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Impact of Artificial Intelligence in Finance and Decision Making

An Exploratory Survey of User Perceptions

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Abstract—

Artificial intelligence is increasingly used in financial services for fraud detection, credit assessment, investment support and digital banking, yet its adoption depends on how users perceive its benefits, risks and trustworthiness. This study examines user perceptions of artificial intelligence in finance, focusing on perceived benefits, perceived risks, trust, explainability, perceived usefulness, adoption intention and perceived effectiveness of financial decisions. A quantitative, cross-sectional design was used, and primary data were collected from 30 respondents through a structured online questionnaire. Descriptive statistics, Cronbach alpha reliability analysis and Spearman rank correlation with Holm adjustment for multiple testing were applied. Perceived benefits and perceived usefulness were positively associated with adoption intention, and adoption intention was positively associated with perceived decision effectiveness; all three associations remained significant after adjustment. The expected negative association between perceived risk and adoption intention was not found, and the trust and explainability hypotheses were not supported. Because the sample was small and concentrated among young respondents in information technology occupations, the findings are exploratory and should not be generalized. The results suggest that perceived value is linked with willingness to use artificial intelligence based financial tools, while the roles of trust and risk need further study.

Keywords—artificial intelligence; finance; decision making; perceived usefulness; trust; explainability; adoption intention; financial technology

I. INTRODUCTION

Artificial intelligence (AI) refers to computational systems that perform tasks commonly associated with human intelligence, such as pattern recognition, prediction, classification and recommendation. In finance, AI and machine learning are used to process large datasets for forecasting, investment analysis, accounting, credit-risk assessment, fraud detection, customer service and personal financial management [1], [2], [3], [4]. These tools can analyse information quickly and consistently, but predictive capability should not be equated with guaranteed success, because financial data may be noisy or incomplete and models trained on historical patterns may not perform consistently under new conditions.

Credit assessment and fraud detection are especially important applications because institutions must evaluate large volumes of transactions and applications. Hybrid machine-learning models have been proposed for loan-risk prediction [5], and explainable deep-learning approaches have been applied to interpretable credit scoring [6]. These applications also raise concerns: data can contain historical inequalities, fraud patterns change over time, and false positives may inconvenience legitimate customers.

Explainable AI (XAI) aims to help people understand why a system produced a particular output, and a systematic review highlights its importance across financial use cases [7]. Transparency, fairness and privacy are related but distinct requirements: an understandable model may still be unfair, and a fair model may still process data in ways that users consider intrusive [8], [9].

Adoption also depends on whether people believe a tool is useful, dependable and appropriate for their needs. Research on investor perceptions of AI adoption in investment services in India considers user perceptions rather than technical performance alone [10]. Trust is particularly important when recommendations affect money or access to financial services, but it should be calibrated rather than blind.

Existing studies have examined forecasting, credit scoring, fraud detection, explainability and fairness largely as separate topics. A need remains for focused empirical work that examines perceived benefits, risks, trust, explainability, adoption intention and perceived decision effectiveness together from the user's perspective. This study therefore aims to examine the perceived impact of AI in finance and financial decision making. Its objectives are (i) to examine the perceived benefits and usefulness of AI in financial analysis and decision making, (ii) to identify the perceived risks and challenges, (iii) to examine the role of trust and explainability, (iv) to study factors associated with the intention to adopt AI-supported financial tools, and (v) to examine the relationship between adoption intention and perceived effectiveness of financial decisions. The findings are exploratory and are based on a small survey sample.

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II. MATERIALS AND METHODS

A. Research Design and Sampling

The study follows a quantitative, empirical and cross-sectional design in which a structured online questionnaire collected respondents' views at one point in time. The design is suitable for describing perceptions and examining associations among measured variables; it does not establish causality. The intended population comprised people who are aware of or use digital financial services, including students and working professionals. Respondents were recruited through an accessible, non-probability (convenience) sample, and the final dataset contained 30 complete submissions. The sample is therefore not statistically representative of all users of financial services.

B. Instrument and Variables

The questionnaire contained 17 questions: demographic items on age group, occupation and familiarity with AI (Q1–Q3); a multiple-response question on AI-based financial tools (Q4); twelve Likert-scale statements (Q5–Q16) coded from 1 (strongly disagree) to 5 (strongly agree); and one optional open-ended question (Q17). The variables were operationalized as follows.

Perceived benefits: mean of Q5–Q7 (efficiency, analytical insight and fraud or security benefits).

Perceived risks: mean of Q9–Q11 (data privacy, algorithmic bias, and limited empathy or handling of complex situations).

Perceived usefulness: Q8, usefulness of AI tools for personal financial management.

Explainability requirement: Q13, requiring an explanation before trusting important AI financial advice. This item does not measure the actual transparency of any particular system.

Comparative trust: Q14, trust in AI-based advice tools compared with human financial planners.

Adoption intention: Q15, intention to use or increase use of AI-supported financial services over the next 12–24 months.

Perceived decision effectiveness: Q16, perceived improvement in the quality of personal financial decisions.

Comfort with autonomous AI investing (Q12) was reported descriptively and was not combined with other items.

C. Research Hypotheses

Six hypotheses guided the analysis (Fig. 1):

H1: Perceived benefits of AI have a positive relationship with intention to adopt AI-supported financial tools.

H2: Perceived risks of AI have a negative relationship with intention to adopt AI-supported financial tools.

H3: Trust in AI has a positive relationship with intention to adopt AI-supported financial tools.

H4: Transparency and explainability have a positive relationship with trust in AI.

H5: Perceived usefulness of AI has a positive relationship with intention to use AI-supported financial tools.

H6: Intention to adopt AI-supported financial tools has a positive relationship with perceived financial decision effectiveness.

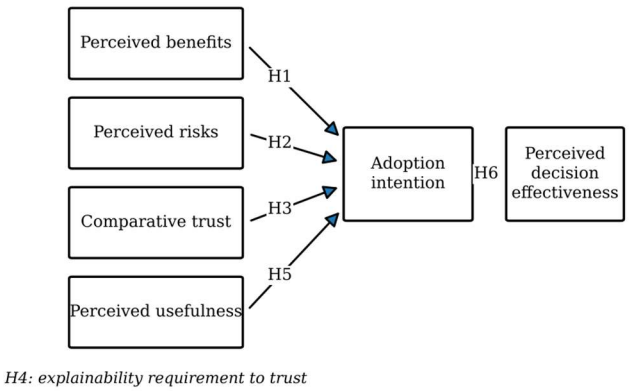


Fig. 1. Conceptual framework and hypotheses (H1–H6).

D. Data Quality and Statistical Analysis

Two exports of the survey data (numeric and label-based) contained the same 30 records and were consistent. No duplicate submission identifiers were found and all required questions were complete. The median completion time was 220 seconds; three submissions took less than 90 seconds and were flagged for review but retained, because duration alone does not establish that a response is invalid. Identifiers were not used in the analysis.

Frequencies and percentages summarized demographic characteristics and tool awareness; means, standard deviations (SD) and medians summarized the Likert items. Cronbach's alpha was computed for the multi-item benefit and risk composites. Spearman rank correlation was used because responses were ordinal and the sample was small. Tests were two-tailed, and Holm adjustment was applied across the six planned tests to limit false-positive conclusions; the significance threshold was 0.05. The analysis is exploratory, no causal claims are made, and non-significance is not interpreted as proof of no relationship.

E. Ethical Considerations

Responses were used only for academic research, participation was voluntary, and results are reported in aggregate without personal identifiers. No personal financial advice is offered on the basis of the results.

III. RESULTS AND DISCUSSION

A. Respondent Profile

The sample was concentrated in the 18–24 age group and in information technology (IT) and software occupations (Table I), so it describes the people who responded and should not be treated as representative of all financial-service users. Most respondents reported at least some familiarity with AI.

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TABLE I
PROFILE OF RESPONDENTS (N = 30)

Characteristic	Frequency	Percentage
Age group		
18–24 years	28	93.3%
25–34 years	1	3.3%
45–54 years	1	3.3%
Occupation		
IT and software	17	56.7%
Engineering and operations	5	16.7%
Academic, research and student	3	10.0%
Other professional field	3	10.0%
Business management and entrepreneurship	1	3.3%
Other / not listed	1	3.3%
Familiarity with AI		
Moderately familiar	9	30.0%
Very familiar	9	30.0%
Somewhat familiar	8	26.7%
Expert	3	10.0%
Very unfamiliar	1	3.3%

B. Awareness of AI-Based Financial Tools

Question Q4 allowed multiple selections, so percentages in Table II are calculated on all 30 respondents and do not sum to 100. AI chatbots and virtual assistants were the most frequently selected category (50.0%), followed by robo-advisory tools (33.3%). Four respondents (13.3%) selected none of the listed tools.

TABLE II
AI-BASED FINANCIAL TOOLS SELECTED (MULTIPLE RESPONSE)

Tool category	Selected	Percentage
AI chatbots / virtual assistants	15	50.0%
Robo-advisory / investment tools	10	33.3%
AI budgeting / expense insights	8	26.7%
Fraud detection / suspicious activity alerts	8	26.7%
AI credit scoring / loan assessment	7	23.3%
Automated / algorithmic trading	6	20.0%
None of the above	4	13.3%

C. Descriptive Analysis of Likert Items

Table III reports item means, SD, medians and the percentage who agreed or strongly agreed. Responses were generally neutral to positive on benefits and usefulness. Fraud and security benefits had the highest benefit mean (3.40). Privacy concern (3.07) and concern about limited empathy or human recourse (3.10) were slightly higher than concern about algorithmic bias (2.87). Respondents were cautious about autonomous investing, with a mean of 2.70 and 56.7% choosing neutral (17 respondents), and only 20.0% trusted AI-based advice more than human planners. Adoption intention averaged 3.27 and perceived decision effectiveness 3.47.

TABLE III
DESCRIPTIVE STATISTICS FOR LIKERT ITEMS (SCALE 1 TO 5)

Item	Mean	SD	Median	Agree (%)
Q5 Efficiency benefit	3.30	1.24	4	53.3
Q6 Analytical insight benefit	3.20	1.03	3	36.7
Q7 Fraud / security benefit	3.40	1.25	4	53.3
Q8 Perceived usefulness	3.20	1.10	3	46.7
Q9 Privacy concern	3.07	1.11	3	36.7
Q10 Algorithmic bias concern	2.87	0.82	3	23.3
Q11 Limited empathy concern	3.10	0.88	3	33.3
Q12 Comfort with autonomous investing	2.70	0.88	3	13.3
Q13 Need for explanations	3.23	1.10	3	40.0
Q14 Trust in AI vs human planners	2.83	0.79	3	20.0
Q15 Adoption intention	3.27	0.91	3	46.7
Q16 Decision effectiveness	3.47	0.90	4	53.3

D. Reliability of Composite Scores

Cronbach's alpha was 0.83 for the three-item perceived-benefits composite, indicating good internal consistency in this sample. For the three-item perceived-risks composite, alpha was 0.67, indicating moderate consistency; the risk results are therefore interpreted cautiously and at item level where needed. Q12, Q13 and Q14 were not combined into a trust score because they represent different concepts.

E. Hypothesis Testing

Table IV and Fig. 2 summarize the Spearman correlations. A hypothesis is described as supported only when the association followed the predicted direction and the Holm-adjusted p-value was below 0.05.

TABLE IV
HYPOTHESIS TESTS (SPEARMAN RANK CORRELATION)

H	Relationship	ρ	Raw p	Holm p	Result
H1	Benefits → adoption	+0.540	0.002	0.013	Supported
H2	Risks → adoption	+0.134	0.480	0.480	Not supported
H3	Trust → adoption	+0.352	0.057	0.170	Not supported
H4	Explainability → trust	+0.252	0.179	0.357	Not supported
H5	Usefulness → adoption	+0.474	0.008	0.041	Supported
H6	Adoption → effectiveness	+0.465	0.010	0.041	Supported

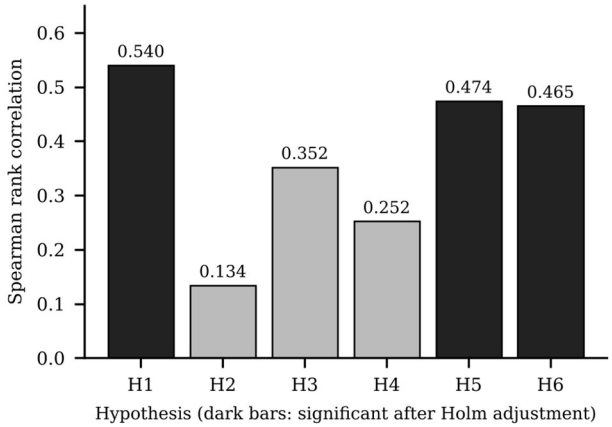


Fig. 2. Spearman correlation for each hypothesis.

H1, H5 and H6 were supported in this sample. Respondents who rated the benefits and usefulness of AI more highly

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reported stronger intentions to use or increase use of AI-based financial services (ρ = 0.540 and 0.474), and those with stronger adoption intention also tended to believe that AI improves financial decisions (ρ = 0.465).

H2 was not supported: the combined risk score was weakly and positively, rather than negatively, associated with adoption intention. H3 (comparative trust and adoption intention) and H4 (explainability requirement and trust) showed positive but non-significant associations after adjustment. As Q13 measures how much respondents require explanations rather than the transparency of a real system, H4 should be read with that limit in mind. In an exploratory item-level follow-up for H2, privacy concern (ρ = −0.030) and bias concern (ρ = +0.048) showed no meaningful association with adoption intention, whereas concern about limited empathy was positively associated (ρ = +0.457, unadjusted p = 0.011). This follow-up was not one of the six primary tests and does not show that greater concern causes greater adoption.

F. Discussion and Implications

The results for H1 and H5 suggest that respondents' views of AI's benefits and usefulness move together with their willingness to use AI-based financial services. For institutions, this points to the importance of demonstrating clear user benefits such as convenience, useful insights and support with routine tasks. These are associations within this sample and do not prove that perceived value causes adoption.

The absence of a negative risk–adoption relationship should not be read as evidence that risk controls are unnecessary. Privacy, bias and limited empathy are distinct concerns that may affect respondents differently. Financial organizations should continue to explain how customer data is protected, how unfair outcomes are monitored, and how customers can reach a human for complex issues. Likewise, the non-significant trust and explainability results do not show that these factors are unimportant; both were measured with single items in a small sample. Eleven respondents gave optional comments, which stressed the need for human confirmation of financial decisions and the risk of irresponsible use; because few were substantive, they are treated only as context.

Because adoption intention and perceived effectiveness are both self-reported, the H6 result reflects perceptions rather than measured improvements in decision accuracy or financial outcomes. A practical approach is to use AI as decision support while keeping human review for high-impact or sensitive decisions. Institutions should explain what a tool does, what data it uses and what its limits are; monitor credit and similar decisions for unequal outcomes and allow customers to question them; and users should review AI-generated suggestions critically and seek qualified human advice for consequential decisions.

G. Limitations

The analysis rests on 30 responses from a non-probability sample in which 93.3% were aged 18–24 and 56.7% worked in IT or software, which limits statistical power and generalizability. Data are self-reported perceptions and intentions rather than observed behaviour or objective outcomes. Most constructs were measured with single items, the risk composite had only moderate reliability, three fast submissions were retained, and the cross-sectional design cannot establish cause and effect.

IV. CONCLUSIONS

This study explored how respondents perceive AI in finance and how those perceptions relate to adoption intention and perceived decision effectiveness. Perceived benefits and perceived usefulness were positively associated with adoption intention, and adoption intention was positively associated with perceived decision effectiveness, all remaining significant after Holm adjustment. The expected negative relationship between perceived risk and adoption was not found, and the trust and explainability hypotheses were not supported after adjustment. Practical value therefore appears to be an important consideration in attitudes toward AI-based financial services, while the roles of risk, trust and explainability require further investigation. Given the sample's size and composition, the findings are an initial exploratory contribution rather than definitive evidence about the wider population.

Future studies should recruit larger and more diverse samples, use validated multi-item scales for usefulness, trust, transparency, risk and adoption intention, compare groups by age, occupation and AI familiarity, and, where feasible, examine actual usage or decision outcomes in addition to self-reported perceptions.

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