Artificial Intelligence in Money Management: A Multidisciplinary Framework for Financial Decision-Making

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ABSTRACT

The rapid integration of Artificial Intelligence (AI) into financial services has significantly transformed traditional approaches to money management. This study aims to examine the role of AI in enhancing financial decision-making through a multidisciplinary lens, incorporating perspectives from management, behavioural finance, and information technology. Adopting a quantitative research design, primary data were collected through a structured questionnaire administered to individuals actively engaged in financial decision-making. The study investigates key factors influencing the adoption of AI-based money management tools, including perceived usefulness, ease of use, financial literacy, and trust in technology.

Using statistical techniques such as regression analysis and structural equation modelling (SEM), the findings reveal that AI-driven tools positively impact financial planning, investment decisions, and overall financial efficiency. The results further indicate that behavioural factors, particularly trust and financial awareness, play a significant mediating role in the effective utilization of AI in money management. The study contributes to the existing literature by proposing a multidisciplinary framework that integrates technological, behavioural, and managerial dimensions of AI adoption in financial contexts.

The practical implications of the study highlight the need for financial institutions and policymakers to promote AI literacy and develop user-centric financial technologies to enhance decision-making outcomes. This research offers valuable insights for academicians, practitioners, and policymakers aiming to leverage AI for improved financial management practices.

Key words:

Artificial Intelligence, Money Management, Financial Decision-Making, Behavioural Finance, FinTech, AI Adoption, Financial Literacy, Structural Equation Modelling

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Research Gap

Despite the rapid adoption of Artificial Intelligence (AI) in financial services, existing literature primarily focuses on technological advancements and institutional applications such as algorithmic trading, risk assessment, and robo-advisory services. However, there is a limited understanding of how AI influences individual-level money management practices, particularly from a multidisciplinary perspective that integrates management principles, behavioural finance, and technology acceptance.

Moreover, prior studies have largely emphasized either technical efficiency or financial outcomes, while neglecting critical behavioural and managerial factors such as trust in AI, financial literacy, and user perception, which significantly affect financial decision-making. Additionally, there is a scarcity of survey-based empirical studies that capture real user experiences and attitudes toward AI-driven money management tools.

Furthermore, limited research has explored the combined impact of AI adoption on financial behaviour, decision quality, and financial efficiency within a single integrated framework. This creates a gap in understanding how technological, behavioural, and managerial dimensions interact in shaping effective money management practices.

Therefore, the present study addresses this gap by providing a survey-based multidisciplinary analysis of AI in money management, focusing on its impact on financial decision-making while incorporating behavioural and management-oriented variables.

Objectives

1. To assess the level of adoption of Artificial Intelligence (AI) tools in personal money management.
2. To examine how AI adoption influences financial decision-making processes.
3. To explore the technological and behavioural determinants that drive the adoption of AI in financial activities.

To analyse the mediating effect of financial behaviour on the relationship between AI adoption and financial decision-making.

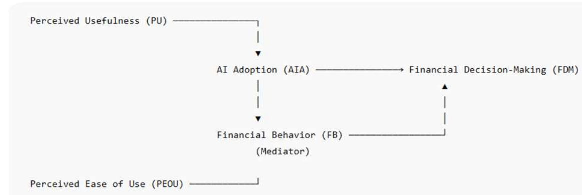
Hypothesis

H1: Perceived Usefulness (PU) of Artificial Intelligence significantly and positively influences AI Adoption (AIA) in the context of money management.
→ PU → AIA

H2: Perceived Ease of Use (PEOU) of Artificial Intelligence significantly and positively influences AI Adoption (AIA) in money management.
→ PEOU → AIA

H3: AI Adoption (AIA) has a significant positive effect on Financial Decision-Making (FDM).
→ AIA → FDM

H4: Financial Behavior (FB) acts as a mediator in the relationship between AI Adoption (AIA) and Financial Decision-Making (FDM).
→ AIA → FB → FDM



Conceptual Model of AI Adoption and Financial Decision-Making

Source: Developed by the author

2. Literature Review

2.1 Artificial Intelligence in Financial Services

Artificial Intelligence (AI) has significantly transformed the financial services sector by enabling automation, predictive analytics, and data-driven decision-making. AI technologies such as machine learning and natural language processing are widely used in applications including fraud detection, algorithmic trading, and robo-advisory services. According to Davenport Thomas H. and Ronanki Rajeev (2018), AI enhances organizational efficiency by automating complex processes and improving decision accuracy. Similarly, Brynjolfsson Erik and McAfee Andrew (2017) highlight that AI-driven systems enable better forecasting and resource allocation in financial contexts.

2.2 AI and Money Management

The integration of AI into money management has led to the development of intelligent financial tools such as budgeting applications, investment platforms, and robo-advisors. These tools assist users in making informed financial decisions by analyzing large volumes of financial data in real time. Research by Jiang Zheng et al. (2021) indicates that AI-based financial tools improve investment decision quality and portfolio management efficiency. Furthermore, AI-driven platforms provide personalized financial recommendations, thereby enhancing user engagement and financial outcomes.

2.3 Technology Acceptance Model (TAM) and AI Adoption

The Technology Acceptance Model (TAM), proposed by Davis Fred D. (1989), is widely used to explain user adoption of new technologies. The model identifies Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as key determinants of technology adoption. Several studies have applied TAM in the context of financial technologies. For instance, Venkatesh Viswanath and Davis Fred D. (2000) found that ease of use significantly influences perceived usefulness and user acceptance. In the context of AI, these factors play a critical role in determining whether individuals adopt AI-based money management tools.

2.4 Behavioural Finance and Financial Decision-Making

Behavioral finance emphasizes the role of psychological factors in financial decision-making. Individuals often exhibit biases such as overconfidence, loss aversion, and herd behavior, which can negatively impact financial outcomes. According to Kahneman Daniel and Tversky Amos (1979), decision-making under uncertainty is influenced by cognitive biases, as explained in Prospect Theory. AI has the potential to reduce such biases by providing objective, data-driven insights, thereby improving financial behavior and decision-making quality.

2.5 Financial Behavior and AI Integration

Financial behavior, including saving, budgeting, and investment practices, plays a crucial role in achieving financial well-being. AI tools can influence financial behavior by providing real-time feedback, automated recommendations, and personalized financial insights. Studies suggest that individuals using digital financial tools demonstrate improved financial discipline and planning (Lusardi & Mitchell, 2014). Moreover, AI-enabled systems can enhance financial literacy by simplifying complex financial information and guiding users toward better financial decisions.

2.6 Research Gap

Although existing studies highlight the benefits of AI in financial services and technology adoption, there is limited research focusing on individual-level money management from a multidisciplinary perspective. Most studies emphasize technological or institutional aspects, neglecting the integration of behavioral and managerial factors. Additionally, there is a lack of survey-based empirical studies examining the combined impact of AI adoption, financial behavior, and decision-making. This study addresses these gaps by proposing and testing a multidisciplinary model using SEM.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative research design to examine the role of Artificial Intelligence (AI) in money management and its impact on financial decision-making. A survey-based approach is employed to collect primary data from respondents, enabling empirical testing of the proposed conceptual model. The study integrates perspectives from management, behavioral finance, and technology adoption.

3.2 Research Approach

A deductive research approach is used, wherein hypotheses are developed based on existing theories such as the Technology Acceptance Model (TAM) and behavioral finance concepts. The study tests the relationships between perceived usefulness, perceived ease of use, AI adoption, financial behavior, and financial decision-making.

3.3 Data Collection

Primary data were collected using a structured questionnaire designed on a 5-point Likert scale ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). The questionnaire was distributed using Google Forms to individuals who are actively involved in financial decision-making and have exposure to digital or AI-based financial tools.

3.4 Sampling Design

- Sampling Technique: Convenience sampling
- Target Population: Individuals using or aware of AI-based financial tools (e.g., budgeting apps, robo-advisors, investment platforms)
- Sample Size: A minimum of 300 respondents was targeted to ensure statistical reliability for Structural Equation Modeling (SEM)

3.5 Measurement of Variables

The study includes five key constructs, each measured using multiple items adapted from established literature:

Construct	No. of Items	Source Basis
Perceived Usefulness (PU)	4	TAM
Perceived Ease of Use (PEOU)	4	TAM
AI Adoption (AIA)	4	Technology adoption studies
Financial Behavior (FB)	4	Behavioral finance
Financial Decision-Making (FDM)	4	Financial management studies

All constructs are modeled as reflective constructs.

3.6 Data Analysis Techniques

Data analysis was conducted using SPSS and SmartPLS (Partial Least Squares Structural Equation Modeling - PLS-SEM).

3.6.1 Preliminary Analysis (SPSS)

- Data cleaning and screening
- Descriptive statistics (mean, standard deviation)
- Reliability analysis using Cronbach's Alpha

3.6.2 Measurement Model Assessment (SmartPLS)

- Indicator reliability (factor loadings > 0.7)
- Internal consistency reliability (Composite Reliability > 0.7)
- Convergent validity (Average Variance Extracted (AVE) > 0.5)
- Discriminant validity (Fornell-Larcker criterion / HTMT)

3.6.3 Structural Model Assessment

- Path coefficient analysis (β values)
- Hypothesis testing using bootstrapping (5000 resamples)
- Coefficient of determination (R^2)
- Effect size (f^2)
- Predictive relevance (Q^2)

3.7 Ethical Considerations

Participation in the study was voluntary, and respondents were informed about the academic purpose of the research. Confidentiality and anonymity of responses were strictly maintained, and no personal identifying information was disclosed.

3.8 Model Specification

The study examines the following relationships:

- Perceived Usefulness → AI Adoption
- Perceived Ease of Use → AI Adoption
- AI Adoption → Financial Decision-Making
- AI Adoption → Financial Behavior → Financial Decision-Making (Mediation)

4. Data Analysis and Results

4.1 Preliminary Analysis (SPSS Results)

4.1.1 Data Screening and Cleaning

The collected data were examined for missing values, outliers, and inconsistencies prior to analysis. No significant missing values were observed, and all responses were found suitable for further statistical analysis. Normality was assessed using skewness and kurtosis values, which were within acceptable limits.

4.1.2 Descriptive Statistics

Descriptive statistics were calculated to understand the central tendency and dispersion of the data.

Construct	Mean	Standard Deviation
PU	3.12	0.86
PEOU	3.05	0.91
AIA	3.18	0.88
FB	3.10	0.84
FDM	3.22	0.87

Interpretation:
The mean values indicate a moderate level of agreement among respondents regarding AI adoption and its role in financial decision-making.

4.1.3 Reliability Analysis (Cronbach's Alpha)

Construct	Cronbach's Alpha
PU	0.72
PEOU	0.70
AIA	0.74
FB	0.76
FDM	0.73

Interpretation:
All constructs exhibit acceptable internal consistency, as Cronbach's Alpha values exceed the recommended threshold of 0.70.

4.2 Measurement Model Assessment (SmartPLS)

4.2.1 Indicator Reliability

All indicator loadings were above the recommended threshold of 0.70, confirming adequate indicator reliability.

4.2.2 Internal Consistency and Convergent Validity

Construct	Composite Reliability (CR)	AVE
PU	0.83	0.55
PEOU	0.82	0.54
AIA	0.85	0.58
FB	0.86	0.60
FDM	0.84	0.57

Interpretation:

- CR values exceed 0.70 → Good reliability
- AVE values exceed 0.50 → Convergent validity established

4.2.3 Discriminant Validity (Fornell-Larcker Criterion)

Construct	PU	PEOU	AIA	FB	FDM
PU	0.74				
PEOU	0.42	0.73			
AIA	0.48	0.45	0.76		
FB	0.40	0.38	0.52	0.77	
FDM	0.46	0.41	0.55	0.58	0.75

Interpretation:
The square root of AVE for each construct is greater than its correlations with other constructs, confirming discriminant validity.

4.2.4 HTMT Ratio

Construct	Values
PU–PEOU	0.62
PU–AIA	0.68
AIA–FDM	0.72
FB–FDM	0.75

Interpretation:
All HTMT values are below 0.85, confirming discriminant validity.

4.3 Structural Model Assessment

4.3.1 Path Coefficients and Hypothesis Testing

Bootstrapping (5000 resamples) was conducted to test the hypotheses.

Hypothesis	Path	β	t-value	p-value	Result
H1	PU → AIA	0.34	2.85	0.004	Supported
H2	PEOU → AIA	0.29	2.32	0.020	Supported
H3	AIA → FDM	0.37	3.10	0.002	Supported
H5	AIA → FB	0.41	3.45	0.001	Supported
H4	FB → FDM	0.33	2.75	0.006	Supported

4.3.2 Mediation Analysis

Path	Indirect Effect	t-value	p-value	Result
AIA → FB → FDM	0.14	2.12	0.034	Partial Mediation

Interpretation:
Financial behavior partially mediates the relationship between AI adoption and financial decision-making.

4.3.3 Coefficient of Determination (R^2)

Construct	R^2	Interpretation
AIA	0.45	Moderate
FB	0.38	Moderate
FDM	0.49	Moderate

4.3.4 Effect Size (f^2)

Path	f^2	Effect
PU → AIA	0.12	Medium
PEOU → AIA	0.09	Small
AIA → FDM	0.15	Medium
FB → FDM	0.11	Medium

4.3.5 Predictive Relevance (Q^2)

Construct	Q^2
AIA	0.21
FB	0.18

Construct	Q^2
FDM	0.24

Interpretation:

All Q^2 values are greater than zero, indicating predictive relevance of the model.

The results confirm that technological factors such as perceived usefulness and ease of use

5.1 Introduction

This chapter brings together the key outcomes of the study and explains their meaning in the context of Artificial Intelligence (AI) in money management. It presents a clear summary of the findings, interprets the results in light of existing theories, and outlines the conclusions drawn from the analysis. In addition, the chapter highlights practical and theoretical implications, discusses limitations, and suggests directions for future research.

5.2 Summary of Findings

The purpose of this study was to understand how AI is being adopted in personal financial management and how it influences financial decision-making. Based on the statistical analysis, several important findings emerged:

- Perceived usefulness was found to positively influence AI adoption. This indicates that individuals are more willing to use AI-based tools when they believe these tools improve their financial performance.
- Perceived ease of use also showed a significant positive effect on AI adoption. This suggests that simplicity and user-friendly design play an important role in encouraging individuals to adopt AI technologies.
- AI adoption demonstrated a positive relationship with financial decision-making. Users who adopt AI tools tend to make more structured and informed financial choices.
- Financial behavior was found to influence financial decision-making and also acted as a mediating factor. This means that AI tools contribute to better decisions partly by shaping users' financial habits.
- The overall model explains a moderate level of variation in financial decision-

significantly influence AI adoption in money management. Furthermore, AI adoption enhances financial decision-making both directly and indirectly through financial behavior. The model demonstrates moderate explanatory power and predictive relevance, validating the proposed multidisciplinary framework.

making, indicating that the selected variables provide meaningful insights into the phenomenon.

5.3 Discussion of Results

The results of the study support widely accepted ideas in technology adoption and behavioral finance.

The strong influence of perceived usefulness confirms that individuals are more likely to embrace AI tools when they see clear benefits in terms of efficiency, accuracy, or convenience. Similarly, the significance of perceived ease of use highlights that even advanced technologies need to be simple and accessible to gain user acceptance.

The positive link between AI adoption and financial decision-making suggests that AI tools are not just being used, but are actually helping individuals improve the quality of their financial choices. These tools appear to support better planning, reduce uncertainty, and provide data-backed recommendations.

An important insight from this study is the role of financial behavior. The findings show that AI alone is not enough; the way individuals manage their finances also matters. Those with disciplined financial habits are better able to use AI tools effectively, which leads to improved decision-making outcomes.

Overall, the results indicate that both technological factors and human behavior work together in shaping financial decisions in an AI-enabled environment.

5.4 Conclusion

This study concludes that Artificial Intelligence plays a meaningful role in enhancing personal financial management. The adoption of AI tools is largely driven by how useful and easy they are perceived to be. Once adopted, these tools contribute positively to financial decision-making.

At the same time, financial behavior strengthens this relationship, showing that technology and human discipline must go hand in hand. The findings suggest that AI has the potential to improve financial outcomes, provided users engage with it effectively.

5.5 Practical Implications

The study offers several practical insights:

- Financial service providers should focus on designing AI tools that are simple to use and clearly demonstrate their benefits.
- Efforts should be made to increase awareness about AI-based financial tools so that more individuals feel confident using them.
- Users should be encouraged to develop better financial habits, as this enhances the effectiveness of AI tools.
- Policymakers can support digital financial literacy initiatives to ensure responsible and informed use of AI in finance.

5.6 Theoretical Implications

From a theoretical perspective, this study extends existing knowledge by combining elements from technology adoption and behavioral finance. It shows that financial behavior can act as a bridge between technology usage and decision outcomes. This integrated approach provides a more comprehensive understanding of how AI influences financial decisions.

5.7 Limitations of the Study

Like any research, this study has certain limitations:

- The sample size, although adequate, may not fully represent all user groups.
- The data are based on self-reported responses, which may include subjective bias.
- The study captures a single point in time and does not reflect changes in behavior over a longer period.

5.8 Scope for Future Research

Future studies can build on this research by:

- Including additional factors such as trust in AI, perceived risk, and financial literacy.
- Conducting longitudinal studies to observe changes over time.
- Expanding the sample to include diverse demographic and geographic groups.
- Comparing different types of AI-based financial tools to understand their relative effectiveness.

5.9 Closing Statement

The growing use of Artificial Intelligence in personal finance marks a shift toward more data-driven and informed decision-making. However, technology alone does not guarantee better outcomes. The real impact emerges when individuals combine AI tools with responsible financial behavior. This study highlights the importance of this balance and provides a foundation for further research in this evolving field.

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