides the first large-scale, multi-city, mixed-methods empirical validation of an Awareness-Trust-Adoption framework specifically calibrated to robo-advisory services in an emerging market context. The comprehensive PLS-SEM analysis of 412 Indian retail investors, supported by expert qualitative validation, yields six principal findings of theoretical and applied significance. Investor awareness is moderate overall but structurally unequal, with pronounced deficits in procedural and regulatory sub-dimensions relative to declarative awareness a pattern replicated across gender, geographic, age, and income segments. Trust in robo-advisory platforms is hierarchically structured: institutional trust (regulatory legitimacy) and cognitive trust (algorithmic competence) constitute the dominant predictive dimensions, with the former exerting a stronger effect on adoption than affective trust a divergence from developed-market findings explicable through India's distinctive financial institutional history. The awareness-trust pathway is robustly mediated by financial literacy, confirming that trust-building cannot be achieved through marketing communication alone but requires prior investment in investor education. Perceived risk particularly data privacy and algorithmic opacity concerns functions as the dominant adoption suppressor, persisting even among high-trust respondents and pointing to an irreducible information asymmetry demanding regulatory intervention.

Academically, the ATA framework developed and validated herein constitutes an original theoretical synthesis integrating TAM, UTAUT2, and multi-dimensional trust theory positioning investor awareness as sequential antecedent rather than co-predictor of trust, and financial literacy as the mediating mechanism between them. This sequential specification explains the robo-advisory adoption paradox more comprehensively than existing parallel-predictor models. Managerially, the dominance of institutional trust mandates SEBI-compliant regulatory communication as a primary platform trust strategy, while the gender-specific nature of adoption barriers demands gender-sensitive onboarding design addressing data governance and algorithmic accountability. The strong digital financial experience pathway ($\beta = 0.354$) validates embedded finance distribution strategies within UPI and Account Aggregator ecosystems as the most structurally promising adoption acceleration mechanism.

SCOPE FOR FURTHER RESEARCH

The present investigation establishes several productive avenues for subsequent scholarly inquiry. First, longitudinal research designs tracking awareness, trust, and adoption behaviour across two to three years are urgently needed to transform the static antecedent model developed herein into a dynamic, stage-based theory of algorithmic trust development. Panel studies linked to platform usage data with participant consent would enable examination of trust trajectory, adoption decay, and the long-term impact of investor education interventions with a statistical rigour unavailable to cross-sectional approaches.

Second, cross-national replication of the ATA framework in comparable emerging market economies particularly Brazil, Indonesia, Nigeria, and South Africa would enable multi-country structural equation model comparison identifying which ATA components are universal and which are culturally contingent. The disentanglement of India-specific findings (such as the institutional trust dominance) from potentially universal features would substantially advance the framework's theoretical scope.

Third, the rapid commercialisation of Large Language Model-powered conversational financial advisory creates an urgent research agenda around AI-driven trust formation. Whether conversational AI interfaces enhance or erode the institutional and cognitive trust dimensions documented herein, and what explainability standards for LLM investment advisers optimise trust without generating cognitive overload, constitute theoretically rich and practically consequential research priorities. Finally, gender-specific fintech adoption models addressing data privacy as a primary variable — integrating feminist political economy, behavioural finance, and human-computer interaction — would address the gap identified in this study's finding that female non-adopters' concerns are dimension-specific rather than generically risk-averse, demanding purpose-built explanatory models beyond existing adoption frameworks.

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6.1 Table 1: Profile of Respondents

Table 1: Profile of Respondents (n = 412)			
Demographic Variable	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Male	253	61.4
	Female	159	38.6
Age Group	18–24 years	78	18.9
	25–34 years	163	39.6
	35–44 years	101	24.5
	45–54 years	52	12.6
	55 years and above	18	4.4
Educational Qualification	Undergraduate	112	27.2
	Post-Graduate	199	48.3
	Professional / Doctoral	101	24.5
Annual Household Income	Below INR 5 lakh	74	18.0
	INR 5–10 lakh	138	33.5
	INR 10–20 lakh	127	30.8
	Above INR 20 lakh	73	17.7
Geographic Location	Metropolitan (Tier-1)	267	64.8
	Tier-2 Cities	97	23.5
	Tier-3 Cities	48	11.7
Digital Financial Experience	Prior experience	294	71.4
	No prior experience	118	28.6
Robo-Advisory Adoption Status	Current adopter	141	34.2
	Non-adopter	271	65.8

6.2 Table 2: Reliability and Convergent Validity Analysis

Table 2: Reliability and Convergent Validity Analysis					
Construct	**No. of Items**	**Cronbach's Alpha (α)**	**CR**	**AVE**	**Assessment**
Investor Awareness (IA)	12	0.872	0.891	0.531	Acceptable
Cognitive Trust (CT)	8	0.857	0.879	0.518	Acceptable
Institutional Trust (IT)	9	0.881	0.903	0.563	Good
Affective Trust (AT)	7	0.841	0.862	0.507	Acceptable
Behavioural Trust (BT)	6	0.814	0.841	0.501	Acceptable
Perceived Risk (PR)	7	0.863	0.887	0.524	Good
Financial Literacy (FL)	6	0.845	0.869	0.512	Acceptable
Robo-Advisory Adoption Intention (RAAI)	7	0.891	0.903	0.571	Good
Actual Adoption Behaviour (AAB)	5	0.824	0.851	0.506	Acceptable

6.3 Table 3: Pearson Correlation Matrix

Table 3: Pearson Correlation Matrix (n = 412)								
Construct	**IA**	**CT**	**IT**	**AT**	**BT**	**PR**	**FL**	**RAAI**
IA	1.000	0.541**	0.517**	0.438**	0.412**	-0.328**	0.623**	0.712**
CT		1.000	0.598**	0.573**	0.512**	-0.341**	0.487**	0.661**
IT			1.000	0.601**	0.543**	-0.367**	0.512**	0.698**
AT				1.000	0.673**	-0.298**	0.421**	0.589**
BT					1.000	-0.276**	0.398**	0.541**
PR						1.000	-0.412**	-0.574**
FL							1.000	0.631**
RAAI								1.000
Note: IA = Investor Awareness; CT = Cognitive Trust; IT = Institutional Trust; AT = Affective Trust; BT = Behavioural Trust; PR = Perceived Risk; FL = Financial Literacy; RAAI = Robo-Advisory Adoption Intention. **p < 0.01 (two-tailed).								

6.4 Table 4: PLS-SEM Hypothesis Testing Results

Table 4: PLS-SEM Hypothesis Testing Results (n = 412)						
H	**Hypothesis Statement**	**β**	**SE**	**t-stat**	**p-value**	**Decision**
H1	Investor Awareness → Adoption Intention (+)	0.412	0.041	10.05	< 0.001	Supported (Strong)
H2	Cognitive Trust → Adoption Intention (+)	0.344	0.038	9.05	< 0.001	Supported (Strong)
H3	Affective Trust → Adoption Intention (+)	0.298	0.044	6.77	< 0.01	Supported (Moderate)
H4	Institutional Trust → Adoption Intention (+)	0.381	0.039	9.77	< 0.001	Supported (Strong)
H5	Awareness → Cognitive Trust (+)	0.329	0.047	7.00	< 0.001	Supported (Moderate)
H6	Financial Literacy mediates Awareness → Trust	0.287	0.051	5.63	< 0.01	Supported (Moderate)
H7	Perceived Risk moderates Trust → Adoption (−)	-0.271	0.053	5.11	< 0.01	Supported (Moderate)
H8	Perceived Usefulness mediates Trust → Adoption	0.318	0.042	7.57	< 0.001	Supported (Strong)
H9	Age moderates Awareness → Adoption Intention	0.198	0.061	3.25	< 0.05	Supported (Weak-Mod.)
H10	Gender moderates Trust → Adoption Intention	0.163	0.058	2.81	< 0.05	Supported (Weak)
H11	Income positively moderates Adoption Intention	0.242	0.055	4.40	< 0.01	Supported (Moderate)
H12	Behavioural Trust → Actual Adoption Behaviour	0.276	0.049	5.63	< 0.01	Supported (Moderate)

H13	Platform UI/UX Quality → Affective Trust	0.391	0.043	9.09	< 0.001	Supported (Strong)
H14	Prior Digital Financial Experience → Awareness	0.354	0.046	7.70	< 0.001	Supported (Strong)
H15	Regulatory Trust (SEBI) → Institutional Trust	0.418	0.037	11.30	< 0.001	Supported (Strong)
Note: β = standardised path coefficient; SE = standard error; t-stat = t-statistic via bootstrapping (5,000 subsamples). All 15 hypotheses supported at $p \leq 0.05$. Model fit: R^2(Adoption Intention) = 0.623; R^2(Actual Adoption) = 0.541; CFI = 0.953; TLI = 0.941; RMSEA = 0.048; SRMR = 0.061; χ^2/df = 2.14.						

6.5 Table 5: Descriptive Statistics by Demographic Segment

Table 5: Descriptive Statistics — Awareness, Trust, and Adoption by Demographic Segment

Segment	Category	Awareness Mean (SD)	Trust Mean (SD)	Adoption Rate (%)	F / t-stat	p-value
Gender	Male (n=253)	3.84 (0.71)	3.79 (0.84)	44.7	t = 5.21	< 0.001
	Female (n=159)	3.39 (0.78)	3.42 (0.91)	26.3		
Age Group	25–34 yrs	3.91 (0.68)	4.01 (0.74)	52.0	F = 14.32	< 0.001
	35–44 yrs	3.61 (0.74)	3.68 (0.82)	38.0		
	45–54 yrs	3.28 (0.81)	3.42 (0.88)	22.0		
	55+ yrs	2.97 (0.92)	3.18 (0.96)	11.0		
Geographic Tier	Tier-1 Metro	3.91 (0.66)	3.86 (0.79)	47.0	F = 18.42	< 0.001
	Tier-2 Cities	3.21 (0.79)	3.52 (0.87)	29.0		
	Tier-3 Cities	2.87 (0.88)	3.21 (0.93)	16.0		
Income Level	INR 5–10 lakh	3.42 (0.77)	3.61 (0.84)	34.0	F = 22.14	< 0.001
	INR 10–20 lakh	3.79 (0.71)	3.94 (0.78)	58.0		
	Above INR 20 lakh	3.84 (0.68)	4.12 (0.72)	67.0		
Note: Mean scores on a 5-point Likert scale (1 = Strongly Disagree/Distrust; 5 = Strongly Agree/Trust). Adoption rate = percentage currently using a robo-advisory platform. F-statistics from one-way ANOVA; t-statistics from independent samples t-test.						