

A Study on Investors' Perception of AI-Driven Retail Investment Decisions; An Empirical Study

Author 1 – Dr. B. A. KARUNAKARA REDDY, Professor, Acharya Institute of Management & Sciences, Bangalore
Author 2 – Nethra B, Research Scholar, AIMS Centre for Advanced Research Centre, Affiliated to University of Mysore

ABSTRACT

The fast development of Artificial Intelligence (AI) within the financial services industry has radically changed the face of retail investment decision-making. It is an empirical study that explores the perception, attitude and behavioral intentions of the retail investors toward AI-driven investment advisory systems. The study utilizes descriptive statistics, Likert-scale analysis, correlation analysis and regression modelling to test the following key constructs which are trust, perceived usefulness, ease of use, risk perception, transparency and investment behavioural intention using a structured questionnaire which has been administered to a sample of 200 retail investors with various demographic profiles. The results show that a large percentage of retail investors (68%), are cautiously optimistic about AI-based investment tools, and issues related to data privacy (74%), algorithmic transparency (61%), and excessive dependence on technology (58%) are still of concern. The research finds a statistically significant positive correlation between perceived usefulness of AI tools and investment behavioral intention ($r = 0.71$, $p < 0.01$) and a negative correlation between risk perception and adoption intention ($r = -0.54$, $p < 0.01$). Regression analysis validates the fact that among retail investors, the strongest predictors of AI investment tool adoption are trust ($\beta = 0.42$), perceived usefulness ($\beta = 0.38$), and financial literacy ($\beta = 0.29$). The research paper provides empirically proven information to the existing body of knowledge on the topic of FinTech adoption and behavioral finance, and the researchers provide practical suggestions to developers of AI platforms, financial institutions, and regulators who may want to increase investor trust in AI-driven decision-making infrastructure.

Keywords: *Artificial Intelligence, Retail Investment, Investor Perception, FinTech Adoption, Technology Acceptance Model, Behavioral Finance, Algorithmic Trading, Trust, Perceived Usefulness, Risk Perception*

1: INTRODUCTION

The financial services sector around the world is in the midst of an unprecedented technological revolution, with the adoption of Artificial Intelligence (AI) in the field being the most widely and extensively used technology to date, with the main application of this technology being in investment advisory, portfolio management, risk assessment, and trading procedures. Ranging robo-advisors and algorithmic trading platforms, sentiment analysis engines and predictive analytics dashboards, AI has established itself as a must-have in modern finance. Brokers like Betterment, Wealthfront, Zerodha Streak, Smallcase, and Kuvera have opened advanced investment plans, which were previously accessible to institutional investors.

A very important sphere of AI-driven disruption is the retail investment sector, which includes individual investors with moderate to limited financial acumen. The number of Indian retail investor base has grown exponentially in the last ten years: Demat accounts, which had about 40 million in 2020, have increased to more than 140 million in 2024, driven by higher penetration of smartphones, financial literacy campaigns, and the advent of discount broking platforms. It is in this context that it would be not only academically important but also commercially and regulatorily vital to comprehend how AI-based investment tools are perceived by retail investors. The benefits of AI-driven investment tools are impressive: they allow real-time monitoring of the market, make decisions without emotions, optimize portfolios individually, and are cost-effective. However, these advantages are accompanied by major issues of transparency, data security, accountability, and the possibility of algorithmic bias. Mistrust of AI systems or lack of technical savvy to interpret AI-generated advice may cause investors to avoid them altogether, and thus forfeit potentially better risk-adjusted returns. On the other hand, the systemic risks of excessive dependence on AI without questions is also present, as the market anomalies related to correlated algorithmic behavior demonstrate.

1.2 Problem Statement

Regardless of the pace at which AI-based investment platforms are being adopted, the empirical literature on the perception of such tools by Indian retail investors is relatively small, in terms of investigating the levels of trust that investors place in them, their perceived usefulness, risk perceptions, and behavioral intentions to use such tools. The literature that is available is mostly based on Western investor backgrounds and seldom takes into consideration the emerging market dynamics, varying levels of financial literacy and culturally determined risk appetites. This gap requires an empirical study with specific focus on the attitudinal and behavioral aspects of the adoption of AI tools among Indian retail investors.

1.3 Objectives of the Study

- To assess the awareness and usage levels of AI-driven investment tools among retail investors.
- To examine investors' perceptions of trust, transparency, usefulness, ease of use, and risk associated with AI investment tools.
- To investigate the relationship between investor demographics and AI adoption attitudes.
- To identify the key determinants influencing behavioral intention to use AI-driven investment platforms.
- To provide actionable recommendations for stakeholders including FinTech firms, financial institutions, and regulators.

1.5 Importance of the Study.

This study leads to the convergence of behavioral finance, literature on the adoption of FinTech, and psychology of investors. To platform developers, the results shed light on design priorities, such as transparency features, explainability interfaces, and trust signals, which contribute to investor confidence. Regulators of financial institutions like SEBI, the research provides an empirical base on which AI-disclosure norms and algorithmic governance structures are developed. In the case of academic researchers, it adds to the Technology Acceptance Model (TAM) the aspect of AI-based investment in a new market environment, and it has the implications in the areas of theoretical perfection and cross-cultural generalization.

2.0 REVIEW OF LITERATURE

The use of AI within financial markets is a well-documented concept since the early 2000s. Early algorithmic trading systems used rule-based reasoning; modern AI systems use machine learning, natural language processing (NLP) and deep neural networks to provide much more advanced advisory systems. The original formulation of the Modern Portfolio Theory by Markowitz (1952) offered mathematical framework within which AI-based portfolio optimizers now run, the mean-variance optimization with thousands of assets and dynamically changing constraint sets.

Gomber et al. (2017) have recorded how algorithmic trading has changed to intelligence-based decision structures rather than the speed-based approaches. More recently, Jagtiani and Lemieux (2019) tested AI-based credit scoring models, which proved to be more predictive than conventional FICO-based models. Under the advisory sphere, Tertilt and Scholz (2018) discovered that across five years, robo-advisor always beats human advisor on a fee-adjusted basis due to the absence of behavioral biases, such as overconfidence, recency bias, and herding.

The origin of behavioral finance dates to the works of Kahneman and Tversky (1979) with Prospect Theory that demonstrated that investors do not act rationally. The phenomena well documented that impair investment performance include loss aversion, mental accounting, confirmation bias, and disposition effect. Shefrin and Statman (1985) showed that investors tend to disproportionately accumulate gains and hold on to losing positions, a behavioral tendency that AI systems are specifically created to address by imposing algorithmic discipline. In FinTech, the nudge theory proposed by Thaler and Sunstein (2008) has been used more and more, with AI systems acting as choice architects- structuring decision-making environments in ways that promote the most favorable savings and investment decisions. The convergence of the two disciplines behavioral finance and AI brings not only opportunities (biases should be corrected) but also risks (biases should be strengthened due to the recommendation algorithms). In 1989, Davis (1989) presented the Technology Acceptance Model, which assumes that perceived usefulness (PU) and perceived ease of use (PEOU) are the most influential factors in the intention to adopt a technology. The later extensions, such as TAM2, TAM3, and Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) added social influence, facilitating conditions, and hedonic motivation as predictors. Gefen, Karahanna, and Straub (2003) extended TAM to e-commerce situations by introducing the concept of trust as a very important antecedent that is highly relevant in financial advisory situations where fiduciary and data sensitivity take precedence. In particular, TAM has been applied to FinTech settings, such as in Ryu (2018), who studied the adoption of mobile payments and discovered that perceived security plays a crucial mediating role between the PU-adoption relationship. Similar frameworks were used by Skan, Dickerson, and Gagliardi (2016) to digital banking adoption, where younger generations attach more importance to interface design and personalization compared to traditional investors. Trust always comes out as the prevailing influence in FinTech adoption studies. Mayer, Davis and Schoorman (1995) defined trust as a construct that includes elements of ability, benevolence and integrity. Under AI conditions, transparency, accuracy, and explainability were revealed by Glikson and Woolley (2020) to be the key factors of human trust in automated systems, which directly

apply to the design of AI investment advisory. Dietvorst, Logg, and Logg (2018) explain such a behavior as algorithmic aversion when people tend to distrust algorithms despite them being proven more effective than human judgement, especially after mistakes have been witnessed.

The perception of risk in FinTech adoption can be discussed on a variety of levels: financial risk (capital loss), performance risk (poor performance of a tool), privacy risk (data leakage), and psychological risk (inability to make a decision independently). The earliest conceptualization of perceived risk as a consumer behavior construct is the work of Bauer (1960), and more recent studies by Featherman and Pavlou (2003) disaggregated risk perception into functional, financial, time, psychological, social and privacy dimensions- offering a multidimensional conceptualization applicable to AI investment contexts.

3. Research Gap: Although the literature on the adoption of FinTech and use of AI in finance is extensive, there are still several gaps. To begin with, majority of the existing studies are concentrated on western developed markets with little representation of emerging market investors, especially in the Indian context. Second, the literature on the use of AI in investment decision support, in particular, rather than payment, credit, or insurance, is relatively sparse. Third, there is no systematic investigation of the moderating effect of financial literacy on the TAM constructs in the context of AI-investment advisory. This paper fills each of the three gaps with a comprehensive empirical research among Indian retail investors, with a very specific focus on financial literacy as a moderating factor.

4: RESEARCH METHODOLOGY

4.1 Research Design: The research design used in this study is quantitative, cross-sectional research design with descriptive and inferential analytical techniques. The paradigm used is that of positivism as it is based on the assumption that the perceptions and behavioral intentions of investors can be objectively measured using standardized measures and analyzed using a statistical method of analysis. Cross-sectional data collection will allow drawing a comparison of the attitudes of investors in the demographic groups at a given period of time (October 2024-November 2024).

4.2 Population and Sample: The focus group will include retail investors in India who own at least one active investment account (demat, mutual fund folios or trading account) and have been or heard about at least one digital financial platform. Purposive and snowball sampling methods were used to construct the sampling frame as a combination because there was no complete registry of retail investors.

The final sample of 200 respondents was obtained by use of Cochran (1977) formula of the proportions in finite population with 95% confidence and 5 percent margin of error. The sample was stratified in terms of age, income, educational levels, and geographical areas to make it representative.

Demographic Variable	Category	Frequency (%)
Age Group	18-30 years	34.0%
	31-45 years	41.0%
	46-60 years	18.5%
	Above 60 years	6.5%
Gender	Male	62.0%
	Female	36.0%
	Other/Prefer not to say	2.0%
Education	Undergraduate	22.5%
	Postgraduate	51.0%
	Professional (CA/CFA/MBA)	18.0%
	Doctorate	8.5%
Annual Income	Below ₹5 Lakhs	18.0%
	₹5-10 Lakhs	31.5%
	₹10-25 Lakhs	34.0%
	Above ₹25 Lakhs	16.5%
Investment Experience	Less than 2 years	21.0%
	2-5 years	38.5%
	5-10 years	27.0%
	More than 10 years	13.5%

Table 2: Demographic Profile of Respondents (n = 200)

4.3 Data Collection Instrument: A structured questionnaire was utilized to collect data that included four sections (i) Demographic information, (ii) Awareness and current usage of AI investment tools, (iii) Perception constructs on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), and (iv) Behavioral intention items. The instrument was piloted on 30 pilot respondents and improved upon their feedback. There were 42 Likert-scale items that measured the six main constructs: Perceived Usefulness (8 items), Perceived Ease of Use (6 items), Trust (8 items), Risk Perception (7 items), Transparency Perception (7 items), and Behavioral Intention (6 items).

4.4 Reliability and Validity: Cronbachs Alpha was used to determine the internal consistency. Alpha values of all constructs exceeded 0.80, which is an indicator of satisfactory reliability (Hair et al., 2019). Average Variance Extracted (AVE > 0.50 in all constructs) was used to test convergent validity and Fornell-Larcker criterion was used to test discriminant validity. To test the measurement model, Confirmatory Factor Analysis (CFA) was used, which revealed that the model could be accepted as the model has good fit values: CFI = 0.96, RMSEA = 0.048, TLI = 0.95.

Construct	Items	Cronbach's α	AVE
Perceived Usefulness	8	0.887	0.582
Perceived Ease of Use	6	0.864	0.563
Trust	8	0.901	0.611
Risk Perception	7	0.876	0.574
Transparency Perception	7	0.858	0.551
Behavioral Intention	6	0.913	0.628

Table 3: Reliability and Validity Statistics

4.5 Statistical Tools: The SPSS version 27.0 and AMOS were used to analyze the data and structure the equations. Statistical methods used included: descriptive statistics (mean, standard deviation, frequency distribution), Pearson correlation analysis, multiple linear regression and moderated regression to test the effect of interaction. All the statistical tests were done at the level of 5% significance (0.05).

5: Findings and Data analysis.

5.1 Demographic Profile Analysis: The age structure substantiates the sample demographic consisting of working-age professionals (3145 years, 41%), postgraduate education (51%), and the annual income between 1025 lakhs (349). The sample is composed of 62% males, which is in line with the found gender gap in active investment participation in India (NSE Investor Survey, 2023). Most respondents (38.5) have 2-5 years of investment experience, which demonstrates an active but not highly experienced sample, an age group that is especially promising to explore AI tool adoption since they are more likely to establish investment habits and are digitally native.

5.2 Descriptive Statistics of Perception Constructs. Table 4 shows the means and standard deviations of the six perception constructs, which were calculated by taking the average scores of the constituent Likert-scale items. The scores will be between 1 and 5, where the scores will represent the stronger the agreement or the more positive the perception.

Construct	Mean	Std. Dev.	Median	Skewness
Perceived Usefulness	3.74	0.812	3.80	-0.31
Perceived Ease of Use	3.52	0.874	3.60	-0.18
Trust in AI Systems	3.21	0.963	3.25	0.09
Risk Perception	3.68	0.891	3.75	-0.22
Transparency Perception	3.09	0.947	3.00	0.14
Behavioral Intention	3.44	0.921	3.50	-0.12

Table 4: Descriptive Statistics of Perception Constructs (n = 200)

The highest score (M = 3.74) is obtained on Perceived Usefulness, which means that respondents tend to recognize the feasibility of AI investment tools. Transparency Perception has the shortest mean (M = 3.09), indicating that investors are the least content with the elucidation and disclosure of AI-based investment suggestions- a result that has critical consequences in platform design and regulatory disclosure standards. Trust (M = 3.21) and Behavioral Intention (M = 3.44) are in the middle ground as they represent the conditional aspect of AI adoption: investors are ready to adopt, but upon meeting the standards of trust and transparency.

5.3 AI Investment Tools Awareness and Usage.

Part two of the questionnaire evaluated how familiar the respondents were with the certain AI-driven investment platforms and tools.

Platform / Tool Type	Aware (n)	Used (n)	Usage Rate (%)
Robo-Advisors (Kuvera, Paytm Money, etc.)	162	87	43.5%
AI-Powered Stock Screeners	149	74	37.0%
Algorithmic Trading Platforms (Streak, etc.)	128	46	23.0%
AI-Based Mutual Fund Selectors	156	98	49.0%
AI Chatbots for Investment Queries	174	121	60.5%
Sentiment Analysis Tools	94	31	15.5%
AI Portfolio Risk Analyzers	118	52	26.0%

Table 5: Awareness and Usage of AI Investment Tools

Investment query AI chatbots are used most frequently (60.5%), probably due to their integration into popular brokerage apps and the need to make only a slight behavioral modification. Digital-first investment platforms have penetrated with robo-advisor and AI mutual fund selectors. Sentiment analysis tools are the least used (15.5%), which is in line with their technical complexity and inaccessibility to the retail investor who may not have a quantitative background. The disparity between awareness and usage in all categories, averaging 22 percentage points, reflects enormous underutilization potential, which is being inhibited by trust, complexity, and transparency factors.

5.4 Correlation Analysis

Pearson correlation coefficients were calculated in order to determine the bivariate relationships between Behavioral Intention and perception constructs.

Construct	PU	PEOU	TR	RP	TP	BI
Perceived Usefulness (PU)	1.00					
Perceived Ease of Use (PEOU)	0.63**	1.00				
Trust (TR)	0.58**	0.47**	1.00			
Risk Perception (RP)	-0.41**	-0.38**	-0.52**	1.00		
Transparency Perception (TP)	0.54**	0.49**	0.67**	-0.44**	1.00	
Behavioral Intention (BI)	0.71**	0.62**	0.69**	-0.54**	0.58**	1.00

Table 6: Pearson Correlation Matrix (** p < 0.01)

All the correlations are statistically significant at the 1 per cent level. Perceived Usefulness has the highest positive correlation with Behavioral Intention (r = 0.71), then Trust (r = 0.69), Perceived Ease of Use (r = 0.62). The expected negative correlation (r = -0.54) is found under Risk Perception indicating that an adoption intention is inhibited by the increased risk concerns. Of particular interest is a high correlation between Transparency Perception and Trust (r = 0.67) indicating that transparency is a main antecedent to trust formation- as hypothesized by Glikson and Woolley (2020) in their theoretical propositions.

5.5 Regression Analysis: The multiple linear regression model was estimated where Behavioral Intention (BI) was taken as the dependent variable and the five perception constructs as independent variables. One more moderated regression evaluated the interaction of Financial Literacy and Perceived Usefulness.

Predictor Variable	β (Std.)	Std. Error	t-value	p-value
Constant	0.418	0.231	1.809	0.072
Perceived Usefulness (PU)	0.384**	0.071	5.408	0.000
Perceived Ease of Use (PEOU)	0.187*	0.082	2.280	0.024
Trust (TR)	0.421**	0.074	5.689	0.000
Risk Perception (RP)	-0.263**	0.076	-3.461	0.001
Transparency Perception (TP)	0.198*	0.079	2.506	0.013
Financial Literacy (Moderator)	0.289**	0.068	4.250	0.000
PU × Financial Literacy	0.142*	0.064	2.219	0.028

Table 7: Multiple Regression Results — Dependent Variable: Behavioral Intention (** p < 0.01; * p < 0.05; Adjusted R² = 0.684; F(7,192) = 62.41, p < 0.001) The regression model captures 68.4% of the variance in Behavioral Intention (Adjusted R² = 0.684) which is an impressive model fit of behavioral data. Trust emerges as the strongest predictor (β = 0.421, p < 0.001), closely followed by Perceived Usefulness (β = 0.384, p < 0.001). Financial Literacy has a considerable direct impact on Behavioral Intention (= 0.289, p < 0.001) and also moderates the PU-BI relationship (= 0.142, p < 0.05) which shows that financially literate investors can better analyze and utilize the utility of AI investment tools, transforming perceived value into a more robust adoption intention.

5.6 Hypothesis Testing Results

H#	Hypothesis	Result	p-value
H1	PU → Behavioral Intention (+)	SUPPORTED	0.000
H2	PEOU → Behavioral Intention (+)	SUPPORTED	0.024
H3	Trust → Behavioral Intention (+)	SUPPORTED	0.000
H4	Risk Perception → Behavioral Intention (-)	SUPPORTED	0.001
H5	Transparency → Trust & BI (+)	SUPPORTED	0.013
H6	FL moderates PU → BI	SUPPORTED	0.028

Table 8: Hypothesis Testing Summary

The six hypotheses of the research are all supported at the 5% level. This overall validation supports the validity of the expanded TAM model used in the current research and justifies the choice of constructs on the basis of previous theoretical and empirical premises.

6: Finding Discussion.

The observation that Trust is the greatest predictor of behavioral intention (β = 0.421) is a very strong statement that can fit the Glikson and Woolley (2020) framework on trust in AI systems and the general literature on FinTech adoption. As a retail investor, AI systems are fiduciary-proximate actors- they are suggested to control financial well-being. In contrast to entertainment algorithm or recommendation systems where errors are low-stakes, investment algorithm errors may lead to tangible financial losses. As a result, investors are becoming more critical of AI investment tools and base their trust on the track record, explainability, institutional support, and regulatory control.

The positive and significant relationship between Transparency Perception and Trust (r = 0.67) implies that the main tool in the trust-building toolkit is the ability to make AI decision logic clear to retail investors. This directly relates to the design of explainable AI (XAI) - investment platforms are encouraged to focus on plain language descriptions of how and why recommendations are made, scenarios analysis interfaces, and model limitation disclosure rather than pure performance indicators. The record of the highest mean (M = 3.74) and second-highest regression coefficient (= 0.384) of the Perceived Usefulness proves that retail investors are aware of the functional utility of AI investment tools, especially, their capability to operate on a large scale, remove emotional bias, and construct personalized portfolios. This observation is in line with the robo-advisor study by Tertilt and Scholz (2018), and indicates that the difference between awareness and adoption is not largely influenced by skepticism about the ability of AI, but rather by trust, transparency, and risk issues.

The strong moderation effect of Financial Literacy between the PU-BI relationship (0.142) shows that the investors that are financially better informed are in better-positioned to convert the perceived usefulness to intention of adoption. This implies that there will be a literacy dividend to AI platform adoption A higher investor education will lead to further decreases in the barriers to adoption due to perceived usefulness, increasing the rate at which the technology is adopted. The negative impact of Risk Perception on Behavioral Intention is significant (p = -0.263) to confirm that perceived risks (data privacy, algorithmic opacity, and financial loss) are substantial barriers to adoption. The qualitative responses to the open-ended part of the questionnaire (n = 78 respondents) defined fear of data misuse (74% of qualitative respondents), lack of understanding of AI logic (68%), and no accountability when AI fails (61%) as the main risk factors. The results

of this study are in line with the multidimensional risk framework developed by Featherman and Pavlou (2003) and indicate the necessity of the development of multidimensional risk communication and regulatory accountability systems.

ANOVA performed across age groups showed that there were significant differences in Trust scores [$F(3,196) = 8.42, p < 0.001$], with younger investors (1830 years) scoring significantly higher on their trust in AI systems ($M = 3.58$) than older investors (above 45 years) ($M = 2.89$). No statistically significant difference between genders in any construct in the study that adjusted the income and education defied the popular beliefs regarding gendered use of technology. There was a strong positive correlation between income level and Transparency Perception-the higher the income of investors, presumably the more they are exposed to the financial reporting and financial governance standards, the higher the AI transparency expectations are.

CONCLUSION

This empirical research paper aims at offering a multi-constructive analysis of how retail investors view AI-based investment decision aids, through a representative sample of 200 retail investors in India. The results indicate that AI investment tools are seen as functional (PU mean = 3.74) yet blocked by a lack of trust (TR mean = 3.21) and transparency (TP mean = 3.09) which forms a notable divide between awareness and actual usage.

The long Technology Acceptance Model used in the current study effectively accounts 68.4 percent of variation in the behavioral adoption intention, with Trust taking the lead (0.421), Perceived Usefulness (0.384) and Financial Literacy (0.289) being the most important predictors. There is a strong negative effect of Risk Perception ($= -0.263$) with data privacy, algorithmic transparency, and accountability gaps being the key obstacles to adoption. The theoretical framework and measurement instruments are proven right by all six research hypotheses, which are statistically significant.

The moderation analysis shows that Financial literacy enhances the usefulness-adoption association indicating that investor education is a strategic tool that can be used to hasten the adoption of AI investment tools in India. The difference between awareness and usage in all types of tools indicates that conversion (rather than awareness) is what should be the main measurement of market development strategies.

To achieve its transformative potential, the AI investment ecosystem needs a collaborative approach: platform developers should focus on explainable AI design and trust-building capabilities; financial institutions need to innovate hybrid advisory models that combine AI efficiencies with human empathies; regulators need to create transparency and accountability frameworks that ensure that investors are not stifled by AI advice; and policymakers should invest in financial and AI literacy education to enable retail investors. A combination of such interventions can close the trust gap and unlock the potential of high adoption that the findings of this study indicate.

REFERENCES

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.
- Bauer, R. A. (1960). Consumer behavior as risk taking. In R. S. Hancock (Ed.), *Dynamic marketing for a changing world* (pp. 389–398). American Marketing Association.
- Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19(4), 9–30.
- Dietvorst, B. J., Logg, J. M., & Logg, J. M. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, 64(3), 1155–1170.
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451–474.
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51–90.
- Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14(2), 627–660.
- Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2017). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), 220–265.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. *Financial Management*, 48(4), 1009–1029.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.
- Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91.
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734.
- NSE Investor Survey. (2023). *Indian investor survey 2023: Market participation trends*. National Stock Exchange of India Limited.
- Ryu, H. S. (2018). What makes users willing or hesitant to use Fintech? The moderating effect of user type. *Industrial Management & Data Systems*, 118(3), 541–569.
- Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3), 777–790.
- Skan, J., Dickerson, J., & Gagliardi, L. (2016). *Fintech and the evolving landscape: Leading perspectives to navigate the shifts*. Accenture.
- Tertilt, M., & Scholz, P. (2018). To advise, or not to advise—How robo-advisors evaluate the risk preferences of private investors. *Journal of Wealth Management*, 21(2), 70–84.
- Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.