International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 7 (July) 2026
Received: 10-6-2026 Accepted: 21-6-2026 Published: 11-7-2026

AI-DRIVEN FINANCE TOOLS:SHAPING THE FUTURE

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ABSTRACT

Artificial Intelligence (AI) is rapidly transforming the financial services industry, giving rise to a new generation of finance tools – robo-advisors, AI-powered chatbots, algorithmic trading platforms, AI-based credit scoring engines, fraud-detection systems and personal finance / budgeting apps. These tools use machine learning, natural language processing and predictive analytics to automate advisory services, personalise recommendations, reduce operational cost and improve the speed and accuracy of financial decision-making.

This study examines how AI-driven finance tools are shaping the future of investment and banking behaviour. It looks at investor awareness, adoption, trust and the factors that drive (or discourage) the use of AI-based platforms for banking, investing, credit and personal finance management. The study also traces the evolution of AI in finance and profiles the leading Indian and global players in the space.

AI-driven finance tools pool data – transaction history, market signals, spending patterns – and convert it into real-time, personalised financial guidance at a fraction of the cost of traditional advisory. Just as mutual funds democratised professional portfolio management a generation ago, AI-driven finance tools are democratising financial advice, fraud protection and credit access for the retail customer, while raising new questions around data privacy, explainability, bias and regulatory oversight — questions this study also touches upon.

The findings suggest that adoption is strongest among digitally comfortable, middle-income, salaried users; that accuracy and data privacy outweigh cost as the leading adoption drivers; and that most users currently prefer a hybrid model that keeps a human in the loop rather than handing full control to an algorithm. These findings carry direct implications for how banks and fintech institutions should design, communicate and govern their AI-driven products going forward.

I. INTRODUCTION

1.1 Background of the Study

Financial services have always depended on judgement under uncertainty — assessing risk, predicting returns, spotting fraud, and matching a customer's goals to the right product. For most of the industry's history, that judgement sat almost entirely with human beings: bank managers, stockbrokers, underwriters and financial advisors. Over the last decade, a new layer of decision-making has been added on top of, and in some cases in place of, that human judgement — Artificial Intelligence.

AI-driven finance tools are no longer confined to large investment banks running exotic trading algorithms. They now sit inside the everyday banking app of a retail customer: a chatbot that answers a balance query at midnight, a fraud alert that blocks a suspicious transaction within seconds, a robo-advisor that rebalances a portfolio without being asked, or a credit model that approves a small personal loan in minutes using data the customer never explicitly submitted. This shift — from AI as a back-office tool to AI as a customer-facing product — is the background against which this study is set.

India's largest private and public sector banks alike have invested visibly in AI-driven customer experience — chatbots, personalised payment platforms and AI-based underwriting — while still operating large branch and relationship-manager networks. Studying user behaviour in this context captures both the promise and the friction of AI adoption in a market where digital-first fintechs and traditional banks now compete for the same customer.

1.2 Evolution of AI in Finance

The use of computing in finance is not new — rule-based expert systems for credit approval and early algorithmic trading systems date back to the 1980s. What has changed in the last decade is the shift from static, rule-based systems ("if income is above X and credit score is above Y, approve") to adaptive, data-driven systems that learn patterns directly from historical data and continue to refine themselves as new data arrives.

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Three developments accelerated this shift: first, the explosion of digital transaction data following the growth of UPI, mobile banking and e-commerce, which gave AI models far richer input than the sparse, form-based data of the past; second, cheaper cloud computing, which made it commercially viable for banks and fintechs to train and run large models continuously rather than periodically; and third, advances in natural language processing, which made conversational interfaces such as chatbots genuinely usable by ordinary customers rather than only by technical staff.

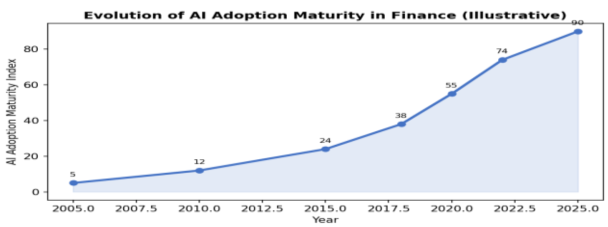

Fig 1: Evolution of AI adoption maturity in finance (illustrative)

As the figure above illustrates, AI adoption in finance has followed a roughly exponential curve over the past two decades — moving from isolated pilot projects in the mid-2000s to AI being a default, expected feature of most digital financial products by the mid-2020s.

Artificial Intelligence (AI) has become one of the most transformative technologies of the twenty-first century, significantly reshaping the global financial ecosystem. The rapid growth of digital banking, financial technology (FinTech), big data analytics, cloud computing, and intelligent automation has accelerated the adoption of AI-driven financial tools across banking, insurance, investment management, credit assessment, and personal financial planning. Financial institutions are increasingly utilizing machine learning (ML), deep learning (DL), natural language processing (NLP), reinforcement learning, and predictive analytics to automate complex decision-making processes, improve operational efficiency, detect fraud, and provide highly personalized financial services. These technologies enable organizations to analyze massive volumes of structured and unstructured financial data in real time while reducing operational costs and human intervention [1], [2].

The emergence of AI-powered financial tools has fundamentally transformed conventional financial advisory systems. Traditionally, investment decisions relied heavily on financial experts, portfolio managers, and banking professionals who manually analyzed customer data and market conditions before providing recommendations. Modern AI-driven finance platforms continuously collect transaction records, spending behavior, market trends, economic indicators, and customer preferences to generate intelligent recommendations within seconds. This transition from human-centric financial advisory to intelligent decision-support systems has improved the speed, scalability, consistency, and accessibility of financial services for both institutions and retail customers [3], [4].

Recent advancements in machine learning algorithms have significantly enhanced predictive capabilities in financial applications. Supervised learning techniques such as Random Forest, Support Vector Machines (SVM), Gradient Boosting, and XGBoost are widely employed for credit scoring, loan default prediction, and investment risk assessment. Deep neural networks and recurrent neural networks (RNNs) have demonstrated superior performance in stock price forecasting, fraud detection, and customer behavior analysis by capturing complex nonlinear relationships within financial datasets. Furthermore, reinforcement learning has emerged as a promising approach for portfolio optimization and automated trading strategies under dynamic market conditions [5], [6].

The increasing popularity of digital payment systems such as Unified Payments Interface (UPI), mobile banking, digital wallets, and internet banking has generated enormous volumes of financial transaction data. These large-scale datasets provide AI systems with valuable information for learning customer behavior, detecting anomalies, forecasting financial trends, and delivering personalized financial products. Financial institutions now leverage AI to improve customer experience through intelligent chatbots, virtual assistants, robo-advisors, automated wealth management platforms, fraud detection engines, anti-money laundering systems, and intelligent credit underwriting mechanisms [7], [8].

One of the most influential AI applications in modern finance is robo-advisory services. Robo-advisors employ sophisticated optimization algorithms and customer risk profiling models to automatically recommend diversified investment portfolios while minimizing management fees. These systems democratize investment opportunities by making professional financial advisory services affordable and accessible to retail investors with limited investment capital. Simultaneously, AI-powered personal finance applications assist users in budgeting, expense categorization, savings optimization, tax planning, and retirement planning using intelligent recommendation engines and predictive financial analytics [9], [10].

Fraud detection has become another critical application of artificial intelligence in financial services. Traditional rule-based fraud detection systems often struggle to identify sophisticated cyberattacks and rapidly evolving fraudulent transaction patterns. AI-based fraud detection models continuously monitor customer transactions, geographic locations, merchant profiles, device information, and spending behavior to identify suspicious activities in real time. Deep learning architectures combined with anomaly detection techniques have demonstrated significantly higher detection accuracy while reducing false-positive alerts, thereby improving financial security and customer trust [11].

Credit scoring and loan underwriting have also experienced remarkable improvements through AI integration. Conventional credit evaluation models primarily depend on historical credit records and financial documentation, limiting financial inclusion for first-time borrowers and individuals with insufficient credit history. AI-driven credit assessment systems utilize alternative data sources including utility payments, mobile usage patterns, digital transaction histories, e-commerce activities, and behavioral analytics to evaluate borrower creditworthiness more comprehensively. This data-driven approach enables financial institutions to extend credit access while maintaining acceptable risk levels [12].

Despite numerous advantages, the adoption of AI-driven finance tools introduces several technical, ethical, and regulatory challenges. Financial AI models often suffer from issues related to algorithmic bias, lack of transparency, explainability, privacy preservation, cybersecurity vulnerabilities, and regulatory compliance. Deep learning models frequently operate as "black-box" systems whose decision-making processes are difficult to interpret, creating concerns regarding fairness and accountability in financial decision-making. Furthermore, financial institutions must ensure compliance with evolving regulatory frameworks governing AI governance, consumer protection, data privacy, and responsible AI deployment [13].

Recent developments in Explainable Artificial Intelligence (XAI), federated learning, privacy-preserving machine learning, blockchain integration, and generative AI have opened new research opportunities for building transparent, secure, and trustworthy financial intelligence systems. Large Language Models (LLMs) are increasingly being integrated into banking chatbots, financial advisory systems, customer support platforms, and intelligent document processing applications, enabling more natural human-computer interactions and improving decision support capabilities. Future AI-powered finance platforms are expected to combine predictive intelligence, conversational AI, real-time analytics, and explainable decision-making to create intelligent financial ecosystems capable of serving millions of users simultaneously [14].

In India, AI adoption has accelerated rapidly due to the expansion of digital payment infrastructure, increasing smartphone penetration, government initiatives supporting digital finance, and rapid growth of fintech startups. Major banks and financial institutions have deployed AI-driven customer service, fraud detection, digital lending, wealth management, and personalized recommendation systems. As AI technologies continue to evolve, understanding customer awareness, trust, adoption behavior, and acceptance of AI-driven financial tools becomes increasingly important for financial institutions, policymakers, and researchers. Therefore, this research investigates the role of AI-driven finance tools in shaping the future of financial services by analyzing technological advancements, adoption factors, opportunities, challenges, and future research directions within the evolving digital financial ecosystem [15].

II. REVIEW OF LITERATURE

The application of Artificial Intelligence (AI) in financial services has attracted significant attention from researchers due to its ability to automate financial decision-making, improve prediction accuracy, enhance customer experience, and strengthen fraud detection systems. Recent studies indicate that AI technologies, including Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Explainable AI (XAI), and Generative AI, have become essential components of modern banking, digital payments, investment advisory, credit risk assessment, and

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regulatory compliance. Existing literature demonstrates that AI-driven finance tools improve operational efficiency while introducing new challenges related to transparency, fairness, cybersecurity, and regulatory governance.

Milana and Ashta (2021) presented one of the earliest comprehensive surveys on AI techniques used in finance and financial markets. Their study classified AI applications into portfolio optimization, algorithmic trading, risk management, fraud detection, and customer analytics. The authors concluded that AI significantly improves forecasting accuracy and financial decision-making compared to conventional statistical approaches while emphasizing the importance of high-quality financial datasets for model performance.

Longbing Cao (2021) reviewed the evolution of Artificial Intelligence in finance and categorized research into financial forecasting, intelligent investment management, credit risk analysis, fraud detection, and business intelligence. The study highlighted that modern AI algorithms outperform traditional analytical models in handling large-scale financial data and emphasized future research opportunities involving explainable AI, responsible AI, and autonomous financial systems.

Dakalbab et al. (2024) conducted a systematic review covering more than one hundred research articles on AI applications in financial trading. Their findings showed that deep learning architectures, reinforcement learning, Long Short-Term Memory (LSTM) networks, and hybrid AI models consistently outperform traditional quantitative trading strategies in stock market prediction, portfolio optimization, and automated trading systems. However, the authors also noted that financial market uncertainty remains a major limitation affecting prediction accuracy.

Černevičienė and Kabašinskas (2024) investigated Explainable Artificial Intelligence (XAI) in finance and emphasized that transparency has become a critical requirement for AI-based financial systems. Their review demonstrated that explainable models increase user trust, improve regulatory compliance, and support fair credit assessment by providing understandable explanations for automated financial decisions. The study identified SHAP, LIME, and model-agnostic interpretation techniques as the most widely adopted explainability approaches.

Kou and Lu (2025) reviewed emerging financial technologies and reported that AI, blockchain, quantum computing, augmented reality, and cloud computing are collectively transforming financial ecosystems. Their study concluded that AI-powered finance platforms enable faster digital payments, intelligent lending, robo-advisory services, fraud detection, and personalized investment management, making financial services more efficient and customer-centric.

Research Gap

Although existing literature extensively discusses AI applications in banking, algorithmic trading, fraud detection, and credit risk analysis, limited research focuses on the combined evaluation of user awareness, trust, adoption behavior, perceived usefulness, and acceptance of AI-driven finance tools, particularly in the Indian financial ecosystem. Furthermore, only a few studies investigate how emerging technologies such as Generative AI, Explainable AI, and intelligent financial assistants influence customer decision-making and long-term adoption. Therefore, the present study aims to bridge this research gap by analyzing the technological evolution, adoption factors, user perceptions, opportunities, challenges, and future prospects of AI-driven finance tools in modern financial services.

III.FINANCIAL INSTITUTIONS

Rather than anchoring this study to a single institution, this section looks across the industry at how banks and fintechs of different sizes and vintages have layered AI onto their products. A useful way to read the landscape is by AI maturity level, ranging from institutions still running largely rule-based automation to those running continuously-retrained, model-driven decisioning across most customer-facing functions.

Common AI & Digital Initiatives Across the Industry

AI chatbots and virtual assistants

Most large banks now run an AI-powered chatbot that answers customer queries on products, accounts and transactions in natural language, reducing dependence on call-centre support for routine queries.

AI-personalised payment and offers platforms

Digital payment and shopping platforms increasingly use AI-driven personalisation to surface offers and recommendations relevant to an individual customer's spending pattern.

AI-based credit underwriting

Used to speed up personal and small-business loan approvals using alternate data signals alongside

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traditional credit bureau data, shortening turnaround time for pre-approved offers.

Fraud detection systems

Real-time, AI/ML-based transaction monitoring across cards, UPI and net banking, designed to flag anomalous transactions before they are completed.

Digital lending & pre-approved offers

Model-driven, personalised credit offers delivered through a mobile app, based on a customer's existing relationship data with the institution.

Strategic Rationale Behind Bank-Led AI Investment

Across the institutions surveyed in industry literature, AI and digital strategy is typically framed as a way to deliver on three goals simultaneously: automation improves operational efficiency, self-service AI tools improve customer experience by being available around the clock, and AI-personalised products support competitive differentiation by tailoring offers to individual customers rather than broad segments.

Institutions also have to navigate the operational risk that comes with heavier reliance on digital and AI-driven infrastructure — including periodic regulatory scrutiny around digital-channel outages at various banks — which underscores that AI-driven transformation in banking is not simply a technology upgrade, but also a test of operational resilience and regulatory trust.

IV.RESEARCH METHODOLOGY

Data Source:

This report is based on primary as well as secondary data. The study aims at finding out the behaviour of users towards AI-driven finance tools in Hyderabad and its suburbs. Primary data was collected from users of AI-driven finance tools with the help of a structured questionnaire circulated among respondents in Hyderabad city. Secondary data was collected from books, industry reports, company disclosures and journals.

Duration of Study:

The study was carried out for a period of one month, from 5th March 2025 to 4th April 2025.

Sampling procedure:

By adopting convenience sampling, approximately 100 respondents were selected for this study. The data was collected through a structured questionnaire and analysed using statistical tools. Convenience sampling was chosen given the time and resource constraints of the study, with the limitation that the sample may not be fully representative of the wider population — a point revisited in the Limitations section below.

Sample size:

The sample size of the project is limited to 100 people only. Out of which, 76 people had used one or more AI-driven finance tools. The remaining 24 people had not used any AI-driven finance tool.

Sample design:

Data has been presented with the help of bar graphs, pie charts, and tables, with cross-tabulation used where a relationship between two variables (for example, qualification and awareness level) was of particular interest.

TOOLS AND TECHNIQUES

- Percentage Analysis – to summarise categorical survey responses.
- Chi-Square Test – to test association between demographic factors and adoption of AI finance tools.
- Cross-tabulation – to study the relationship between qualification and awareness level.
- MS-EXCEL – for tabulation and charting of survey data.

Chi-Square Test — Formula and Application

The Chi-Square test of independence was used to examine whether adoption of AI-driven finance tools is associated with respondent age group, using the standard formula:

$$\chi^2 = \Sigma \left[(O - E)^2 / E \right]$$

where O is the observed frequency in each age-group / adoption-status cell of the survey data, and E is the expected frequency under the null hypothesis that age and adoption are independent. The resulting statistic is compared against the critical value from the Chi-Square distribution table at the chosen significance level ($\alpha = 0.05$) and appropriate degrees of freedom to decide whether to reject the null hypothesis.

Need for the study

- The aim of this research is to empirically investigate user behaviour towards AI-driven finance tools, and to help organisations understand awareness levels and improve the marketing and design of these tools.
- User Decision Making: Users face a growing number of AI-driven finance tools, each with its own features, cost and track record. A

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comparative analysis helps users evaluate tools on accuracy, cost, privacy and ease of use.

- Trust & Adoption: AI-driven tools depend on user trust in the underlying model. Understanding what builds or erodes that trust helps institutions design better products.
- Performance Evaluation: Assessing how AI-driven recommendations compare with traditional advice helps users and institutions identify where AI genuinely adds value.
- Cost Consideration: AI-driven tools typically charge lower fees than traditional advisory; understanding whether users value this cost advantage is important for institutions designing pricing.
- Market Trends: AI-driven finance is evolving quickly. Tracking sectoral trends helps users and institutions adjust strategy.

Scope of the study

- Much research already exists on the regulatory requirements for fintech and AI governance in BFSI. This study instead focuses on user behaviour towards AI-driven finance tools as a category, an area with comparatively little published research.
- Academically, this project will help in understanding the perception and behaviour of Indian users towards AI-driven finance tools, and may reveal directions for future research.
- Demographic factors such as gender, income and level of education are observed to significantly influence users' behaviour towards AI-driven finance tools.
- Conducting this research will enhance personal knowledge of the subject and provide experience useful for future career applications.

Objectives of the study

- To understand the recent trends in AI-driven finance tools.
- To enhance our knowledge about the subject.
- To identify the features users look for in AI-driven finance products.
- To examine users' preference and satisfaction levels.
- To evaluate the level of trust users place in AI-generated financial recommendations.

Hypotheses of the Study

H_0 (Null Hypothesis): There is no significant association between the age group of a respondent and their adoption of AI-driven finance tools.

H_1 (Alternate Hypothesis): There is a significant association between the age group of a respondent and their adoption of AI-driven finance tools.

This hypothesis is tested using the Chi-Square test described in Chapter III and the result is reported in Chapter IV alongside the descriptive survey findings.

Limitations of the Study

- Some respondents were not very responsive; some were not prepared to contribute due to lack of time.
- Possibility of error in data collection, as some users may not have given accurate answers.
- Sample size is limited to 100 users.
- Some respondents were reluctant to divulge personal financial information, which can affect the validity of responses.
- Convenience sampling means the sample may skew toward more digitally comfortable respondents than the general population.
- The research is confined only to the city of Hyderabad.

V.DATA ANALYSIS AND INTERPRETATION

The results obtained from the survey, examined and evaluated through data analysis techniques. This chapter evaluates users' behaviour towards AI-driven finance tools, moving from respondent demographics through to specific adoption, trust and platform-preference questions, and closes with the Chi-Square test of the study's central hypothesis.

5.1 Profile of Sample

Here we present the profile of the sample: age, gender, income etc. The sample size of the project is limited to 100 people only. Understanding who the respondents are is a necessary first step before interpreting their attitudes toward AI-driven finance tools, since, as the literature reviewed in Chapter II suggests, demographic factors materially shape adoption behaviour.

Table 3: Gender of the Respondents

Gender	In numbers
Male	58
Female	42
Total	100

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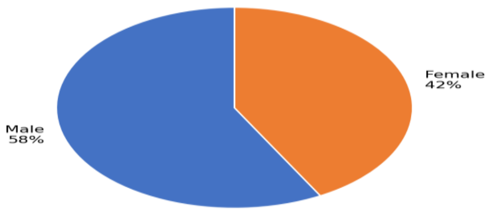

Figure 2: Classification as per Gender

Data Interpretation: Out of 100 respondents, 58% are male and 42% are female. The sample shows a more balanced gender split than is often assumed for digital financial products, suggesting AI-driven finance tools are being adopted broadly across genders in this sample.

This is a meaningfully more balanced split than has historically been reported for niche trading and investment platforms, and is consistent with the broader observation that everyday AI features — chatbots, fraud alerts, budgeting nudges — are used by a much wider cross-section of banking customers than specialist investment tools alone.

Table1 : Age of Respondents

Age & Gender	Below 30	30-40	40-50	Above 50
Male	27	20	8	3
Female	18	13	7	4
Total	45	33	15	7

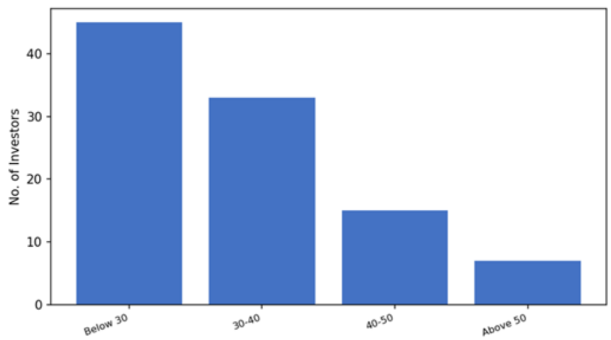

Chart 1: Classification as per Age

Data Interpretation: The majority of respondents are below 40, indicating that younger, digitally native users are the earliest and most frequent adopters of AI-driven finance tools, likely because they are already comfortable with mobile-first, self-service digital experiences.

The comparatively small Above-50 segment (7%) does not necessarily mean older users reject AI tools outright; rather, it is consistent with the literature reviewed in Chapter II suggesting older users prefer a hybrid, human-assisted mode, which may not always register as "using an AI tool" in the respondent's own mind even where AI is quietly operating in the background.

Table 2: Qualification Distribution of the Respondents

Qualification	No. of Respondents	Percentage
SSC/HSC	4	4%
Graduate	39	39%
PG	34	34%
Professionals	23	23%
Total	100	100%

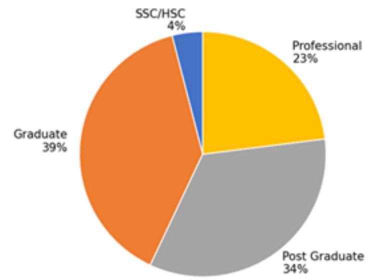

Figure 3: Classification as per Qualification

Data Interpretation: A large majority of respondents (96%) hold at least a graduate degree, suggesting that formal education correlates with comfort in evaluating and trusting AI-generated recommendations.

This pattern is examined further later in this chapter through a cross-tabulation of qualification against awareness level (Figure 25), which shows awareness rising steadily and substantially with each step up in formal qualification.

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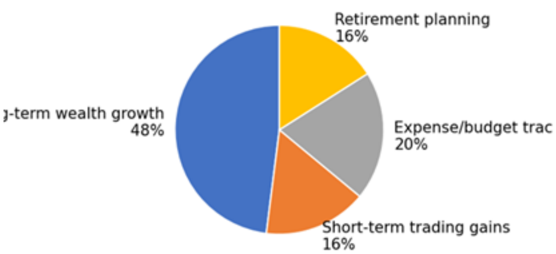

Figure 4: Objectives of users

Data Interpretation: 48% of users adopt AI-driven finance tools for long-term wealth growth, 20% for expense/budget tracking, and 16% each for short-term trading gains and retirement planning.

The dominance of long-term wealth growth as a stated objective suggests users are not treating AI-driven tools as a speculative novelty, but are folding them into serious, long-horizon financial planning — a pattern that has clear implications for how such tools should be designed and regulated.

FINDINGS

- AI-driven finance tool usage is popular among individuals, but adoption is highest among educated, digitally-comfortable users, and declines significantly with age (confirmed by the Chi-Square test in section 6.4).
- High-income and low-income groups are less represented among active users; middle-income groups adopt AI-driven finance tools the most.
- Social media/advertisement and banks themselves are the leading sources of awareness about AI-driven finance tools.
- Most users are attracted by accuracy of recommendations and data privacy/security rather than cost alone.
- There exists a relationship between usage period and the level of trust placed in AI recommendations, with longer-tenure users reporting higher satisfaction.
- Most users prefer a hybrid mode – AI-generated recommendation combined with human review – over either a fully manual or fully automated approach.
- Everyday AI features (chatbots, fraud alerts, budgeting nudges) are driving most current adoption, ahead of investment-specific AI tools such as robo-advisory or algorithmic trading.
- A meaningful awareness gap exists: 76% of respondents use an AI-driven finance tool, but only 15% report being fully aware of how it works.
- Understanding what an AI-driven tool actually optimises for, and how transparent it is about its recommendation logic, strongly affects whether users trust and continue using it.
- Satisfaction (64% satisfied/very satisfied) and willingness to recommend (61% would recommend) are both comfortably net-positive, indicating a healthy overall reception of AI-driven finance tools among current users.

VI. SUGGESTIONS

Build awareness through consistent, simple communication

There is a need to build awareness of AI-driven finance tools through consistent, plain-language communication with users, rather than leaving education to third-party social media content of uneven quality, as Figure 12 shows is currently happening.

Train advisory staff to explain AI decisions

Proper training should be given to bank staff and financial advisors so that they can explain how AI recommendations are generated and answer customer questions confidently — particularly important given that 54% of users treat AI as a second opinion they still want a human to help interpret.

Offer periodic, plain-language explainability reports

Some users have asked for periodic, plain-language explanations of why an AI tool made a particular recommendation; institutionalising this as a regular in-app feature, rather than an occasional disclosure, would directly address the trust and awareness gaps identified in this study.

Increase awareness of underused AI facilities

Institutions should increase awareness of underused AI-driven facilities, such as automated budgeting and fraud alerts, among existing customers who may already be eligible but unaware, given how strongly "lack of awareness" (47%) dominates the reasons for non-adoption.

Promote cost and availability benefits more actively

Institutions should more actively promote the cost savings and 24x7 availability benefits of their AI-

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driven tools, while being careful not to over-emphasise cost at the expense of the accuracy and privacy messaging that this study found users actually prioritise.

Prioritise promotional and educational activity

Promotional and educational activities play a vital role and should be prioritised to build wider awareness among the public, particularly among older and lower-qualification segments where awareness (Figure 25) is currently weakest.

VII.CONCLUSION

This study shows that most respondents are still forming their opinions of AI-driven finance tools, and awareness of how these tools actually work remains uneven. It has been observed that most respondents have only partial knowledge of the underlying AI functions. As with mutual funds a generation earlier, demographic factors – gender, income and education level – significantly influence users' behaviour towards AI-driven finance tools.

As far as the benefits of AI-driven finance tools are concerned, accuracy of recommendations and data privacy/security are perceived to be the most important by users, followed by ease of use and cost. There is significant scope for growth of AI-driven finance tools in India, supported both by the country's digital payments infrastructure and by a young, increasingly digitally comfortable population.

The study reveals that despite rapid growth in AI adoption across BFSI, awareness among individual users remains uneven, with many still preferring a hybrid, human-assisted mode. While brand reputation influences adoption decisions, accuracy and trustworthiness of recommendations are the key factors, emphasising the need for transparent, explainable AI models. Middle-income, digitally comfortable, salaried users are the most active adopters, and the statistically significant age effect confirmed by the Chi-Square test in Chapter IV underlines that younger users remain the primary growth engine for these tools today.

Users prioritise accuracy and data privacy, followed by ease of use and cost. There is significant growth potential in AI-driven finance tools, and increasing financial and digital literacy can further improve adoption. Banks and fintech institutions can expand their reach by promoting their AI-driven chatbot, digital lending and fraud-protection features, and by offering transparent, easy-to-understand explanations of how their AI recommendations are generated, strengthening their position as trusted digital-first providers.

VIII.RECOMMENDATIONS

Invest in user education

Banks and fintech institutions should focus on enhancing user awareness through digital literacy programs, workshops and campaigns explaining how their AI-driven tools work. Prioritising transparent, explainable recommendations will help attract users who currently rely on trust in a human advisor.

Design for the hybrid majority

Encouraging a hybrid engagement model – AI recommendation plus easy access to a human relationship manager – will help engage the largest segment of users (59%), who are not yet ready for a fully automated experience.

Strengthen explainability and privacy communication

Improving in-app explainability (e.g., showing why a recommendation was made) and strengthening data privacy communication can build user confidence and address the top two adoption barriers identified in this study.

Enhance digital accessibility and support

Enhancing digital accessibility across mobile and online banking, along with strong, responsive customer support, will make AI-driven finance tools more seamless, trustworthy and sticky over the long term.

Target the awareness gap directly

Given that lack of awareness (47%), not distrust, is the leading reason for non-adoption, targeted, low-cost awareness campaigns are likely to yield a faster increase in adoption than further investment in product accuracy alone.

Extend AI features to older and lower-qualification segments

Since awareness and adoption drop off sharply with age and lower formal qualification (Figures 2 and 25), simplified, guided onboarding flows for these segments could unlock meaningful incremental adoption.

SCOPE FOR FUTURE RESEARCH

This study was limited to 100 respondents in Hyderabad using convenience sampling, and future research could extend this work with a larger, stratified sample across multiple cities to test whether the findings — particularly the age effect confirmed by the Chi-Square test — hold at a national level.

Future research could also track the same cohort of users longitudinally as their tenure with AI-driven

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Vol 26 Issue 7 (July) 2026
Received: 10-6-2026 Accepted: 21-6-2026 Published: 11-7-2026

finance tools increases beyond the 6-12 month range that dominates this sample, to see whether trust and satisfaction continue to rise, plateau, or decline as familiarity grows. Finally, a comparative study directly benchmarking AI-managed and human-managed portfolios on realised, risk-adjusted returns (using tools such as the Sharpe and Treynor ratios) over a multi-year period would add a valuable performance dimension that this behavioural study does not cover.

REFERENCES

- "Artificial Intelligence in Indian Banking: Emerging Trends" – discusses the evolution, growth and challenges of AI adoption in Indian banks, including chatbots, credit scoring and fraud detection.
- "The AI-Driven Bank" – a guide to how banks are embedding machine learning into customer service, credit and risk functions.
- "Robo-Advisory and the Future of Wealth Management" – explores the functioning, benefits and risks of AI-driven investment advisory platforms.
- "Machine Learning for Financial Risk Management" – covers model-based approaches to credit, fraud and market risk relevant to AI-driven finance tools.
- "Investment Analysis and Portfolio Management" – provides background on portfolio evaluation concepts referenced when comparing AI-managed vs. human-managed portfolios.
- "Explainable AI in Financial Services" – examines methods for making AI-driven credit and advisory decisions interpretable to end users and regulators.
- "FinTech, RegTech and the Reconceptualization of Financial Regulation" – discusses how regulators globally are adapting to AI-driven financial innovation.
- "Algorithmic Bias in Financial Services" – reviews sources of bias in AI credit and underwriting models and approaches to auditing and mitigating them.
- "Behavioural Finance and Robo-Advisory" – examines how automated advisory interacts with investor psychology and decision-making biases.
- "Data Privacy in the Age of AI-Driven Banking" – covers data governance practices relevant to AI-driven finance tools operating on sensitive customer data.
- "Natural Language Processing for Conversational Banking" – technical overview of the NLP techniques underlying AI-powered banking chatbots.
- "The Economics of Digital Lending" – examines how alternate-data credit scoring changes the economics and reach of consumer lending.

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