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Impact of Artificial Intelligence Tools on the Financial Decision-Making of Young Individuals in India

Dr. Chandan Karki[1*] | Murari[2]

[1]Professor, Department of Commerce, Motilal Nehru College, University of Delhi, New Delhi, India
[2]Research Scholar, Motilal Nehru College, University of Delhi, New Delhi, India

[*]Corresponding Author: karki@mln.du.ac.in

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ABSTRACT

The complete overhaul of personal finance through Artificial Intelligence (AI) technology creates two effects. The Indian digital finance market provides various tools such as robo-advisors and budgeting applications and generative chatbots, but their specific effects on young adult users (18–30) remain understudied. The current study uses a convergent mixed-method approach with 200 participants to study AI effects on saving, investing, and budgeting behavior among Indian youth. The research uses quantitative methods that include Pearson/Spearman correlation analysis and Kruskal-Wallis testing and qualitative methods that use thematic analysis to identify a "Privacy Paradox" and a model of "Calculated Trust". The artificial intelligence system provides cognitive advantages and financial benefits to users, yet it creates two major obstacles through high-risk perception and user anxiety about losing financial skills. The study concludes with targeted recommendations for Explainable AI (XAI) and algorithmic literacy. The implementation of these frameworks will create an educational system which uses AI as teaching support instead of using it as a learning tool. The development of critical engagement skills as an essential requirement for creating a technologically skilled yet financially independent generation.

***Keywords**: Artificial Intelligence, Personal Finance, Indian Youth, Robo-advisors, Financial Literacy.*
***JEL Classification:** G11, G17, D81, O33.*

Introduction

The intersection of technology and finance has transitioned from digital recordkeeping to predictive ecosystems governed by Artificial Intelligence. India has become an ideal market for retail AI adoption because its strong digital public infrastructure system which includes UPI together with its large population of digitally native young people.

The financial socialization process in India used to function through communal methods which depended on traditional knowledge and family ties and local trusted agents. Young people today shift their financial trust from personal bonds to non-transparent algorithms which are becoming the new standard. The shift from social trust to technological trust creates a significant mental transformation. Users demonstrate high confidence in "black-box" systems which use simple user interfaces to hide the mathematical rules that determine mutual fund selection and credit scoring.

The applications use their structural design to implement gamification methods which maintain user engagement. The system uses dopamine-based push notifications together with interactive goal-tracking bars and reward animations to create a psychological state where users cannot discern between gaming and making important financial commitments. The design elements create an exceptional retail market surge which results in financial market participants skipping the important barriers that help them

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make responsible investment decisions. Investors who view their investments as similar to mobile games will experience a reduced sense of danger when they risk losing their money.

The fast adoption of AI technology creates an Empowerment-Vulnerability Paradox. The AI tools make advanced investing easier to understand because they decrease the need for mental effort which requires two different levels of thinking. The excessive ease of "single-click" investing together with algorithmic nudges will create passive user behavior which hides their actual comprehension of financial dangers while this leads to "financial deskilling".

The study aims to investigate modern consumer protection through its technological assessment. The regulatory framework needs knowledge about AI's impact on human reasoning to develop algorithm transparency regulations and to create financial literacy educational standards for students who use machine learning models as financial advisors.

Review of Literature

The existing literature demonstrates that AI tools which include robo-advisors provide wealth management services to a wider audience through their ability to reduce costs and their capacity to decrease common trading problems which traders experience.

The research of Srivastava and Dwivedi (2025) demonstrates how AI-based decision tools improve speed and accuracy, but they create two problems because they make users less likely to participate in decision-making processes and they create weaknesses when algorithms encounter difficulties (Srivastava and Dwivedi 2025).

Verma (2025) investigates robo-advisor adoption in India and finds that resistance factors (lack of perceived control, fear of errors, opacity of algorithm) significantly reduce usage intentions (Verma, 2025).

Ribeiro (2025) conducted a systematic literature review which shows how AI impacts consumer behavior and provides evidence that AI technology helps people make decisions while delivering personalized recommendations and enhancing user experience yet its complete capabilities remain unutilized.

Cardillo (2024) conducts a comprehensive literature analysis which evaluates all robo-advisor research studies from 2017 until 2022. The research results show that robo-advisors help users to achieve better portfolio diversification at lower investment costs. The existing research studies examine investment practices of institutional investors and wealthy individuals without studying investment patterns among young retail investors.

Bhatia (2020) presents evidence from India that shows retail investors can benefit from robo-advisory services which help them to overcome their behavioural biases that cause over-trading and loss aversion. Bhatia (2020) shows that three main issues which include infrastructure problems and trust issues and lack of regulatory clarity create major obstacles to progress.

Riandhi (2025) shows through his hybrid review of AI applications in consumer behavior studies that most research studies base their findings on consumer adoption and marketing results instead of evaluating decision-making performance and consumer behavior development over time (Riandhi, 2025).

Cognizant (2025) Consumers prefer to use artificial intelligence technology during the information-gathering stage according to the Cognizant "AI Inclination Index" research which shows people use AI less during their purchasing and product usage stages of financial services (Cognizant, 2025).

Fatima & Chakraborty (2024) The researchers investigated AI implementation at Indian robo-advisor platforms and discovered that users showed high interest yet their trust and understanding of algorithms and perceived value of services remained inconsistent (Fatima & Chakraborty, 2024).

The study by Chandani (2025) proves that researchers need to investigate both the current development of robo-advisors in India and their effects on user behaviour because this area remains unexplored.

Kulkarni (2025) shows that the design elements of robo-advisors which include algorithm transparency and user interface and recommendation explanation will determine how investors choose to use these systems (Kulkarni, 2025).

According to Draws et al. [2021], an algorithm that functions in an opaque fashion with no transparency from its decision-making process to its data inputs will make customers distrust the system since they believe it treats them unjustly and uses their personal data without consent. The "Black Box" issue represents a major obstacle which prevents financial institutions from adopting AI technology. Users frequently do not understand the underlying logic which governs an AI system's recommendations (Draws et al., 2021).

According to (D'Acunto, Prabhala, & Rossi (2019), Robo-advisors first appeared as automated financial planning systems which used algorithms to deliver services without needing human workers after the 2008 Global Financial Crisis (D'Acunto, Prabhala, & Rossi, 2019).

Fisch, Bai, & Muro (2019) The research studies conducted in developed countries which include the US and Germany demonstrated that robo-advisors decrease traditional behavioral finance biases through their system which prevents users from holding losing assets for excessive time periods and trading too frequently (Fisch, Bai, & Muro, 2019).

Zarifis & Cheng (2024) demonstrate that users who ask generative-AI tools vague questions will develop trust through human-likeness and transparency although trust does not increase through human-mimicking interaction when users ask specific questions (Zarifis & Cheng, 2024).

Adanyin (2024) emphasises that users' perceptions of fairness and equal treatment by AI systems influence adoption and sustained use (Adanyin, 2024). The issues which youth in India experience through financial exclusion and algorithmic bias will decrease the effectiveness of AI tools which they use.

Research Gap: Current research disproportionately focuses on macro-level fintech inclusion or institutional adoption, largely ignoring the micro-level cognitive processes of the 18–30 demographic in emerging dual-economies like India. This study bridges that gap.

Research Methodology

The research employed a **Convergent Mixed-Method Research Design** which used Pragmatism as its foundation to gather both quantitative and qualitative data at the same time.

- **Population & Sample:** The purposive sampling method resulted in valid responses from 200 Indian youth who belonged to the age group of 18 to 30 and included both students and young professionals who had previously used AI financial tools.
- **Instrumentation:** The research study used a digital questionnaire framework which required participants to answer questions based on three core constructs that were measured through a 5-point Likert scale according to the Extended Technology Acceptance Model (TAM) which includes Trust in AI and Perceived Influence and Risk Perception. The study collected qualitative data through open-ended phenomenological questions which allowed participants to share their personal experiences.
- **Data Analysis:** EXCEL functioned as the data analysis tool which provided descriptive statistics and Cronbach's Alpha reliability measurement and Pearson/Spearman correlation results and Fornell-Larcker validity assessment and Kruskal-Wallis/Spearman hypothesis testing.
- **Primary Objective:** To conduct a dual examination of the effects brought by AI tools which include robo-advisors budgeting apps and chatbots on the financial decision-making processes and trust parameters and risk perceptions of Indian youth who belong to the 18 to 30 age group...

Objectives of Study

- To examine the impact of Artificial Intelligence tools on financial decision-making among young individuals in India
- To identify different AI-based financial tools used by young individuals
- To evaluate trust in AI-based financial recommendations
- To analyze the influence of AI tools on financial behavior
- To examine risk perception associated with AI-based financial tools

Quantitative Dimensions

Uses structured Likert-scale surveys to measure AI tool adoption frequency and to measure trust levels and to create statistical links between risk perception and its effect on behavior.

The central analytical framework was executed across seven rigorous statistical phases.

Phase 1 — Data Screening & Normality Testing

The initial testing phase confirms the dataset's basic security measures and delivery abilities before any testing processes are started. Three sequential checks were performed: missing value analysis, outlier identification, and normality testing.

Phase 2 — Descriptive Statistics

Descriptive statistics form the basis of knowledge regarding central tendency and dispersion for all scale items. This research focuses on three constructs: trust in AI recommendations, perceived influence on financial decision-making, and risk perception, which have been evaluated using a survey of 200 people using a 5-point Likert scale.

Phase 3 — Reliability Analysis (Cronbach's Alpha)

Reliability analysis involves testing the consistency of multi-items scale in measuring a unifying concept. The reliability coefficient used to determine this concept is known as Cronbach's Alpha (α). The acceptable level of reliability is 0.70, while the good level of reliability is 0.80, and an excellent level is 0.90. The study analyses 200 complete responses which covered all three constructs

Phase 4 — Pearson Correlation Analysis

The Pearson correlation analysis investigates the linear connections which exist between construct-level composite scores. The three items that make up each construct were used to calculate its score through average measurement. The study presents correlation results through Pearson's r which includes corresponding significance levels.

Phase 5 — Convergent & Discriminant Validity

The measurement model required theoretical validation which we accomplished through the computation of factor loadings and Average Variance Extracted and Composite Reliability.

The validity analysis shows that the scales successfully measure their intended targets through convergent validity and their established measures show different results through discriminant validity. The two elements of the study function as essential requirements for establishing valid results through structural and correlational research methods.

Phase 6 — Hypothesis Testing

We used statistical hypothesis testing methods to evaluate the relationships between different variables and the differences between groups which they found through descriptive and correlational analysis methods. The Shapiro-Wilk test results showed that Trust and Influence and Risk composite scores did not follow a normal distribution which required using non-parametric tests that included the Kruskal-Wallis H test for group testing and Spearman's Rank Correlation for testing relationships between two variables.

Hypothesis Testing

In view of the fact that the data was not normally distributed, robust non-parametric tests were used.

H1: **Frequency of AI tool usage significantly affects Trust in AI. (***Test:* Kruskal-Wallis H Test).

H2: **Trust is positively correlated with Perceived Influence on Decision-Making. (***Test:* Spearman's Rank Correlation).

H3: **Risk Perception is significantly correlated with Trust in AI. (***Test:* Spearman's Rank Correlation).

Phase 7 — Integrated Summary & Discussion

The last stage in this research integrates results of all six stages of analysis into one single story that evaluates the overall measurement system and highlights potential directions for future research along with study limitations.

Qualitative Dimensions

Uses open-ended questionnaire sections and semi-structured thematic narratives to explore the reasons and methods behind cognitive offloading and the emotional friction that comes from using a "black-box" algorithm.

Discussion & Key Findings

Phase 1: Data Screening & Normality Testing

Missing values were minimal because only 0.5% of the data was missing and listwise deletion created a clean dataset which contained 200 participants. The analysis showed that no extreme multivariate outliers existed because all Z scores were below three.

We assessed normality through Skewness and Kurtosis and the Kolmogorov-Smirnov (K-S) test. The items showed moderate negative skewness which ranged from -0.23 to -1.31 and this indicates that people tended to agree with the items. We found that all K-S tests showed uniform significance at $p < .001$ which demonstrated that the empirical distributions did not match a perfect normal curve, thus requiring non-parametric tests to evaluate the hypotheses.

Phase 2: Descriptive Statistics

Table 1: Descriptive Statistics

Construct / Item	Mean (M)	Std. Deviation (SD)	Interpretation
Trust in AI Recommendations	**3.43**	**0.83**	Moderate
T1: Trust financial recommendations	3.32	0.91	Moderate lean
T2: AI advice appears reliable	3.92	1.12	High lean
T3: Confident using suggestions	3.04	0.97	Moderate lean
Perceived Influence on Decision-Making	**3.82**	**0.95**	High
I1: Influence on saving decisions	3.56	1.12	High lean
I2: Affect investment choices	3.70	1.03	High lean
I3: Reduce effort required	4.20	1.08	Very High lean
Risk Perception	**4.08**	**1.02**	Very High
R1: AI involves certain risks	4.10	1.09	High lean
R2: Concern about possible errors	3.98	1.08	High lean
R3: Concern about data privacy	4.17	1.14	Very High lean

Interpretation

The data shows two different ways people behave. The data shows that people want to "cognitive offloading" because they found the effort-reduction item to be the most important item in the dataset. Risk Perception scores showed persistent superiority across all tests, especially about data privacy. The research shows that young Indians use AI for better productivity, but they experience high levels of anxiety while doing so.

Phase 3: Reliability Analysis

All constructs exceeded the acceptable >0.70 threshold, with no items flagged for deletion.

- **Trust in AI:** $\alpha = 0.762$ (Acceptable)
- **Perceived Influence:** $\alpha = 0.859$ (Good)
- **Risk Perception:** $\alpha = 0.914$ (Excellent)

Phase 4: Pearson Correlation Analysis

A correlation matrix was constructed to quantify the linear associations among the composite variables.

Table 2 Correlation Analysis

Construct	1. Trust	2. Influence	3. Risk
1. Trust in AI	**3.43 (0.83)**	0.71	0.41
2. Perceived Influence	0.71	**3.82 (0.95)**	0.57
3. Risk Perception	0.41	0.57	**4.08 (1.02)**

$p < .01$

Interpretation

- **The Trust-Influence Gateway (r = .71):** The research results demonstrate that trust acts as the main factor which connects positive correlation between two variables and their resulting behavioral changes. The study found that when users achieved higher levels of trust they became more likely to change their saving and investment practices.
- **The Calculated Trust Paradox (r = .41):** The data demonstrates that trust and risk relationship both inverses and creates a moderate positive connection. Users who utilize and trust AI the most are also the most aware of its inherent risks (data privacy, algorithmic errors).
- No multicollinearity was identified in the text; maximum correlation was detected at less than 0.85.

Phase 5: Convergent & Discriminant Validity

The Trust in AI dimension shows standardized factor loadings between 0.78 and 0.90 and an average variance extracted value of 0.689 and a composite reliability value of 0.869. The Perceived Influence dimension shows standardized factor loadings between 0.85 and 0.89 and an average variance extracted value of 0.781 and a composite reliability value of 0.914. The Risk Perception dimension shows standardized factor loadings between 0.92 and 0.93 and an average variance extracted value of 0.854 and a composite reliability value of 0.946.

All metrics exceeded standard thresholds because Loadings reached above 0.70 and AVE reached above 0.50 and CR reached above 0.70 which proved excellent Convergent Validity. The research established Discriminant Validity through the Fornell-Larcker criterion because all constructs' square root AVE values exceeded their correlation with other constructs.

Phase 6: Hypothesis Testing

In view of the fact that the data was not normally distributed, robust non-parametric tests were used.

H1: *Result:* $H(3) = 11.38$, $p = 0.010$

- *Decision:* **Reject Null Hypothesis.** Daily users demonstrate statistically higher trust levels than infrequent users, indicating trust is built through continuous experiential engagement.

H2: *Result:* $r_s = 0.576$, $p < 0.001$

- *Decision:* **Reject Null Hypothesis.** There is a highly significant positive relationship, reiterating that behavioral influence is gated by user trust.

H3: *Result:* $r_s = 0.233$, $p < 0.001$

- *Decision:* **Reject Null Hypothesis.** Though the effect size is weak, the statistically significant positive relationship confirms that informed users maintain both high trust and high risk-awareness concurrently.

Qualitative Thematic Insights

Table 3: Qualitative Dimensions

Theme	Codes	Interpretation
AI-Assisted Financial Planning	Budgeting, tracking, planning	AI supports financial discipline
Trust and Reliability	Verification, accuracy, trust	Users cautiously rely on AI
Perceived Benefits	Convenience, speed, insights	AI improves efficiency
Challenges and Concerns	Privacy, inaccuracy, dependence	Users remain cautious
Behavioral Changes & Future Adoption	Savings, planning, adoption	AI influences financial behavior

- An analysis was done on the responses of phenomenology surveys made on a larger scale through thematic regression to uphold the claim with evidence apart from the quantitative statistics.
- **AI-Assisted Financial Planning (Empowerment):**The participants used AI technology to maintain their financial responsibilities. The budgeting apps which offered users fast access to their financial information through visual dashboards helped users to implement better saving strategies.
- **The Black-Box Fear (Vulnerability):**People were worried about data privacy issues because they could not see how algorithms would operate. Users expressed hesitation to follow investment advice if they could not understand the underlying mathematical logic.
- **Retention of Personal Agency:**Young Indians conduct verification activities even though they utilize artificial intelligence. The majority of users do not implement AI trades without verification because they check algorithmic recommendations against their family members and financial experts.

Key Findings

The integration of quantitative matrices with qualitative themes gives a deeper insight into how young Indians interact with financial technology.

- **The Trust-Influence Nexus**

The study's most significant discovery (r = 0.71) proves that trust is not merely a passive attitude. The study shows that trust functions as an active force which brings about changes in people's behavior. When a 22-year-old trusts a robo-advisor, they actively shift capital and alter their savings rate. Fintech developers face an enormous fiduciary duty to create algorithms which maintain both unbiased results and mathematical accuracy.

- **The Privacy Paradox & Calculated Trust**

The Indian youth demographic exhibits its main distinction through the demonstration of the "Privacy Paradox." Users recorded peak scores for Risk Perception (M=4.08), which showed their intense fear about both data exploitation and potential mistakes. However, users continue to use the service despite their existing fears. The positive correlation between Risk and Trust (rs = 0.233) reveals a model of Calculated Trust. Young users possess advanced awareness because they use AI for its benefits while they proceed to test its maximum boundaries.

- **The Threat of Financial Deskilling**

Artificial intelligence improves budgeting efficiency by 4.20 million but the qualitative data indicates it creates "financial deskilling" for users. The system provides users with direct access to advanced trading features which leads them to ignore essential cognitive processes that develop authentic financial understanding. Young investors who want to fix their portfolios need basic skills to handle situations when algorithms break down or markets experience extreme unpredictable movements.

Conclusion

The integration of Artificial Intelligence into the personal finance routines of Indian youth represents a fundamental paradigm shift from traditional human-led management to an algorithmically mediated experience. This study shows through solid evidence that AI tools have a major impact on how people between 18 and 30 years old manage their saving and spending and investment activities.

The transition requires deep understanding of the "Empowerment-Vulnerability Paradox" which defines the process. Young users face two opposing outcomes because AI tools bring them exceptional benefits yet they create threats of data exploitation and financial deskilling.

The data shows that Indian youth use two patterns of trust which they describe as "Calculated Trust" and "Skeptical Adoption" to navigate their environment. The users depend on technology because it provides better results yet they choose to keep their personal control by checking algorithm suggestions against human decision-making. The development of AI tools will determine their function as educational support systems or as systems that hinder transformation into learning tools through the implementation of Explainable AI (XAI) and strict regulatory control and improved understanding of algorithms. The complete combination of these elements will create an artificial intelligence system which empowers people to achieve financial success while developing independence.

Practical Recommendations

The research results demonstrate that we can implement AI technology in personal finance through the following practical frameworks which will lead to responsible AI technology implementation.

- **For Fintech Developers: Transition to Explainable AI (XAI)** The "black-box" system used by current algorithms creates extreme anxiety for users. Fintech platforms must transition to Explainable AI (XAI). The algorithms should deliver simple explanation output which includes brief understandable reasons instead of providing direct "Buy/Sell" signals. The system establishes permanent trust through its transparent operations which also helps users maintain their skills by functioning as an educational tool.
- **For Policymakers & Regulators (RBI/SEBI)** The high risk-perception scores regarding data privacy requirements regulatory intervention. Authorities must establish frameworks that require retail-facing financial AI systems to disclose their algorithms and share their data.
- **For Educational Institutions: Algorithmic Literacy** Educational curricula must be updated to include "Algorithmic Literacy"—teaching students how to critically evaluate AI-generated financial advice, recognize algorithmic biases, and use AI as an analytical partner.

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