Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2025): 8.619 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 12 | Issue: 6 | June 2025 -Peer-Reviewed Journal

ARTIFICIAL INTELLIGENCE IN FINANCIAL ANALYSIS

Sudeep Tholar[1], Sowmya D.S[2]
[1]*MBA Student RV Institute of Management, Bengaluru*
[2]*Assistant Professor, RV Institute of Management, Bengaluru*

Article DOI: https://doi.org/10.36713/epra22818
DOI No: 10.36713/epra22818

1. ABSTRACT

This study examines the role of artificial intelligence in financial analysis through a comprehensive survey of 240 respondents across various age groups and educational backgrounds. Using chi-square and regression analyses, the research investigates relationships between demographic factors, AI understanding, and attitudes toward AI financial applications. Key findings reveal a significant association between age group and trust in AI financial systems ($\chi^2(20) = 44.9$, $p = 0.001$, Cramer's $V = 0.216$), with middle-aged respondents (45-54 years) demonstrating the highest trust levels. Additionally, AI understanding significantly predicts comfort with AI analyzing personal financial data ($\beta = 0.167$, $p = 0.016$), though the effect is modest ($R^2 = 0.0240$). The study identifies investment management (24.6%) and fraud detection (22.9%) as the areas most improved by AI, while revealing substantial concerns regarding algorithmic bias (65.8% moderately to extremely concerned) and data security (only 4.6% expressing complete trust). These insights provide valuable guidance for financial institutions implementing AI solutions and highlight the importance of transparency and education in fostering AI adoption.

KEYWORDS: *Artificial Intelligence, Financial Analysis, Trust, Algorithmic Bias, Transparency, Consumer Attitudes*

2. INTRODUCTION

Artificial intelligence technologies are transforming the financial sector as they are progressively integrated into its different domains. Applications of AI span from algorithmic trading and portfolio optimization to fraud detection to customer service, changing the way of doing, and delivering, financial analysis (Malali & Gopalakrishnan, 2020). The first evolution is characterized by both substantial opportunities and challenges for the financial institution and its customers.

AI systems in finance use Big data, sophisticated algorithms, and computational resources to find patterns, predict the future and automate the decision making processes that were usually accomplished by an analyst human (Anil & Misra, 2022). Improved efficiency, lower costs, increased accuracy and the democratization of high end financial analysis previously reserved for institutional Investor and/or high net worth individuals (Bhatia et al., 2021).

However, the implementation of AI in financial analysis carries with it certain issues that are crucial in identifying the transparency, the susceptibility of the algorithms to certain biases and data security (Singh & Pathak, 2020). Since these technologies are becoming increasingly accessible, knowing how various groups of people perceive and trust the use of AI in financial tools is critical to effective utilization and adoption.

As a specific case of where AI is being adopted and applied in the financial system, the Indian financial landscape is highly interesting given its combination of rapid technological advancement with inequality in digital and financial literacy and inclusion amongst the Indian population (Rai & Shekha, n.d.). This is a special environment where not only the use cases of traditional financial practices are integrated with cutting edge AI applications, but the benefits and limitations of the technological shift itself are very benign.

Precisely, the focus of this study is to investigate consumer attitudes and perceptions towards AI in financial analysis, especially regarding the effects of factors such as age, educational level, and understanAId of AI technologies on incorporating trust, comfort and acceptance of AIpowered financial services. The research studies these relationships to offer findings intended to inform financial institutions, regulators, and technology

developers in developing AI solutions that appropriately respond to consumer concerns in ways that fully realize the promises of these advanced technologies.

3. BACKGROUND

Artificial intelligence is the latest step in financial sector digital transformation where it is becoming integrated within financial analysis. In order to understand the current landscape, one must first recognize the path of AI in finance, major applications in AI, key challenges and contextual differences for AI adoption in India.

Evolution of AI in Financial Analysis

From a simple rule based expert system to sophisticated machine algorithms which can handle the complex and unstructured data (Malali & Gopalakrishnan, 2020). The early applications of AI were more based on automating routine tasks whereas modern AI systems have more advanced pattern recognition, natural language processing, predictive analytics that make it possible to augment or even replace traditional human analysis (Anil & Misra, 2022).

Due to the exponential growth in computing power, the vast availability of big data, improvements in the design of algorithms, and competitive pressures in the industry (Srivastava, 2018), the adoption of AI in finance has also been accelerated. As such, AI capabilities are seen as essential rather than optional by financial institutions, which in turn make huge investments in both inhouse development and partnerships with fintech companies (Singh & Pathak, 2020).

Key Applications in Financial Analysis

There is a whole range of financial analysis activity in which AI applications are felt. Robo-advisors offer investment management using algorithms to manage client risk profiles and goals making investment advice democratised (Bhatia et al, 2021). Machine learning models allow to process mountains of historical time series data, news sentiment and macroeconomic indicators to uncover what's not visible to human analysts for market forecasting and trend analysis (Kulshrestha & Srivastava, 2020).

With its ability to analyze both traditional and alternative data sources, AI has revolutionized risk assessment and credit scoring enabling the opening of doors for financial services to previously underserved populations (Anil & Misra (2022). The fraud detection systems utilize the anomaly detection algorithms for detecting the suspicious transactions in real time and thus help in strengthening the security measures (Malali & Gopalakrishnan, 2020). AI based chatbots and virtual assistants have enhanced customer service by offering 24 x 7, support on routine queries (Singh & Pathak, 2020).

Challenges and Concerns

There is a risk – because of its many challenges, AI in financial analysis is still far from perfect. Algorithmic bias is a very critical issue, because models trained on historical data might reinforce or make the existing inequalities in financial systems worse (Rai & Shekha, n.d.). Sophisticated AI algorithms have a 'black box' nature making them hard for users to grasp what is being decided and how decisions are made, raising regulatory compliance questions (Bhatia et al., 2021).

Due to data privacy and security concerns during processing of sensitive financial information through AI systems that could also be prone to adversarial attacks (Shrivastava & Mahajan, 2016), protecting financial information becomes paramount. Furthermore, there is still no consensus regarding the right balance of human judgment and AI automation, which includes currently debated cases of whether AI should help or replace human analysts in specific fields (Joshi, E. et al., 2021).

AI Adoption in Indian Financial Context

AI and its wider adoption in finance in India is a story of rapid advancement of tech sector in India amidst disparate levels of digital literacy and financial inclusion (Srivastava, 2018). However, fintech innovation of the country has seen a great boom both from the existing institutions as well as the startups using AI for numerous financial applications (Singh & Pathak, 2020).

India's regulatory environment continues to adapt, considering the velocity of AI innovation with consumer protection and systemic stability in mind (Rai & Shekha, n.d.). Other cultural factors affecting AI adoption include variable degrees of technological trust across particular demographic segments and regions (Joshi et al., 2021). Given the large unbanked and underbanked populations that could reap the advantages of alternative credit scoring

and available financial services, the potential for AI to bridge financial inclusion gaps in India is especially vast (Bhawna & Gupta, 2025).

4. PROBLEM STATEMENT

Artificial intelligence has increasingly been integrated into financial analysis, and yet there is still a vast lack of knowledge as far as various demographic groups understand, trust and interact with these technologies. However, it is poorly documented how users' understanding of AI correlate with their comfort with AI-powered financial tools thus presenting a challenge in designing and prototyping such features effectively. In addition to this, algorithmic bias, data security and the correct balance between human insight and AI automation remain impediments to wider adoption.

Currently, financial institutions do not have comprehensive insights into which specific AI applications are seen as most valuable by consumers and how the perception of AI applications by age, educational background or levels of financial literacy differs. Such a knowledge gap hinders the development of targeted consumer strategy to engage with consumer concerns and help build trust related to AI financial systems. While there are high potential benefits of AI in democratizing financial analysis, there is also much to be concerned about related to transparency, bias, and privacy, a careful empirical investigation is required to figure out how to implement them in a balanced way in the financial sector.

5. LITERATURE REVIEWS

Author/ year	Objective	Methodology	Key Findings	Summary
Malali & Gopalakrishnan (2020)	To provide an overview of AI applications in Indian banking and financial industry.	Literature review and industry analysis.	Identified key AI applications in customer service, fraud detection, and risk assessment; highlighted adoption challenges including legacy systems and data privacy concerns.	Offers a comprehensive overview of early AI adoption in India's financial sector, establishing the foundation for understanding current implementation patterns.
Anil & Misra (2022)	To analyze AI implementation in peer-to-peer lending platforms in India.	Cross-case analysis of multiple P2P lending platforms.	Found AI significantly improves credit scoring accuracy and reduces default rates; implementation varies widely across platforms with regulatory compliance posing challenges.	Provides focused insights on a specific financial subsector, demonstrating tangible benefits of AI in alternative lending while highlighting implementation variations.
Bhatia et al. (2021)	To discover the operational architecture and consumer perception of robo-advisory services.	Qualitative research using semi-structured interviews with industry experts.	Identified key components of successful robo-advisory platforms; found trust and transparency are critical factors influencing consumer adoption.	Examines the human-AI interface in investment advisory, revealing factors that influence trust in automated financial advice.
Singh & Pathak (2020)	To explore the emerging role of AI in the Indian banking sector.	Conceptual analysis and case examples.	AI adoption is transforming customer service, risk management, and fraud detection; significant implementation barriers include technological infrastructure and skilled workforce shortages.	Highlights the transformative potential of AI in traditional banking while acknowledging practical implementation challenges in the Indian context.

Rai & Shekha (n.d.)	To compare global AI trends in financial markets with India's approach and regulatory challenges.	Comparative analysis and regulatory review.	Regulatory frameworks lag technological developments globally; India faces unique challenges in adapting international best practices while addressing local market needs.	Provides valuable regulatory perspective, highlighting the gap between technological advancement and governance frameworks in financial AI.
Kulshrestha & Srivastava (2020)	To develop an AI approach that combines technical and fundamental analysis for portfolio optimization.	Empirical testing of hybrid AI models on Indian stock market data.	Hybrid models integrating both technical and fundamental analysis outperformed single-approach models in portfolio optimization; demonstrated 12-15% improved returns.	Offers quantitative evidence of AI's effectiveness in investment strategies when multiple analytical approaches are synthesized.
Bhawna & Gupta (2025)	To explore AI applications in streamlining accounting and finance processes in India.	Comprehensive review of AI use cases in financial operations.	AI significantly improves efficiency in financial reporting, audit processes, and compliance management; implementation requires organizational restructuring and training.	Focuses on operational finance applications, providing forward-looking insights into how AI transforms back-office financial functions.
Shrivastava & Mahajan (2016)	To analyze artificial intelligence research output in India through scientometric analysis.	Bibliometric analysis of research publications (1968-2014).	AI research in India has grown significantly but lags behind global leaders; computer science dominates with limited cross-disciplinary work with finance.	Provides historical context on India's AI research landscape, highlighting the gap between academic research and financial applications.
Joshi et al. (2021)	To review the efficacy of AI usage in financial decision-making within Indian organizations.	Qualitative review of implementation cases.	AI demonstrates high efficacy in data-driven decisions but implementation success varies widely; organizational culture significantly impacts adoption success.	Examines organizational factors affecting AI implementation success, emphasizing the human and cultural dimensions of technology adoption.
Srivastava (2018)	To outline strategic directions for AI development in India across sectors, including finance.	Policy analysis and strategic framework development.	Recommends focused investment in AI research, public-private partnerships, and regulatory frameworks; financial sector identified as high-impact area for AI development.	Provides policy-level perspective on AI development in India, positioning financial applications within broader national AI strategy.

5.1 RESEARCH GAP

While existing literature explores AI applications in Indian banking (Malali & Gopalakrishnan, 2020; Singh & Pathak, 2020) and robo-advisory services (Bhatia et al., 2021), significant empirical gaps remain. Current research lacks comprehensive examination of how **age demographics influence trust levels** in AI financial systems, despite our findings showing significant association (χ^2=44.9, p=0.001). Additionally, although understanding of AI weakly predicts comfort with personal data analysis (β=0.167, p=0.016, R^2=0.0240), deeper investigation into factors affecting this relationship is needed. Furthermore, existing literature inadequately addresses the substantial

concerns about AI bias and security (65.8% moderately to extremely concerned), particularly regarding implementation of transparency mechanisms that 74.2% of respondents consider critically or very important.

6. RESERCH DESIGN

Research Approach

This study employed a quantitative research methodology using a structured survey to collect data on respondents' perceptions, experiences, and attitudes regarding artificial intelligence in financial analysis. This approach allowed for statistical analysis of relationships between key variables and identification of patterns across demographic groups.

Research Objectives

The research was guided by the following specific objectives:

1. **To examine the association between age group and level of trust in AI financial systems.**
    - *Rationale:* To understand how demographic factors influence trust, a critical precursor to AI adoption in financial contexts.
2. **To determine if understanding of AI predicts comfort with AI analyzing personal financial data.**
    - *Rationale:* To assess whether education and familiarity with AI technologies can mitigate privacy and security concerns.
3. **To identify which financial services are perceived as most improved by AI applications.**
    - *Rationale:* To guide prioritization of AI implementation efforts toward areas with greatest perceived value.
4. **To assess the level of concern regarding algorithmic bias in AI financial systems across demographic groups.**
    - *Rationale:* To understand the extent of concerns about fairness and equity in AI-powered financial analysis.

Sampling

Data was collected from 240 respondents representing various age groups, educational backgrounds, and levels of familiarity with both financial concepts and AI technologies. The sample was characterized by:

- **Age Distribution:** Predominantly mid-career professionals (35-44 years: 41.7%; 25-34 years: 27.1%)
- **Education:** Highly educated (Bachelor's degree: 56.3%; Master's degree: 20.0%)
- **Financial Familiarity:** Moderate to basic knowledge (Moderately familiar: 35.8%; Somewhat familiar: 33.3%)
- **AI Understanding:** Mid-level knowledge (Moderate understanding: 36.7%; Basic understanding: 25.4%)

While convenience sampling was utilized, efforts were made to include respondents across various age groups and backgrounds to capture diverse perspectives.

Data Collection Instrument

A structured questionnaire consisting of 16 closed-ended questions was developed to collect data. The instrument included:

- **Demographics:** Age group, education level, familiarity with financial concepts, understanding of AI
- **Experience with AI Financial Tools:** Tools used, sources shaping perception, services improved
- **Attitudes and Perceptions:** Confidence in AI vs. humans, perceived impact, concern about bias, comfort with personal data analysis, trust in AI security, views on AI replacing analysts, importance of transparency, benefits vs. risks assessment

The questionnaire used various response formats including multiple-choice for demographic questions and Likert scales for attitudinal items.

Data Analysis Techniques

Data analysis was conducted using Jamovi statistical software. The primary analytical techniques included:

- **Descriptive Statistics:** Frequencies and percentages for all variables to summarize overall patterns
- **Chi-Square Test of Independence:** Used to examine the association between Age Group (categorical) and Trust in AI Financial Systems (categorical)
- **Linear Regression:** Used to assess if Understanding of AI (ordinal treated as continuous) predicts Comfort with AI Analyzing Personal Financial Data (ordinal treated as continuous)

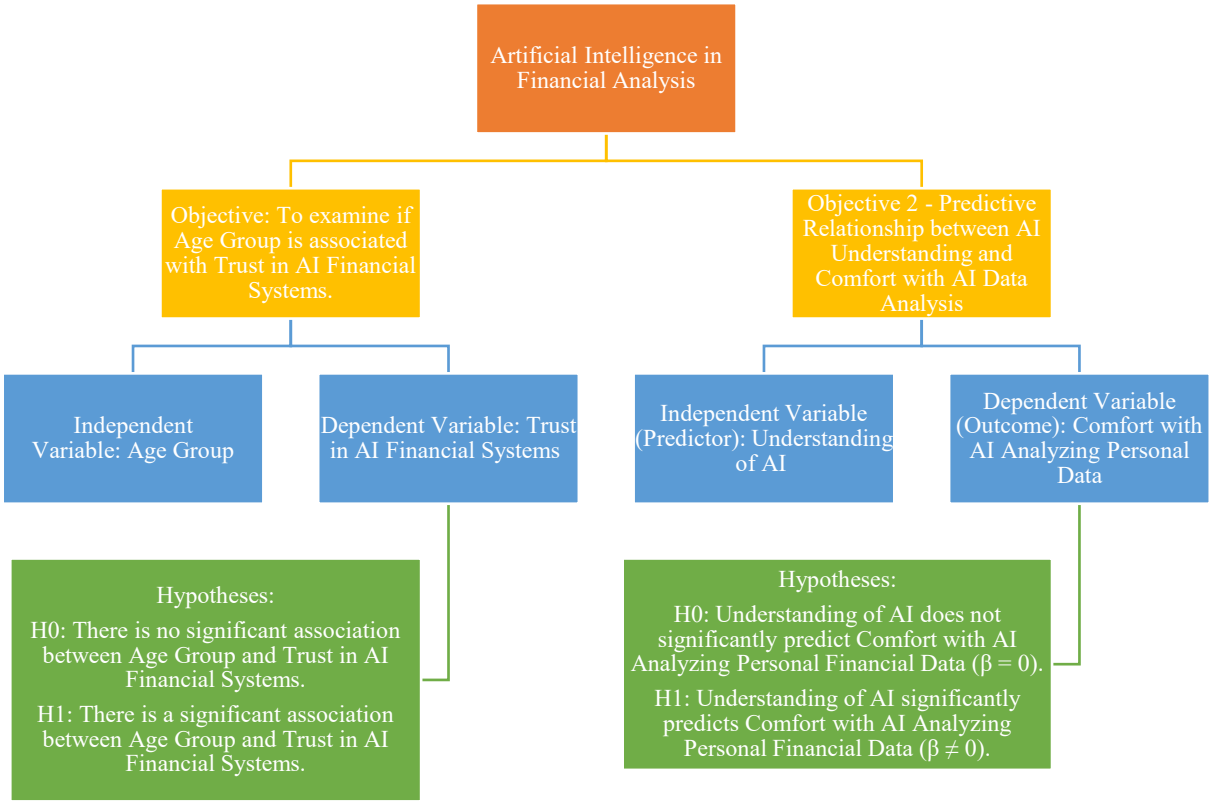
The significance level was set at 0.05 for all inferential tests.

Ethical Considerations

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2025): 8.619 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 12 | Issue: 6 | June 2025 -Peer-Reviewed Journal

The study was conducted in accordance with ethical research standards. Participation was voluntary, and informed consent was obtained from all respondents prior to survey completion. Data collection was anonymous, with no personally identifiable information recorded. Respondents were informed about the purpose of the study and how their data would be used. The research protocol was reviewed to ensure compliance with ethical guidelines for social science research.

7. CONCEPTUAL FRAMEWORK



8. DATA ANALYSIS AND FINDINGS

Data analysis

Hypotheses

- **Null Hypothesis (H0):** There is no significant association between Age Group and Trust in AI Financial Systems.
- **Alternative Hypothesis (H1):** There is a significant association between Age Group and Trust in AI Financial Systems.

Variables

- **Independent Variable:** Age Group (Categorical/Ordinal)
  - *Source:* Q1: "What is your age group?" (Column B in Excel)
  - *Levels:* 18-24 years, 25-34 years, 35-44 years, 45-54 years, 55-64 years, 65 years or older
- **Dependent Variable:** Trust in AI Financial Systems (Categorical/Ordinal)
  - *Source:* Q13: "What is your level of trust in the security of AI financial systems?" (Column N in Excel)
  - *Levels:* Complete trust, High trust, Moderate trust, Low trust, No trust at all

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2025): 8.619 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 12 | Issue: 6 | June 2025 -Peer-Reviewed Journal

Statistical Test: Chi-Square Test of Independence

Contingency Tables

		Trust in AI Financial Systems					
Age Group		**Moderate trust**	**High trust**	**Low trust**	**Complete trust**	**No trust at all**	**Total**
35-44 years	Observed	33	18	29	4	9	93
	Expected	34.10	21.313	24.025	4.263	9.300	93.00
25-34 years	Observed	31	8	19	1	4	63
	Expected	23.10	14.438	16.275	2.888	6.300	63.00
45-54 years	Observed	8	16	2	3	2	31
	Expected	11.37	7.104	8.008	1.421	3.100	31.00
18-24 years	Observed	7	12	5	2	3	29
	Expected	10.63	6.646	7.492	1.329	2.900	29.00
55-64 years	Observed	8	1	6	1	5	21
	Expected	7.70	4.813	5.425	0.963	2.100	21.00
65 years or older	Observed	1	0	1	0	1	3
	Expected	1.10	0.688	0.775	0.138	0.300	3.00
Total	Observed	88	55	62	11	24	240
	Expected	88	55	62	11	24	240

χ^2 Tests			
	Value	**df**	**p**
χ^2	44.9	20	0.001
χ^2 continuity correction	44.9	20	0.001
N	240		

Nominal	
	Value
Contingency coefficient	0.397
Phi-coefficient	NaN
Cramer's V	0.216

Interpretation

The Chi-square test examined the association between Age Group and Trust in AI Financial Systems. Results indicate a statistically significant relationship ($\chi^2(20) = 44.9$, $p = 0.001$), so we **reject the null hypothesis**. The moderate effect size (Cramer's V = 0.216) suggests a meaningful association. Examining the contingency table reveals distinct patterns across age groups: the 35-44 cohort shows generally expected trust distributions; 25-34 year-olds display higher-than-expected moderate trust but lower high trust; 45-54 year-olds show notably higher high trust levels than expected; 18-24 year-olds demonstrate greater high trust; while 55-64 year-olds exhibit more "no trust at all" responses than expected. These findings suggest age significantly influences trust in AI financial systems, with middle-aged respondents (45-54) showing the most positive attitudes.

Hypotheses

- **Null Hypothesis (H0):** Understanding of AI does not significantly predict Comfort with AI Analyzing Personal Financial Data ($\beta = 0$).
- **Alternative Hypothesis (H1):** Understanding of AI significantly predicts Comfort with AI Analyzing Personal Financial Data ($\beta \neq 0$).

Variables

- **Independent Variable (Predictor):** Understanding of AI (Ordinal, treated as Numeric)
  - *Source:* Q4: "How would you rate your understanding of artificial intelligence in general?" (Column E in Excel)
  - *Levels (to be recoded):* No understanding=1, Limited understanding=2, Basic understanding=3, Moderate understanding=4, Good understanding=5, Excellent understanding=6
- **Dependent Variable (Outcome):** Comfort with AI Analyzing Personal Data (Ordinal, treated as Numeric)

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2025): 8.619 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 12 | Issue: 6 | June 2025 -Peer-Reviewed Journal

- *Source:* Q12: "How comfortable are you with AI analyzing your personal financial data?" (Column M in Excel)
- *Levels (to be recoded):* Very uncomfortable=1, Somewhat uncomfortable=2, Neutral=3, Somewhat comfortable=4, Very comfortable=5

Statistical Test: Linear Regression

Linear Regression

Model Fit Measures						
			Overall Model Test			
Model	**R**	**R²**	**F**	**df1**	**df2**	**p**
1	0.155	0.0240	5.86	1	238	0.016
Note. Models estimated using sample size of N=240						

Omnibus ANOVA Test					
	Sum of Squares	**df**	**Mean Square**	**F**	**p**
Understanding of AI	8.15	1	8.15	5.86	0.016
Residuals	331.04	238	1.39		
Note. Type 3 sum of squares					

Model Coefficients - Comfort with AI Analyzing Personal Data						
			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept	2.192	0.2856	1.6293	2.755	7.67	<.001
Understanding of AI	0.167	0.0689	0.0310	0.302	2.42	0.016

Assumption Checks

Normality Test (Shapiro-Wilk)	
Statistic	**p**
0.966	<.001

Interpretation

Linear regression analysis was conducted to assess whether Understanding of AI predicts Comfort with AI Analyzing Personal Financial Data. The results show a statistically significant, though modest, predictive relationship ($\beta = 0.167$, $p = 0.016$). Therefore, we **reject the null hypothesis**. For each one-unit increase in AI understanding (on a 6-point scale), comfort with AI analyzing personal financial data increases by approximately 0.167 units on its 5-point scale. The model explains only 2.4% of the variance in comfort levels ($R^2 = 0.0240$), indicating that while AI understanding is a significant predictor, numerous other factors likely influence comfort with AI data analysis. The Shapiro-Wilk test ($p < 0.001$) indicates non-normal distribution of residuals, suggesting some caution in interpreting precise coefficient values, though the relationship direction and significance remain valid.

DESCRIPTIVE STATISTICS

Descriptive Statistics for AI in Financial Analysis Survey (N=240)

Question	Most Common Response	%	Second Most Common	%	Key Distribution Pattern
1. Age Group	35-44 years	41.7%	25-34 years	27.1%	Predominantly mid-career professionals
2. Education	Bachelor's degree	56.3%	Master's degree	20.0%	Highly educated sample (76.3% bachelor's or higher)
3. Familiarity with Finance	Moderately familiar	35.8%	Somewhat familiar	33.3%	Moderate to basic financial knowledge
4. Understanding of AI	Moderate understanding	36.7%	Basic understanding	25.4%	Mid-level AI knowledge predominates
5. AI Tools Used	Robo-advisors	27.9%	AI-driven personal finance apps	22.1%	Investment tools are most common

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2025): 8.619 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 12 | Issue: 6 | June 2025 -Peer-Reviewed Journal

6. Sources of AI Perception	News media and journalism	24.6%	Professional training	23.3%	Media and work exposure lead
7. Most Improved Service	Investment management	24.6%	Fraud detection	22.9%	Investment and security lead benefits
8. AI vs Human Confidence	Equally confident in both	37.5%	Somewhat more confident in humans	35.0%	Balanced but slight preference for humans
9. AI Improvement Impact	Moderate improvement	35.0%	Substantial improvement	27.5%	Generally positive impact perception
10. Bias Concern	Moderately concerned	35.4%	Very concerned	30.4%	Significant concern about AI bias
11. AI Makes Finance Accessible	Agree	35.0%	Neither agree nor disagree	27.1%	Moderate agreement on democratization
12. Comfort with AI Data Analysis	Neutral	26.7%	Somewhat uncomfortable	35.0%	Slight discomfort with personal data use
13. Trust in AI Security	Moderate trust	37.1%	Low trust	27.9%	Limited to moderate trust levels
14. AI Replacing Analysts	Neutral - Balance ideal	37.5%	Somewhat negative	27.1%	Preference for human-AI collaboration
15. Importance of Transparency	Critically important	38.8%	Very important	35.4%	High value on transparency (74.2%)
16. Benefits vs. Risks	Benefits somewhat outweigh risks	30.4%	Benefits and risks are balanced	27.5%	Cautiously positive outlook

FINDINGS

Based on the analysis of 240 survey responses regarding AI in financial analysis:

1. **Age Influences Trust in AI Systems:** A significant association exists between Age Group and Trust in AI Financial Systems ($\chi^2(20) = 44.9$, $p = 0.001$, Cramer's V = 0.216), with middle-aged respondents (45-54 years) showing higher trust levels than expected, while older respondents (55-64 years) demonstrate more "no trust at all" responses.
2. **Understanding Predicts Comfort:** A modest but significant relationship exists between Understanding of AI and Comfort with AI analyzing personal financial data ($\beta = 0.167$, $p = 0.016$, $R^2 = 0.0240$), indicating that greater comprehension of AI technology is associated with increased comfort sharing personal financial information.
3. **Investment Management & Fraud Detection Lead Benefits:** Respondents identify Investment management and portfolio optimization (24.6%) and Fraud detection and security (22.9%) as the areas most improved by AI, suggesting these applications have demonstrated the most visible value.
4. **Balanced AI-Human Preference:** The largest group of respondents (37.5%) prefer a balanced approach where AI and humans work together rather than AI replacement of analysts, with only a small minority favoring complete AI replacement of human analysts.
5. **High Value on Transparency:** An overwhelming majority (74.2%) consider transparency about AI use in financial services either "Critically important" (38.8%) or "Very important" (35.4%), highlighting the need for disclosure and explainability.
6. **Significant Bias Concerns Exist:** A substantial majority (65.8%) express moderate to extreme concern about potential biases in AI financial systems, with 30.4% "Very concerned" and 35.4% "Moderately concerned," indicating widespread apprehension about algorithmic fairness.
7. **Cautiously Positive Overall Perception:** A plurality of respondents (57.9%) believe benefits of AI outweigh risks to some degree, with 30.4% stating benefits somewhat outweigh risks, though a significant 27.5% see benefits and risks as balanced.
8. **Limited Trust in AI Security:** Trust in AI financial systems' security is predominantly moderate (37.1%) or low (27.9%), with only a small percentage expressing complete trust (4.6%), indicating significant concerns about data protection and system integrity.

9. CONCLUSION AND SUGGESTIONS

CONCLUSION

This study on Artificial Intelligence in Financial Analysis reveals significant insights regarding user perceptions and attitudes. Analysis of 240 survey responses shows a nuanced view of AI's role, with a significant association

between age and trust in AI financial systems (χ^2=44.9, p=0.001, Cramer's V=0.216), particularly with middle-aged respondents (45-54) showing higher trust levels while older groups express more skepticism. Though AI understanding weakly predicts comfort with personal data analysis (β=0.167, p=0.016, R^2=0.0240), most respondents remain cautious about data sharing. Investment management (24.6%) and fraud detection (22.9%) emerge as areas where AI shows most value. The majority (74.2%) consider transparency "Critically/Very important," while 65.8% express moderate to extreme concern about algorithmic bias. Overall, respondents favor a balanced human-AI collaboration approach (37.5%) rather than complete AI replacement of human analysts, with a cautiously positive view that benefits somewhat outweigh risks (57.9%).

SUGGESTIONS

1. **Implement Age-Targeted Education:** Develop tailored educational programs addressing the specific concerns of different age groups, particularly focusing on increasing trust among older users (55+) who show higher skepticism.
2. **Enhance Transparency Frameworks:** Establish clear, comprehensive disclosure protocols for AI use in financial services, addressing the 74.2% who consider transparency critically or very important.
3. **Prioritize Security and Bias Mitigation:** Invest in robust security measures and bias detection algorithms to address the significant concerns about both data protection (65.7% expressing moderate/low/no trust) and algorithmic fairness (65.8% moderately to extremely concerned).
4. **Focus AI Development on Proven Value Areas:** Concentrate innovation efforts on investment management and fraud detection, where users already perceive significant benefits.
5. **Adopt Human-AI Collaborative Models:** Design systems that leverage AI capabilities while maintaining meaningful human oversight, aligning with the 37.5% preference for balanced human-AI approaches.
6. **Develop Trust-Building Data Practices:** Create transparent data handling protocols that progressively build user comfort with AI analysis of financial information, addressing the low R^2 (0.0240) between AI understanding and comfort sharing data.
7. **Improve Explainability:** Enhance the ability of AI systems to explain their recommendations and decisions in user-friendly terms, addressing the significant skepticism regarding AI-only decision making.

10. REFERENCES

1. *Malali, A. B., & Gopalakrishnan, S. (2020). Application of artificial intelligence and its powered technologies in the indian banking and financial industry: An overview. IOSR Journal Of Humanities And Social Science, 25(4), 55-60.*
2. *Anil, K., & Misra, A. (2022). Artificial intelligence in Peer-to-peer lending in India: a cross-case analysis. International Journal of Emerging Markets, 17(4), 1085-1106.*
3. *Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: a qualitative research to discover robo-advisory services. Qualitative Research in Financial Markets, 13(5), 632-654.*
4. *Singh, T., & Pathak, N. (2020). Emerging role of artificial intelligence in Indian banking sector. Journal of Critical Reviews, 7(16), 1370-1373.*
5. *Rai, P., & Shekha, C. Artificial Intelligence in Financial Markets: Global Trends, Regulatory Challenges, and Comparative Analysis with India.*
6. *Kulshrestha, N., & Srivastava, V. K. (2020, June). Synthesizing Technical Analysis, Fundamental Analysis & Artificial Intelligence–An Applied Approach to Portfolio Optimisation & Performance Analysis of Stock Prices in India. In 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 1185-1188). IEEE.*
7. *Bhawna, & Gupta, P. (2025). Empowering Financial Efficiency in India: Harnessing Artificial Intelligence (AI) for Streamlining Accounting and Finance. Generative Artificial Intelligence in Finance: Large Language Models, Interfaces, and Industry Use Cases to Transform Accounting and Finance Processes, 407-428.*
8. *Shrivastava, R., & Mahajan, P. (2016). Artificial intelligence research in India: A scientometric analysis. Science & Technology Libraries, 35(2), 136-151.*
9. *Joshi, V., Sharma, M., & Ranjan, P. (2021). Artificial Intelligence and Financial Decision Making-Review of efficacy in Usage within Financial Organizations in India. Turkish Online Journal of Qualitative Inquiry, 12(7).*
10. *Srivastava, S. K. (2018). Artificial Intelligence: way forward for India. JISTEM-Journal of Information Systems and Technology Management, 15, e201815004.*