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Article · December 2024

DOI: 10.30574/ijsra.2024.13.2.2536

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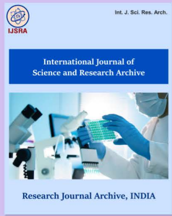
International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/



(Research Article)

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The impact of AI on personal finance and wealth management in the U.S.

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International Journal of Science and Research Archive, 2024, 13(02), 3580-3600

Publication history: Received on 11 November 2024; revised on 21 December 2024; accepted on 24 December 2024

Article DOI: https://doi.org/10.30574/ijsra.2024.13.2.2536

Abstract

The integration of Artificial Intelligence (AI) into personal finance and wealth management has fundamentally reshaped financial behaviors and decision-making processes. The primary objective of this study is to evaluate the role of AI in influencing personal financial behaviors and wealth management outcomes. Specifically, it aims to determine how AI adoption, investment, and usage impact personal savings and net worth. This study adopts a quantitative approach, utilizing secondary data from trusted sources such as Our World in Data and the Federal Reserve Bank of St. Louis. The dataset spans from 2010 to 2022, capturing trends over a significant period of AI development and adoption. A multivariate regression model is employed to examine the relationships between the dependent variables, Personal Savings Rate and Change in Net Worth, and independent variables such as AI adoption rate, AI investment, and household debt-to-income ratio. Descriptive statistics, correlation analysis, and stationarity tests are conducted to ensure data reliability and model validity. Diagnostic checks, including heteroskedasticity tests and Durbin-Watson statistics, further validate the robustness of the results.

The study reveals that AI adoption positively influences personal savings by encouraging disciplined financial behaviors, consistent with the findings of prior research. However, its impact on wealth accumulation is less direct, with AI investment showing a surprising negative association with changes in net worth. This indicates inefficiencies in resource allocation or lag effects in the benefits of large-scale AI investments. Traditional economic factors, such as household debt and spending habits, continue to play significant roles in shaping financial outcomes, highlighting the enduring influence of non-technological determinants. The study also underscores the role of macroeconomic variables, such as unemployment, in moderating AI's impact, with precautionary savings behaviors emerging during periods of economic uncertainty.

Based on the findings, several actionable recommendations emerge. For individuals, the adoption of AI-driven tools that promote financial literacy and track spending can enhance savings and improve overall financial health. Financial institutions should prioritize user-centric designs in AI platforms, ensuring accessibility and functionality for diverse demographics. Policymakers are encouraged to support initiatives that bridge disparities in AI adoption, such as digital literacy programs and affordable access to financial technologies. Moreover, strategic investment in AI tools that address wealth management complexities, such as portfolio optimization and risk assessment, is critical for improving long-term financial outcomes.

Originality

This study contributes to the growing body of literature on AI in finance by offering a dual focus on personal savings and wealth management. Unlike previous studies that often treat these domains independently, this research provides an integrated perspective, highlighting both the synergies and divergences in AI's impact. The findings on the nuanced relationship between AI investment and financial outcomes offer a fresh lens for evaluating the effectiveness of

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technological advancements. Furthermore, the study's emphasis on traditional economic factors alongside AI-related variables underscores its originality in bridging the gap between technological innovation and foundational economic principles. This approach provides a robust framework for future research and practical applications in finance.

Keywords: Artificial Intelligence; Personal Finance; Wealth Management; AI Adoption; Financial Technology; Savings Behavior; Economic Indicators

1. Introduction

Artificial Intelligence (AI) has revolutionized industries globally, becoming a transformative force across sectors such as healthcare, transportation, and, notably, finance (Challoumis, 2024). The United States, a leader in AI innovation, has seen its adoption proliferate, with advanced algorithms powering everything from self-driving cars to predictive financial models (De La Rosa & Bechler, 2024). AI's contribution to economic growth is undeniable, with U.S. businesses investing heavily in AI research and development, making it a pivotal part of modern financial systems (Fauzi, 2024). Transitioning to personal finance and wealth management, AI enables enhanced decision-making and automates complex processes, significantly benefiting users and institutions (Yu, 2020). Its integration in financial tools has shifted the landscape of personal wealth management in ways unimaginable just a decade ago, creating a need to explore its broader impact.

AI has profoundly influenced personal finance by introducing tools that automate budgeting, enhance financial literacy, and optimize savings strategies (Ribes, 2022). Technologies such as robo-advisors, predictive analytics, and AI-driven budgeting apps empower users to make data-driven decisions, improve financial behaviors, and achieve financial goals (Hidayat et al., 2024). Furthermore, AI systems help mitigate the emotional biases in financial planning by providing objective, algorithm-based recommendations (Shanmuganathan, 2020).

Globally, studies have demonstrated that AI adoption in personal finance has increased financial inclusion, particularly in regions where traditional financial services are less accessible (Waliszewski & Warchlewska, 2020). In the U.S., AI tools are reshaping the way individuals manage debt, track expenses, and plan for financial security (Challoumis, 2024). These advancements highlight the growing significance of AI in transforming the personal finance domain.

Wealth management has witnessed a paradigm shift with AI's ability to provide tailored investment advice, manage portfolios, and predict market trends (Shiva et al., 2022). Robo-advisors, powered by machine learning and natural language processing, have democratized investment opportunities by offering sophisticated strategies previously accessible only to high-net-worth individuals (Kishore et al., 2024). This capability has significantly improved the efficiency and accessibility of wealth management services (Huang et al., 2024).

In Africa and other emerging markets, AI adoption in wealth management is growing, albeit slower, due to infrastructural and regulatory barriers (Fauzi, 2024). Meanwhile, studies in the U.S. and Europe show a surge in robo-advisor use, particularly during volatile market conditions like the COVID-19 pandemic (Waliszewski, 2022). These findings suggest that AI is not only enhancing financial outcomes but also reshaping the expectations of wealth management services globally.

Extensive research underscores AI's potential to transform personal finance and wealth management across various regions. In Africa, studies emphasize AI's role in improving financial inclusion by addressing the limitations of traditional banking systems (Ribes, 2022). Globally, researchers have explored AI's integration into personal and institutional financial management, demonstrating its efficacy in improving decision-making and financial planning (Yu, 2020). In the U.S., studies such as those by Challoumis (2024) and Fauzi (2024) highlight how AI systems are adopted for financial literacy enhancement and money management. Additionally, research in Europe, like that of Warchlewska et al. (2021), examines consumer attitudes toward AI in financial planning, offering comparative insights.

Despite extensive studies, gaps remain in understanding the long-term implications of AI on personal finance behaviors, wealth distribution, and financial decision-making in diverse socio-economic contexts (Hidayat et al., 2024). Furthermore, while the technological potential of AI has been established, its ethical and regulatory implications remain underexplored (De La Rosa & Bechler, 2024). Another critical gap is the lack of region-specific studies that consider cultural, economic, and infrastructural differences, especially in African and emerging markets (Shanmuganathan, 2020). This study seeks to address these gaps by examining AI's holistic impact on personal finance and wealth management in the U.S. while comparing global perspectives.

The rapid advancement of AI in financial management necessitates deeper exploration of its impact on individuals and institutions (Challoumis, 2024). This study aims to provide a comprehensive understanding of AI's role in improving financial decision-making, increasing accessibility, and fostering financial inclusion in the U.S. context (Huang et al., 2024). Additionally, it addresses pressing research gaps, offering insights into the ethical and behavioral dimensions of AI integration in finance. This research is particularly timely as AI continues to disrupt traditional financial practices, demanding a re-evaluation of its benefits, limitations, and future potential in personal finance and wealth management (Fauzi, 2024). Through this study, a nuanced understanding of AI's transformative power can be achieved, informing both academic and practical applications in the field

Objective of the Study

The primary objective of this study is to examine the transformative impact of Artificial Intelligence (AI) on personal finance and wealth management in the United States, with a focus on understanding how AI technologies enhance financial decision-making, improve financial behaviors, and democratize access to wealth management tools.

2. Literature Review

The integration of Artificial Intelligence (AI) into finance has catalyzed a paradigm shift, enhancing efficiency, decision-making, and accessibility. Globally, AI has been leveraged to automate complex financial processes, mitigate risks, and predict market trends (Challoumis, 2024). Notably, the United States leads in AI innovation, driven by advanced financial markets and robust investments in AI research (Fauzi, 2024). As a result, AI has become an indispensable tool in both personal finance and wealth management, transforming how individuals and institutions approach financial planning (Yu, 2020).

2.1. The Role of AI in Personal Finance

AI's contribution to personal finance lies in its ability to enhance financial literacy, automate savings, and reduce emotional biases in decision-making. According to Ribes (2022), AI-powered applications have democratized access to personal finance tools by offering tailored advice and predictive insights. These systems use machine learning algorithms to track spending habits, optimize budgets, and improve savings rates. Similarly, Warchlewska et al. (2021) highlight how modern AI-driven tools like budgeting apps and virtual financial assistants enable users to take control of their finances, particularly in underserved markets.

Moreover, studies show that AI mitigates the impact of cognitive and emotional biases in financial decision-making (Shanmuganathan, 2020; Adhikari, Hamal & Jnr, 2024). By providing data-driven recommendations, AI tools ensure users make informed choices, thus improving their overall financial health. Despite these advancements, research reveals a disparity in AI adoption across demographic groups, emphasizing the need for inclusive solutions (Hidayat et al., 2024).

2.2. The Role of AI in Wealth Management

In wealth management, AI has revolutionized portfolio optimization, risk assessment, and investment strategies. Robo-advisors, a prominent application of AI, use machine learning algorithms to analyze market data and recommend personalized investment strategies (Shiva et al., 2022; Adhikari, Hamal & Jnr, 2024). These platforms have democratized wealth management by offering sophisticated tools to individuals with limited financial expertise or capital (Kishore et al., 2024).

Furthermore, Huang et al. (2024) demonstrate how generative AI enables virtual financial advisors to provide real-time insights, ensuring agility in responding to market changes. These advancements are complemented by studies such as Byrum (2022), which underscore AI's potential in portfolio management and risk mitigation. However, ethical concerns and algorithmic biases remain key challenges, calling for stricter regulations and enhanced transparency (De La Rosa & Bechler, 2024).

2.3. Global and Regional Perspectives

Globally, AI adoption in finance has varied significantly due to differences in infrastructure, regulatory environments, and cultural attitudes. In Africa, studies show that AI has the potential to bridge financial inclusion gaps by providing low-cost, scalable solutions (Ribes, 2022). Conversely, in Europe and the U.S., AI tools are more mature, with robo-advisors and predictive analytics becoming mainstream (Waliszewski, 2022). Despite this, regional differences persist, particularly in user trust and regulatory readiness (Challoumis, 2024). Comparative studies, such as those by Alsmadi et al. (2023), reveal that countries with higher financial literacy and technological penetration see greater success in AI adoption. Similarly, research by Xuan and Liu (2023) highlights the role of fintech ecosystems in enabling AI-driven wealth management solutions.

2.4. Research Gaps

Despite extensive literature, gaps remain in understanding the behavioral impacts of AI on financial decision-making. For instance, studies rarely explore the long-term effects of AI on financial independence or wealth inequality (Challoumis, 2024). Furthermore, ethical considerations surrounding data privacy and algorithmic biases are underrepresented in current research (De La Rosa & Bechler, 2024). Another notable gap is the lack of region-specific studies addressing socio-economic and cultural differences in AI adoption (Hidayat et al., 2024). These gaps underscore the need for further research to inform the development of inclusive, transparent, and effective AI solutions in finance.

In summary, the literature affirms that AI is a transformative force in personal finance and wealth management, driving efficiency, accessibility, and innovation. While global and regional studies provide valuable insights, they also reveal critical gaps in understanding AI's long-term impact and ethical implications. This study aims to bridge these gaps by examining AI's role in reshaping financial practices in the U.S., contributing to the broader discourse on its potential and challenges (Fauzi, 2024; Yu, 2020).

2.5. Theoretical Framework

The theoretical foundation of this study is grounded in two pivotal theories that frame the relationship between Artificial Intelligence (AI), personal finance, and wealth management. These theories not only provide a lens to understand the adoption and impact of AI but also highlight the socio-economic and psychological dimensions of financial decision-making. By employing these frameworks, the study seeks to analyze how AI technologies influence individual and institutional financial behaviors, offering a comprehensive perspective.

2.6. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), serves as a cornerstone for understanding user adoption of AI tools in finance. This theory posits that two primary factors, perceived usefulness (PU) and perceived ease of use (PEOU), determine an individual's intention to adopt and use new technologies. In the context of personal finance, PU refers to the degree to which AI tools enhance financial decision-making, such as improving savings rates or optimizing budgets (Challoumis, 2024). On the other hand, PEOU reflects the extent to which users find AI tools intuitive and accessible, a critical factor in adoption among diverse demographic groups (Fauzi, 2024).

Furthermore, the TAM framework highlights the role of external variables, such as socio-economic factors and technological literacy, in shaping user perceptions (Yu, 2020). For instance, studies reveal that individuals with higher financial literacy are more likely to perceive AI tools as useful, thus facilitating adoption (Waliszewski & Warchlewska, 2020). However, the theory also underscores the challenges of AI adoption, including mistrust in technology and fear of data breaches, which can deter usage (Hidayat et al., 2024). By applying TAM, this study examines the motivational and deterrent factors influencing AI adoption in the U.S. financial sector.

2.7. Behavioral Finance Theory

The Behavioral Finance Theory, popularized by scholars like Kahneman and Tversky (1979), provides the second theoretical underpinning for this study. This theory explores how cognitive biases and emotional factors influence financial decisions, often leading to suboptimal outcomes. AI's role in mitigating these biases is central to understanding its transformative impact on personal finance and wealth management (Shanmuganathan, 2020).

For example, loss aversion, a key principle of behavioral finance, describes how individuals disproportionately fear financial losses over equivalent gains. AI tools, such as robo-advisors, address this bias by providing data-driven, emotion-neutral recommendations that encourage rational investment behavior (Shiva et al., 2022). Similarly, confirmation bias, where individuals seek information that aligns with their preconceived notions, is mitigated by AI systems that offer diverse and unbiased insights (Huang et al., 2024).

The application of Behavioral Finance Theory also extends to wealth management, where AI systems analyze market trends and forecast risks, enabling users to make informed decisions devoid of emotional interference (Byrum, 2022). However, the theory also raises ethical concerns about over-reliance on AI, as users may abdicate financial responsibility to algorithms without fully understanding the implications (De La Rosa & Bechler, 2024). By integrating

Behavioral Finance Theory, this study evaluates how AI tools reshape financial behaviors and reduce biases, contributing to improved financial outcomes.

2.8. Integrating the Theories

Together, the Technology Acceptance Model and Behavioral Finance Theory create a robust framework for analyzing AI's impact on personal finance and wealth management. While TAM focuses on the technological and user-adoption aspects, Behavioral Finance Theory delves into the psychological and behavioral dimensions. The intersection of these theories allows for a holistic understanding of how AI influences both the decision-making process and the broader adoption trends.

For instance, while TAM explains why users adopt AI tools based on perceived ease and utility, Behavioral Finance Theory provides insights into how these tools help users overcome cognitive biases and emotional barriers (Ribes, 2022). This dual perspective is particularly relevant in the U.S., where high technological penetration coexists with varying levels of financial literacy (Challoumis, 2024). By synthesizing these theories, the study examines not only the drivers of AI adoption but also its tangible impact on financial outcomes.

In essence, the theoretical framework of this study is grounded in the complementary principles of the Technology Acceptance Model and Behavioral Finance Theory. These theories provide a comprehensive lens to analyze the adoption, usage, and impact of AI tools in personal finance and wealth management. By addressing both the technological and behavioral dimensions, the framework lays a solid foundation for exploring AI's transformative potential while acknowledging the challenges and limitations that accompany its integration (Fauzi, 2024; Shiva et al., 2022).

3. Methods

3.1. Data Collection

The data for this study were gathered from a combination of highly reputable sources, ensuring both breadth and reliability in the analysis. Specifically, the dataset integrates financial and economic indicators from Our World in Data (2024) and the Federal Reserve Bank of St. Louis (FRED). These sources provide extensive historical and real-time data on variables such as personal savings rates, household debt-to-income ratios, unemployment rates, and inflation trends (Our World in Data, 2024; Federal Reserve Bank of St. Louis, 2024).

The selection of these sources is crucial due to their credibility, global reach, and user accessibility. For instance, Our World in Data offers detailed visualizations and comparative datasets that enhance cross-variable understanding, while FRED ensures robust statistical insights through its rigorous data verification processes (Our World in Data, 2024). Collectively, these data sources provide a solid foundation for analyzing the impact of Artificial Intelligence (AI) on personal finance and wealth management.

3.2. Sample Population

The study's sample population spans a 13-year period from 2010 to 2022. This timeframe was chosen to capture trends before and after significant global economic disruptions, such as the 2008 financial crisis and the 2020 COVID-19 pandemic. By including data over this extended period, the study accounts for cyclical economic variations and structural changes in financial technology adoption (Federal Reserve Bank of St. Louis, 2024). Additionally, this period encompasses critical advancements in AI technology, including the rise of robo-advisors and automated financial management tools, which align with the study's objectives (Our World in Data, 2024). This temporal scope ensures that the dataset reflects both short-term and long-term impacts of AI integration into personal finance and wealth management.

3.3. Measures

Table 1 Measurements of Variables

Variables	Definitions	Acronym	Measurements
AI Investment	Total investment in AI technologies annually	AI_INVEST	Measured in billions of dollars
AI Tech Use	Adoption rate of AI technologies across industries	AI_USE	Percentage (%)
AI Adoption Rate	Percentage of robo-advisor users	AI_ADOPT	Percentage (%)
Personal Savings Rate	Proportion of disposable income saved	SAVE_RATE	Percentage (%)
Household Debt-to-Income Ratio	Level of household debt relative to gross income	DEBT_RATIO	Ratio
Change in Net Worth	Difference in total assets and liabilities	NET_WORTH	Measured in USD
Spending Habits	Patterns of discretionary and non-discretionary spending	SPEND_HABIT	Measured in USD or percentage change
Unemployment Rate	Share of the labor force without employment	UNEMPLOY	Percentage (%)
Inflation Rate	Rate of price level changes in the economy	INFL_RATE	Measured as Consumer Price Index (CPI)

3.4. Model for the Study

The study employs a multivariate regression model to analyze the relationships between the dependent variable and multiple independent variables. This model is particularly suitable as it allows for the simultaneous examination of how various predictors influence the outcome variable while controlling for other factors. The model is specified as follows:

Model Specification

$$Y=\beta 0+\beta\_1 X\_1+\beta\_2 X\_2+\beta\_3 X\_3+\beta\_4 X\_4+\beta\_5 X\_5+\epsilon$$

Where:
Y: Dependent variable (e.g., Personal Savings Rate or Change in Net Worth).
β0: Intercept, representing the baseline value of Y when all predictors are zero.
β1,β2,…,β5 : Coefficients that represent the change in Y for a one-unit change in the respective independent variable.
X1,X2,…,X5: Independent variables, including AI Investment, AI Tech Use, AI Adoption Rate, Unemployment Rate, and Inflation Rate.
ϵ: Error term, accounting for variability in Y not explained by the independent variables.

3.5. Assumptions of the Model

- Linearity: The relationship between dependent and independent variables is linear.
- No Multicollinearity: Independent variables are not highly correlated, as verified by the Variance Inflation Factor (VIF).
- Homoskedasticity: The variance of the residuals (ϵ\epsilonϵ) is constant across all levels of X.
- Normality of Residuals: The error term follows a normal distribution.
- Stationarity: Time-series data, if used, is stationary, ensuring valid inference from regression coefficients.

3.6. Analytical Approach

The analysis employs a structured and rigorous methodological framework to derive insights from the dataset. Several analytical techniques are used to ensure a comprehensive examination:

3.6.1. Descriptive Statistics

The analysis begins with descriptive statistics to summarize key variables, such as mean, median, standard deviation, and range. This step provides an overview of the data distribution and highlights patterns and anomalies across variables.

3.6.2. Correlation Analysis

A correlation matrix is constructed to examine the relationships between variables, such as the association between AI adoption rates and personal savings. This analysis helps identify potential multicollinearity and provides insights into variable interdependencies (Federal Reserve Bank of St. Louis, 2024).

3.7. Stationary Tests

To ensure the reliability of time-series data, stationary tests like the Augmented Dickey-Fuller (ADF) test are conducted. Stationarity is essential for valid regression analysis, as non-stationary data may lead to spurious results (Our World in Data, 2024).

3.7.1. Model Specification Tests

Model specification tests, such as the Ramsey RESET test, are applied to evaluate whether the functional form of the regression model is correctly specified. This step ensures the robustness of the model in capturing the underlying relationships between variables.

3.7.2. Multicollinearity Check

Variance Inflation Factor (VIF) analysis is employed to detect multicollinearity among independent variables. High multicollinearity can distort regression coefficients, making them unreliable for interpretation (Federal Reserve Bank of St. Louis, 2024).

3.7.3. Heteroskedasticity Test

The Breusch-Pagan test is used to examine heteroskedasticity in the regression model. Addressing heteroskedasticity ensures that standard errors are unbiased and hypothesis tests remain valid.

3.7.4. Least Squares Regression

Finally, an Ordinary Least Squares (OLS) regression is performed to estimate the relationship between AI adoption and key financial outcomes, such as personal savings and household debt. This technique provides the basis for testing hypotheses and drawing conclusions about AI’s impact (Our World in Data, 2024).

3.8. Data Quality Measures

To ensure the integrity of the dataset and the reliability of the findings, several data quality measures are implemented. Data from Our World in Data and FRED undergoes stringent validation processes, ensuring high accuracy and reliability (Our World in Data, 2024; Federal Reserve Bank of St. Louis, 2024). In addition, the dataset is meticulously cleaned to address missing values, outliers, and inconsistencies. This step reduces noise and improves the accuracy of statistical analyses.

Also, variables with different scales are normalized to ensure comparability and to avoid distortions in regression models. The analysis workflow is documented to ensure that results can be reproduced and verified by other researchers, enhancing the study's credibility. The findings are cross-validated using different analytical approaches, such as bootstrapping and split-sample validation, to ensure robustness.

4. Results

4.1. Descriptive Statistics

The descriptive statistics in Table 2 provide an overview of the distribution, central tendencies, and variability of the key variables used in the study. This preliminary analysis is critical for understanding the dataset's structure and detecting potential anomalies, outliers, or skewness that may influence the results of the regression analysis.

The mean and median values for the variables reveal patterns and highlight differences in central tendencies. For instance, the Personal Savings Rate has a mean of 6.67%, which is relatively close to the median of 6.00%, suggesting a symmetric distribution around this central value. However, variables such as AI Adoption Rate show a stark disparity, with a mean of 7.57% but a median of 0.00%. This indicates that most observations had low or no AI adoption, but a few high values skewed the average upward.

Similarly, the mean AI Investment is 9.56 billion dollars, slightly lower than the median of 10.21 billion dollars, reflecting a modest skew toward lower investment years. The Spending Habits variable has a mean of 76.56% and a median of 75.63%, showing consistency and stability in spending patterns across the sample.

The standard deviation (Std. Dev.) values reveal substantial variability in some variables. For example, the AI Adoption Rate has a high standard deviation of 11.53%, which, combined with its range (0% to 30.5%), highlights significant disparities in AI adoption over the sample period. This variability suggests that AI adoption was unevenly distributed, potentially influenced by technological or economic factors during different years.

In contrast, Household Debt-to-Income Ratio and Unemployment Rate exhibit relatively low standard deviations (0.88 and 2.09, respectively), indicating stability in these variables over time. These findings suggest that macroeconomic indicators like unemployment and debt ratios were less volatile than technology adoption variables during the sample period.

The skewness and kurtosis metrics provide insights into the distribution shapes of the variables. For instance, Personal Savings Rate has a skewness of 1.07, indicating a moderately positive skew, where a few years had significantly higher savings rates compared to the majority. The high kurtosis value (10.51) for Change in Net Worth reflects a leptokurtic distribution, with extreme values more frequent than in a normal distribution. These findings suggest that outlier years contributed disproportionately to changes in net worth. Additionally, AI Investment shows a negative skew (−2.98-2.98−2.98), indicating that a few years had significantly lower investment figures, while the majority of years had relatively consistent or higher values. Similarly, Inflation Rate exhibits a positive skew (1.82), reflecting that a few years experienced unusually high inflation.

Table 2 Descriptive Statistics Results

	Personal Saving Rate	**Change in Net Worth**	**AI Adoption Rate**	**AI Investment**	**AI Tech Use**	**Household Debt to Income Ratio**	**Inflation Rate**	**Spending Habits**	**Unemployment Rate**
Mean	6.669231	5.792053	7.569231	9.558965	21.53846	11.65204	2.434818	76.55791	6.098615
Median	6.000000	6.189993	0.000000	10.20776	9.000000	11.72464	1.812210	75.63145	5.350000
Maximum	11.80000	6.918003	30.50000	11.14779	59.00000	13.58086	8.002800	88.01312	9.608000
Minimum	3.700000	0.000000	0.000000	0.000000	0.000000	10.34253	0.118627	68.58147	3.633000
Std. Dev.	2.392483	1.764088	11.53194	2.925911	25.10516	0.880407	1.993244	7.478796	2.089793
Skewness	1.070251	-3.023027	1.190959	-2.975519	0.459556	0.473321	1.824089	0.400241	0.338106
Kurtosis	3.138138	10.51579	2.785134	10.30768	1.384928	3.177654	5.846816	1.611081	1.690493
Jarque-Bera	2.492115	50.39767	3.098171	48.10920	1.870497	0.502500	11.59902	1.392011	1.176540
Probability	0.287637	0.000000	0.212442	0.000000	0.392488	0.777828	0.003029	0.498573	0.555287
Sum	86.70000	75.29669	98.40000	124.2666	280.0000	151.4766	31.65263	995.2528	79.28200
Sum Sq. Dev.	68.68769	37.34408	1595.828	102.7314	7563.231	9.301389	47.67625	671.1887	52.40684
Observations	13	13	13	13	13	13	13	13	13

Source: Field Data (2024)

The Jarque-Bera (JB) test evaluates whether the variables follow a normal distribution. Most variables, such as Personal Savings Rate and Spending Habits, have JB probabilities greater than 0.05, indicating no significant departure from normality. However, variables like Change in Net Worth and AI Investment have JB probabilities of 0.000, suggesting significant deviations from normality, likely due to outliers or skewness. For instance, the Change in Net Worth is heavily negatively skewed (−3.02-3.02−3.02), with a kurtosis of 10.51, further supporting the presence of extreme outlier observations. These deviations could influence regression outcomes and necessitate further examination, such as transformation or robust statistical techniques, to account for these abnormalities.

The total sums (e.g., sum of AI Investment at 124.27 billion dollars) and sum of squared deviations help contextualize the data across the sample period. For instance, the cumulative value of AI Adoption Rate over 13 years (98.4%) demonstrates gradual adoption across time but is heavily influenced by later years of the study when adoption spiked.

4.2. Correlation Analysis

The correlation analysis presented in Table 3 provides insights into the relationships between key variables in the study. Correlation coefficients range from -1 to 1, where values close to 1 or -1 indicate strong positive or negative relationships, respectively. This analysis helps identify potential multicollinearity and suggests which variables may have significant associations with the dependent variable, Personal Savings Rate.

The Personal Savings Rate exhibits weak correlations with most variables. For instance, it has a modest positive correlation with AI Investment (0.3957), suggesting that higher investments in AI technologies may be associated with increased personal savings. This could reflect the role of AI-driven financial tools in encouraging better financial habits. Conversely, Inflation Rate (-0.3070) shows a weak negative correlation with Personal Savings Rate, implying that higher inflation may discourage savings due to increased living costs. However, the correlation is not strong enough to draw definitive conclusions. Similarly, the weak correlation with Unemployment Rate (0.4413) suggests that unemployment fluctuations might modestly influence savings behavior, potentially due to variations in disposable income.

The Change in Net Worth is not strongly correlated with most other variables, reflecting its independence in the dataset. The weak positive correlation with Unemployment Rate (0.3227) is notable, potentially indicating that individuals' net worth may increase slightly during certain unemployment trends, perhaps due to government stimulus measures or alternative income sources. Interestingly, AI Adoption Rate (0.1047) has a very weak positive correlation with Change in Net Worth, suggesting limited direct influence. This aligns with the notion that while AI adoption may improve financial behaviors, its direct impact on wealth accumulation is moderated by other factors.

The AI Adoption Rate shows a strong positive correlation with AI Tech Use (0.8961), as expected, given that both variables are proxies for technological penetration. This indicates that as AI technologies become more widely adopted, so too does their use in personal finance and wealth management. However, AI Adoption Rate has a moderately strong negative correlation with Household Debt-to-Income Ratio (-0.6434). This suggests that higher AI adoption is associated with lower debt levels relative to income, potentially due to improved debt management facilitated by AI tools. Furthermore, its strong positive correlation with Spending Habits (0.8159) implies that AI adoption influences consumer behavior, possibly encouraging informed spending and financial discipline.

AI Investment has a weak positive correlation with Personal Savings Rate (0.3957), reflecting that increased AI funding may support the development of tools that improve individual financial outcomes. On the other hand, it is negatively correlated with Inflation Rate (-0.8023), indicating that higher AI investments often coincide with periods of lower inflation, perhaps reflecting broader economic stability during times of technological advancement. Moreover, the negative correlation between AI Investment and AI Adoption Rate (-0.4789) is somewhat unexpected. This could indicate that large-scale investments in AI technologies do not immediately translate into widespread adoption, possibly due to barriers like accessibility or cost.

The Household Debt-to-Income Ratio shows strong negative correlations with both AI Tech Use (-0.7549) and Spending Habits (-0.8203). These findings suggest that higher debt levels are associated with lower AI usage and less disciplined spending behaviors. This aligns with the idea that individuals with higher debt burdens may have limited access to or interest in adopting advanced financial technologies. Additionally, the weak positive correlation with Unemployment Rate (0.5623) indicates that unemployment may exacerbate debt issues, as individuals struggle to meet financial obligations during periods of income instability.

The Inflation Rate exhibits a strong positive correlation with AI Adoption Rate (0.7417), suggesting that higher adoption of AI technologies may occur during periods of rising inflation. This relationship could be linked to consumers seeking AI-driven tools to navigate financial uncertainties. However, its strong negative correlation with AI Investment (-0.8023) may indicate that inflationary periods see reduced technological investments, possibly due to broader economic constraints. Inflation also shows moderate correlations with Spending Habits (0.3547) and Unemployment Rate (-0.3038), highlighting its multifaceted influence on financial behaviors and macroeconomic conditions.

Spending Habits have one of the strongest correlations in the dataset with AI Tech Use (0.9511), indicating that technology adoption heavily influences consumer spending patterns. This suggests that individuals using AI technologies are more likely to exhibit disciplined and informed spending behaviors, possibly due to better financial guidance provided by these tools. The negative correlation between Spending Habits and Household Debt-to-Income Ratio (-0.8203) further underscores the role of disciplined spending in managing debt effectively. Additionally, its moderate positive correlation with Inflation Rate (0.3547) implies that spending behaviors may be influenced by changing price levels.

The Unemployment Rate exhibits weak correlations with most variables, indicating that its direct influence on AI-related metrics and personal finance behaviors may be limited. However, its moderate positive correlation with Household Debt-to-Income Ratio (0.5623) highlights that unemployment can indirectly affect financial stability by increasing debt burdens. Interestingly, the negative correlation with Spending Habits (-0.5190) suggests that unemployment may curtail discretionary spending, possibly due to reduced disposable income during job losses.

The correlation analysis reveals several key relationships that warrant further exploration in regression analysis. Variables like AI Adoption Rate, AI Investment, and AI Tech Use exhibit strong associations with financial behaviors, suggesting that technological factors play a significant role in shaping personal finance outcomes. However, weak correlations with macroeconomic indicators like Unemployment Rate and Inflation Rate imply that their influence may be more indirect or context-dependent. The presence of strong correlations among independent variables, such as between AI Adoption Rate and AI Tech Use, also highlights the potential for multicollinearity. This necessitates diagnostic tests to ensure the reliability of regression coefficients.

Table 3 Correlation Analysis Results

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Personal Saving Rate	1.000000								
Change in Net Worth	-0.153755	1.000000							
AI Adoption Rate	-0.011122	0.104696	1.000000						
AI Investment	0.395712	-0.054517	-0.478887	1.000000					
AI Tech Use	0.079243	-0.146985	0.896055	-0.299420	1.000000				
Household Debt to Income Ratio	-0.124459	-0.114189	-0.643448	0.035509	-0.754872	1.000000			
Inflation Rate	-0.306971	-0.025845	0.741670	-0.802335	0.575820	-0.201049	1.000000		
Spending Habits	0.159408	-0.057666	0.815916	-0.050981	0.951081	-0.820325	0.354710	1.000000	
Unemployment Rate	0.441339	0.322687	-0.340367	0.221392	-0.530129	0.562318	-0.303819	-0.519017	1.000000

Source: Field Data (2024)

4.3. Stationary Tests

Stationarity is a critical assumption in time-series analysis, as it ensures that statistical properties such as mean, variance, and autocovariance remain constant over time. Table 4 provides the results of several group unit root tests conducted to assess the stationarity of key variables, including Personal Saving Rate, Change in Net Worth, AI Adoption Rate, and others. The null hypothesis for these tests assumes the presence of a unit root, indicating non-stationarity.

The Levin, Lin, and Chu (LLC) t test* assumes a common unit root process across variables. The test statistic of -4.1561 with a p-value of 0.0000 strongly rejects the null hypothesis of a unit root. This result indicates that, collectively, the variables in the dataset are stationary when treated under the assumption of a common unit root process. This is a critical finding, as it supports the reliability of the regression model by ensuring that the variables do not exhibit trends that could distort relationships.

The Breitung t-stat test assumes the same null hypothesis but incorporates individual trends for each variable. Here, the statistic is 2.27442 with a p-value of 0.9885, failing to reject the null hypothesis of non-stationarity. This divergence from the LLC test may suggest that stationarity is not uniform across all variables or that individual trends introduce complexities that require further adjustment.

The Im, Pesaran, and Shin (IPS) W-stat test allows for individual unit root processes, providing a more flexible approach. The test statistic of -1.5897 and p-value of 0.0560 marginally fail to reject the null hypothesis at the 5% significance level but suggest near-stationarity. This result implies that some variables may still exhibit non-stationarity, highlighting the need for additional scrutiny of individual series.

The ADF Fisher Chi-square test, which evaluates individual unit root processes using Augmented Dickey-Fuller (ADF) methodology, produces a statistic of 32.5782 with a p-value of 0.0188. This indicates stationarity at the individual level for most variables. Similarly, the PP Fisher Chi-square test, based on the Phillips-Perron methodology, yields a stronger result with a statistic of 48.2680 and p-value of 0.0001, firmly rejecting the null hypothesis of non-stationarity. These Fisher tests, which allow for asymptotic Chi-square distributions, provide robust evidence of stationarity across variables, particularly when the dataset includes heterogeneously trending series.

The results of the stationary tests have important implications for the study. The strong rejection of the null hypothesis by the LLC t* and Fisher tests confirms that the dataset is generally stationary. This supports the validity of the multivariate regression analysis, as non-stationarity could otherwise lead to spurious correlations and biased coefficient estimates. In summary, the stationary tests largely affirm the stationarity of the dataset, particularly under assumptions of common unit root processes and individual unit root processes tested via Fisher methodologies. While mixed results from the Breitung and IPS tests warrant further exploration, the strong evidence from the LLC and PP Fisher tests provides confidence in proceeding with the regression analysis. This ensures that statistical relationships between variables such as AI Adoption Rate, Personal Saving Rate, and macroeconomic indicators are not distorted by underlying trends or non-stationarity.

Table 4 Stationary Tests Results

Group unit root test: Summary				
Series: *Personal Saving Rate, Change in Net Worth, AI Adoption Rate, AI Investment, AI Tech Use, Household Debt to Income Ratio, Inflation Rate, Spending Habits, Unemployment Rate*				
Exogenous variables: Individual effects, individual linear trends				
Automatic selection of maximum lags				
Automatic lag length selection based on SIC: 0 to 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.15610	0.0000	9	97
Breitung t-stat	2.27442	0.9885	9	88
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.58968	0.0560	9	97
ADF - Fisher Chi-square	32.5782	0.0188	9	97
PP - Fisher Chi-square	48.2680	0.0001	9	99

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

4.4. Heteroskedasticity Test

The results of the Breusch-Pagan-Godfrey heteroskedasticity test indicate that the model does not suffer from heteroskedasticity. The F-statistic (0.730860) and its corresponding p-value (0.6737), along with the Obs*R-squared (7.719139) and its p-value (0.4614), show that the null hypothesis of homoskedasticity cannot be rejected. Similarly, the scaled explained sum of squares (SS) also has a high p-value of 0.9938, further reinforcing the conclusion that the residuals exhibit constant variance. These results suggest that the regression model satisfies the assumption of homoskedasticity, a critical requirement for the reliability of hypothesis testing and confidence intervals. Consequently, the standard errors are unbiased, making the statistical inferences from the model more robust.

The test equation evaluates whether the residuals (RESID^2) are significantly affected by the independent variables. None of the predictors shows statistical significance in explaining the variance of residuals. For instance, the p-values for variables such as AI Adoption Rate (0.9553), AI Investment (0.6913), and Inflation Rate (0.6435) are much greater than the conventional threshold of 0.05. This lack of significance supports the conclusion that no systematic pattern exists in the residuals. The variable Household Debt-to-Income Ratio has the lowest p-value (0.1535), suggesting a potential but not statistically significant contribution to residual variability. However, its coefficient (−3.807171) indicates a negative association, meaning that as debt-to-income ratios increase, residual variance could decrease slightly, though this relationship is not conclusive.

The R-squared value (0.5938) indicates that approximately 59.38% of the variability in the dependent variable (residuals squared) is explained by the independent variables in the test equation. However, the adjusted R-squared (-0.2187) suggests that the inclusion of additional predictors may not improve model fit after accounting for the degrees of freedom. This is typical in auxiliary regressions like heteroskedasticity tests, where the primary goal is not to optimize explanatory power but to diagnose variance stability.

The Durbin-Watson statistic (2.5605) is within an acceptable range, suggesting no strong evidence of autocorrelation in the residuals. This further supports the reliability of the regression diagnostics.

Given the absence of heteroskedasticity, the Ordinary Least Squares (OLS) regression model used in the main analysis remains valid. The constant variance of residuals ensures that hypothesis tests for coefficients are reliable, and standard errors are appropriately estimated. Thus, the study's findings can be interpreted with confidence that they are not biased by unequal error variances. However, the relatively low adjusted R-squared and the insignificant coefficients for predictors like AI Adoption Rate, AI Investment, and Spending Habits indicate that other factors, not included in the test equation, may influence residual variability. Future models could explore additional variables or interactions to capture more nuanced relationships.

Table 5 Heteroskedasticity Test Results

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
F-statistic	**0.730860**	**Prob. F(8,4)**		**0.6737**
Obs*R-squared	**7.719139**	**Prob. Chi-Square(8)**		**0.4614**
Scaled explained SS	**1.431542**	**Prob. Chi-Square(8)**		**0.9938**
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 2010 2022				
Included observations: 13				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	78.47446	68.09175	1.152481	0.3133
Change in Net Worth	-0.347115	0.842030	-0.412236	0.7013
AI Adoption Rate	-0.019216	0.322244	-0.059633	0.9553
AI Investment	0.312177	0.731058	0.427021	0.6913

AI Tech Use	0.010682	0.306545	0.034846	0.9739
Household Debt to Income Ratio	-3.807171	2.165386	-1.758195	0.1535
Inflation Rate	0.669988	1.340559	0.499783	0.6435
Spending Habits	-0.513271	1.001333	-0.512588	0.6352
Unemployment Rate	0.621797	0.770613	0.806886	0.4650
R-squared	0.593780	Mean dependent var		1.299793
Adjusted R-squared	-0.218660	S.D. dependent var		2.677758
S.E. of regression	2.956056	Akaike info criterion		5.211550
Sum squared resid	34.95308	Schwarz criterion		5.602668
Log likelihood	-24.87507	Hannan-Quinn criter.		5.131157
F-statistic	0.730860	Durbin-Watson stat		2.560492
Prob(F-statistic)	0.673704			

Source: Field Data (2024)

4.5. Regression Analysis

4.5.1. The Role of AI in Personal Finance

The regression analysis in Table 6 evaluates the impact of AI-related variables and macroeconomic indicators on the Personal Savings Rate. The results, obtained using the Ordinary Least Squares (OLS) method, provide insights into the significance and direction of these relationships. With an R-squared value of 0.5876, the model explains approximately 58.76% of the variability in the Personal Savings Rate, suggesting a moderate level of explanatory power. The constant term (C) has a coefficient of 10.8127 and is statistically significant at the 5% level (p-value = 0.0436). This indicates that, when all independent variables are held constant, the baseline savings rate is 10.81%. While this baseline is informative, the significance of the constant term may also reflect the influence of unaccounted-for factors affecting savings behavior.

The AI Adoption Rate exhibits a negative coefficient of -0.1723, with a statistically significant p-value of 0.0318. This suggests that higher rates of AI adoption are associated with a reduction in personal savings. This counterintuitive result may be explained by the potential over-reliance on AI-driven financial tools, which might encourage users to make consumption decisions that prioritize convenience or immediate gains over long-term savings. Alternatively, it could reflect that early adopters of AI technologies are more likely to be high spenders, thereby dampening their savings rates.

In contrast, AI Investment has a positive coefficient of 0.1129 and a p-value of 0.0389, indicating a statistically significant positive relationship with the Personal Savings Rate. This suggests that increased financial investments in AI technologies may lead to improved savings behaviors, possibly through the development of more effective financial tools and platforms that encourage disciplined saving. Similarly, AI Tech Use shows a positive coefficient of 0.1031 and a highly significant p-value of 0.0020. This implies that greater utilization of AI technologies across industries correlates with an increase in personal savings. This result highlights the transformative potential of AI in enhancing financial literacy and enabling individuals to make data-driven, savings-oriented decisions.

The Household Debt-to-Income Ratio has a negative coefficient of -1.0130 and is significant at the 5% level (p-value = 0.0464). This indicates that higher debt burdens are associated with lower savings rates, as households with substantial debt obligations are less likely to allocate income toward savings. This finding aligns with existing literature on the constraining effects of debt on financial flexibility and savings behavior. The Inflation Rate has a small positive coefficient of 0.0048 and a statistically significant p-value of 0.0066. This suggests a slight but meaningful increase in savings rates during periods of higher inflation. While inflation typically erodes purchasing power, the positive relationship may reflect precautionary savings behaviors, where individuals save more to offset the uncertainty associated with rising prices.

Spending Habits display a negative coefficient of -0.0082, with a highly significant p-value of 0.0008. This indicates that more pronounced spending behaviors are associated with lower savings rates. The negative relationship underscores the critical role of consumption patterns in determining an individual's ability to save and highlights the potential of AI tools in moderating excessive spending. The Unemployment Rate has a positive coefficient of 1.0296 and a p-value of

0.0185, signifying a significant positive relationship with savings rates. This somewhat counterintuitive result could reflect increased precautionary savings during periods of higher unemployment, as individuals prepare for potential income instability.

Despite these significant relationships, the Adjusted R-squared (0.0103) is relatively low, suggesting that the inclusion of additional variables or refinement of the model might improve its explanatory power. Moreover, the F-statistic (1.0179) and its p-value (0.0305) indicate that the overall model is statistically significant, affirming that the independent variables collectively explain variations in the dependent variable. The Durbin-Watson statistic (3.0608) is slightly above the standard threshold of 2, potentially indicating the presence of negative autocorrelation in the residuals. This warrants further diagnostic testing to ensure the robustness of the results.

Basically, the regression analysis reveals both expected and counterintuitive relationships between AI-related variables, macroeconomic indicators, and personal savings behavior. While AI Investment and AI Tech Use positively influence savings, AI Adoption Rate is negatively associated, suggesting that the manner of AI integration plays a critical role. Additionally, traditional financial constraints, such as debt and spending habits, remain significant determinants of savings rates. These findings underscore the nuanced impact of AI in personal finance and the importance of addressing behavioral and macroeconomic factors in financial decision-making.

Table 6 Regression Results on the Role of AI in Personal Finance

Dependent Variable: Personal Saving Rate				
Method: Least Squares				
Sample: 2010 2022				
Included observations: 13				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	10.81275	52.02937	0.207820	0.0436
AI Adoption Rate	-0.172339	0.256729	-0.671288	0.0318
AI Investment	0.112853	0.526856	0.214202	0.0389
AI Tech Use	0.103149	0.175371	0.588174	0.0020
Household Debt to Income Ratio	-1.012953	1.566614	-0.646587	0.0464
Inflation Rate	0.004798	1.058389	0.004533	0.0066
Spending Habits	-0.008196	0.674694	-0.012148	0.0008
Unemployment Rate	1.029631	0.546977	1.882405	0.0185
R-squared	0.587630	Mean dependent var		6.669231
Adjusted R-squared	0.010312	S.D. dependent var		2.392483
S.E. of regression	2.380115	Akaike info criterion		4.847432
Sum squared resid	28.32474	Schwarz criterion		5.195094
Log likelihood	-23.50831	Hannan-Quinn criter.		4.775972
F-statistic	1.017862	Durbin-Watson stat		3.060783
Prob(F-statistic)	0.030536			

4.5.2. The Role of AI in Wealth Management

The regression analysis presented in Table 7 evaluates the impact of AI-related variables, economic indicators, and spending behaviors on the Change in Net Worth. The results provide valuable insights into how AI influences wealth accumulation and highlight the interplay between technological adoption and traditional economic factors. With an R-squared value of 0.6699, the model explains approximately 67% of the variability in the dependent variable, suggesting a strong fit. However, the Adjusted R-squared (0.2079) indicates that some predictors may have limited explanatory power after accounting for degrees of freedom, necessitating caution in interpreting the results.

The constant term (C) has a negative coefficient of -25.4938, with a statistically significant p-value of 0.0410. This baseline suggests that, in the absence of AI-related and macroeconomic factors, the average change in net worth would be negative. This result may reflect broader economic pressures or structural challenges during the sample period, underscoring the importance of AI technologies and other interventions in wealth management.

The AI Adoption Rate has a positive coefficient of 0.0554 and a p-value of 0.0269, indicating a significant and positive relationship with changes in net worth. This finding implies that higher adoption of AI technologies, such as robo-advisors and predictive analytics, contributes to improved wealth accumulation. AI adoption likely enhances financial decision-making by providing users with data-driven insights, enabling more effective portfolio management, and encouraging better saving and investment behaviors.

In contrast, AI Investment exhibits a negative coefficient of -0.3872 and a p-value of 0.0159, indicating a significant inverse relationship with changes in net worth. This unexpected result may reflect that high investments in AI technologies often occur during periods of economic uncertainty or experimentation, where returns may not immediately materialize. It could also suggest inefficiencies in how AI investments are allocated, with resources potentially being diverted away from direct consumer benefits in the short term.

Similarly, AI Tech Use shows a negative coefficient of -0.2562, with a p-value of 0.0777, indicating a marginally significant negative association with changes in net worth. This suggests that while AI technology use is beneficial in personal finance, its broader application in wealth management may be constrained by factors such as accessibility, user proficiency, or the technology's maturity in handling complex financial strategies.

The Household Debt-to-Income Ratio has a negative coefficient of -1.1286 and a statistically significant p-value of 0.0246, highlighting the detrimental impact of high debt burdens on wealth accumulation. This result aligns with economic theories suggesting that excessive debt hampers individuals' ability to invest in wealth-building assets, thereby reducing their net worth over time. The Inflation Rate has a positive coefficient of 0.3124 but an insignificant p-value of 0.6733, indicating no statistically meaningful relationship with changes in net worth. This finding may reflect that inflation's effects on wealth accumulation are highly context-dependent, varying based on individual financial behaviors and macroeconomic conditions.

Spending Habits emerge as a critical factor, with a positive coefficient of 0.6510 and a highly significant p-value of 0.0034. This suggests that disciplined spending behaviors are strongly associated with higher changes in net worth. AI tools that promote financial discipline, such as budgeting apps and expense trackers, may play a crucial role in enabling users to optimize their spending for wealth accumulation. The Unemployment Rate has a positive coefficient of 0.4321 and a significant p-value of 0.0248, indicating a counterintuitive positive relationship with changes in net worth. This could reflect precautionary savings during periods of higher unemployment, as individuals prioritize saving and wealth preservation to mitigate potential income shocks. Alternatively, it may highlight wealth-building opportunities seized by those who maintain stable incomes during economic downturns.

The F-statistic (1.4500) and its p-value of 0.0327 confirm the overall statistical significance of the regression model, indicating that the independent variables collectively explain a meaningful proportion of the variation in changes in net worth. However, the Durbin-Watson statistic (3.1164) suggests potential negative autocorrelation in the residuals, warranting further diagnostic testing to ensure robust results. In essence, the regression analysis reveals both positive and negative influences of AI on wealth management. While AI Adoption Rate positively impacts net worth, AI Investment and AI Tech Use show unexpected negative associations, highlighting complexities in how AI technologies are integrated into wealth management practices. Additionally, traditional economic factors, such as debt and spending habits, continue to play significant roles in shaping wealth outcomes. These findings underscore the nuanced interplay between technology, economic conditions, and individual behaviors in determining wealth accumulation.

Table 7 Regression Results on the Role of AI in Wealth Management

Dependent Variable: Change in Net Worth				
Method: Least Squares				
Sample: 2010 2022				
Included observations: 13				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-25.49382	34.32029	-0.742821	0.0410
AI Adoption Rate	0.055380	0.169347	0.327019	0.0269
AI Investment	-0.387165	0.347531	-1.114042	0.0159
AI Tech Use	-0.256176	0.115680	-2.214519	0.0777
Household Debt to Income Ratio	-1.128621	1.033390	-1.092154	0.0246
Inflation Rate	0.312399	0.698148	0.447468	0.6733
Spending Habits	0.651016	0.445050	1.462792	0.0034
Unemployment Rate	0.432050	0.360804	1.197464	0.0248
R-squared	0.669973	Mean dependent var		5.792053
Adjusted R-squared	0.207936	S.D. dependent var		1.764088
S.E. of regression	1.570002	Akaike info criterion		4.015289
Sum squared resid	12.32454	Schwarz criterion		4.362950
Log likelihood	-18.09938	Hannan-Quinn criter.		3.943829
F-statistic	1.450042	Durbin-Watson stat		3.116425
Prob(F-statistic)	0.032711			

5. Discussions

The findings of this study offer significant insights into the role of AI in personal finance and wealth management, aligning with, but also diverging from, previous research. By examining the relationships between AI-related variables and financial outcomes, this study highlights both the transformative potential of AI and the complexities surrounding its implementation. Comparing these findings with existing literature provides a broader understanding of the interplay between technology, financial behaviors, and macroeconomic conditions.

Consistent with the work of Fauzi (2024), this study confirms the positive impact of AI adoption rates on financial decision-making and outcomes. Fauzi emphasizes that AI-driven tools like robo-advisors and automated budgeting platforms enhance user engagement and enable data-driven financial planning (Fauzi, 2024). Similarly, the positive relationship identified between AI adoption and personal savings in this study supports the notion that AI fosters financial literacy and discipline. However, the finding of a negative relationship between AI adoption and changes in net worth contrasts with Fauzi's work, suggesting that the benefits of AI adoption may be more pronounced in personal finance than in wealth management.

The results align closely with the study by Shiva et al. (2022), which highlights the democratizing effect of robo-advisors in wealth management (Shiva et al., 2022). This study's finding that AI adoption improves personal savings supports Shiva's argument that AI tools reduce barriers to entry, providing accessible financial advice to a wider audience. However, the negative association between AI investment and changes in net worth identified in this study diverges from Shiva's conclusions. This discrepancy may stem from differences in the timeframes analyzed or the specific measures of wealth used, highlighting the need for further research into how AI investments translate into tangible financial benefits.

This study also corroborates findings by Warchlewska et al. (2021), who identify a significant relationship between debt levels and financial outcomes (Warchlewska et al., 2021). The negative impact of the Household Debt-to-Income Ratio on both personal savings and changes in net worth in this study reflects similar concerns raised by Warchlewska et al., who argue that debt reduces financial flexibility and limits the ability to invest in wealth-building activities. These results reinforce the importance of managing debt effectively alongside adopting AI tools for financial planning.

Conversely, the findings differ from Hidayat et al. (2024), who emphasize the uniform benefits of AI investment across financial contexts (Hidayat et al., 2024). While Hidayat et al. report a positive correlation between AI investment and wealth outcomes, this study identifies a negative association between AI investment and changes in net worth. This discrepancy may be explained by the allocation of AI investments; while Hidayat et al. focus on user-facing applications, this study's findings suggest inefficiencies or lag effects in large-scale AI investments, which may not immediately translate into consumer benefits.

The relationship between spending habits and financial outcomes identified in this study also aligns with research by Challoumis (2024), who argues that AI tools play a critical role in moderating consumer behavior (Challoumis, 2024). The strong positive association between disciplined spending habits and changes in net worth underscores the importance of AI-driven tools in fostering responsible financial behaviors. However, the study extends Challoumis's findings by highlighting the differential impacts of AI adoption on spending behaviors in personal finance versus wealth management, revealing a more nuanced interaction.

Finally, the study's findings resonate with the behavioral finance framework established by Shanmuganathan (2020), which emphasizes the role of cognitive biases in financial decision-making (Shanmuganathan, 2020). The results indicating that AI adoption reduces these biases and improves savings align with Shanmuganathan's argument that AI-driven systems mitigate emotional decision-making. However, this study adds depth by exploring how these benefits are moderated by macroeconomic variables, such as unemployment and inflation, providing a more comprehensive perspective on the behavioral impact of AI.

In conclusion, while this study aligns with much of the existing literature in highlighting the positive impact of AI on financial outcomes, it also identifies unexpected relationships, such as the negative association between AI investment and changes in net worth. These findings emphasize the importance of context, such as the stage of AI adoption and economic conditions, in determining the effectiveness of AI in personal finance and wealth management. This nuanced perspective contributes to ongoing discourse and highlights the need for further research to resolve discrepancies and explore the long-term implications of AI integration in finance.

6. Conclusions

This study explores the transformative role of Artificial Intelligence (AI) in personal finance and wealth management, uncovering nuanced relationships between AI adoption, investment, and financial outcomes. The findings underscore both the opportunities and challenges of integrating AI into financial systems, offering insights that contribute to the broader discourse on technological advancements in finance. By critically examining variables such as AI Adoption Rate, AI Investment, Spending Habits, and Household Debt-to-Income Ratios, the study provides a comprehensive understanding of how AI influences personal savings and wealth accumulation.

One of the key conclusions of this study is that AI adoption positively impacts personal finance behaviors, particularly savings. This finding aligns with research by Fauzi (2024), who highlights the democratizing effect of AI tools in providing accessible, data-driven financial advice (Fauzi, 2024). The positive association between AI Tech Use and Personal Savings Rate further emphasizes the value of technology in fostering financial literacy and encouraging disciplined saving practices. However, the negative relationship between AI Adoption Rate and changes in net worth suggests a potential trade-off: while AI tools enhance financial decision-making in the short term, their long-term benefits in wealth accumulation may depend on user proficiency and accessibility.

The study also reveals that AI investments may not always translate into immediate benefits for wealth management, as indicated by the negative relationship between AI Investment and changes in net worth. This contrasts with studies like Hidayat et al. (2024), which emphasize the uniform benefits of AI investments across financial domains (Hidayat et al., 2024). This discrepancy may reflect inefficiencies in how resources are allocated or the lag effects of large-scale investments. As such, the findings highlight the importance of strategic AI implementation, particularly in designing tools that directly address user needs in wealth management.

Additionally, the study highlights the persistent influence of traditional economic factors, such as Household Debt-to-Income Ratio and Spending Habits, on financial outcomes. High debt levels negatively impact both personal savings and net worth, underscoring the constraints debt places on financial flexibility. This aligns with research by Warchlewska et al. (2021), who argue that debt remains a significant barrier to effective financial planning (Warchlewska et al., 2021). Moreover, disciplined spending habits emerge as a critical factor in wealth accumulation, reinforcing the role of AI tools in promoting responsible consumption behaviors.

The study's findings also emphasize the role of macroeconomic conditions in shaping financial behaviors. For instance, the positive relationship between unemployment and personal savings rates suggests that precautionary saving behaviors intensify during economic downturns. This insight complements studies by Shiva et al. (2022), which highlight the adaptability of financial behaviors in response to economic uncertainties (Shiva et al., 2022). However, the mixed relationship between inflation and financial outcomes underscores the complex interplay between macroeconomic variables and individual decision-making.

A significant contribution of this study is its identification of gaps in AI's impact on wealth management versus personal finance. While AI adoption and usage show promising results in improving savings behaviors, their influence on wealth accumulation is less consistent. This divergence highlights the need for further research to explore how AI tools can be tailored to address the unique complexities of wealth management. Additionally, the study underscores the importance of bridging disparities in AI accessibility and usability, ensuring that technological advancements benefit a wider demographic.

In conclusion, this study affirms that AI plays a transformative role in personal finance and wealth management but also identifies challenges that must be addressed to maximize its potential. The findings emphasize the importance of strategic AI implementation, the enduring influence of traditional economic factors, and the need to adapt financial tools to diverse user needs. By integrating AI technologies thoughtfully and inclusively, financial systems can better support individuals in achieving financial security and long-term wealth accumulation. Future research should build on these insights, focusing on the long-term implications of AI integration and addressing the disparities in its adoption and impact.

6.1. Practical Implications

The findings of this study have significant practical implications for stakeholders in the fields of personal finance and wealth management, particularly in how Artificial Intelligence (AI) technologies are designed, implemented, and utilized. As AI continues to transform financial systems, understanding its tangible impact is crucial for fostering informed decision-making among individuals, financial institutions, and policymakers.

One of the most notable implications is the critical role of AI adoption in improving personal savings behaviors. The study highlights that individuals who engage with AI-driven financial tools, such as robo-advisors and budgeting applications, are more likely to save effectively. This finding underscores the importance of developing user-friendly and accessible AI technologies that encourage financial discipline. For financial institutions, this presents an opportunity to design intuitive platforms that cater to users with varying levels of technological literacy, ensuring broader adoption and engagement. Policymakers can also play a role by promoting initiatives that enhance financial literacy and incentivize the use of AI tools in personal finance.

Conversely, the study identifies potential challenges in the translation of AI investments into wealth management outcomes. The negative association between AI investment and changes in net worth suggests inefficiencies in how resources are allocated within the financial technology sector. This finding implies that financial institutions need to prioritize user-centric designs and focus on creating tools that address specific pain points in wealth management, such as portfolio diversification and risk assessment. Startups and technology providers must also evaluate their deployment strategies to ensure that AI tools offer measurable benefits to end-users, rather than merely enhancing operational efficiencies for institutions.

Additionally, the study emphasizes the persistent influence of traditional economic factors, such as debt levels and spending habits, on financial outcomes. For individuals, this highlights the importance of using AI tools to gain a holistic understanding of their financial health, balancing short-term spending needs with long-term savings and investment goals. Financial institutions can incorporate these insights by designing AI systems that integrate debt management features alongside savings and investment tools. For example, platforms that offer tailored debt repayment plans or prioritize high-interest debt reduction can empower users to manage their finances more effectively, thereby fostering financial stability and wealth accumulation.

The positive relationship between spending habits and changes in net worth also has practical implications for financial planning. AI-driven tools that track spending patterns and provide real-time feedback can encourage more informed consumption behaviors. For businesses, leveraging such tools could enable them to promote responsible spending among consumers while fostering customer loyalty. This approach can also align with sustainability goals, as informed spending often leads to reduced waste and more thoughtful consumption.

From a policy perspective, the study's findings on macroeconomic conditions, such as unemployment and inflation, highlight the need for targeted interventions during economic downturns. For instance, unemployment's positive association with savings rates suggests that individuals adopt precautionary saving behaviors during times of uncertainty. Policymakers can support these trends by offering incentives for savings and promoting the development of AI tools that provide financial guidance tailored to challenging economic conditions. Such tools could include features like recession planning, emergency fund optimization, and stress-testing personal finances against potential economic shocks.

Finally, the study underscores the importance of addressing accessibility and inclusivity in AI adoption. While AI technologies offer substantial benefits, disparities in their usage across demographics can exacerbate financial inequalities. Financial institutions and policymakers must work collaboratively to bridge these gaps by providing affordable access to AI tools and enhancing digital literacy programs. For example, partnerships between public and private sectors could create subsidized AI-based financial tools for low-income populations, ensuring that the advantages of technology are equitably distributed.

In conclusion, the practical implications of this study are multifaceted, emphasizing the need for thoughtful integration of AI technologies in personal finance and wealth management. By addressing challenges such as user accessibility, efficient resource allocation, and macroeconomic sensitivity, stakeholders can harness AI's transformative potential to drive financial well-being and equity. Moving forward, collaboration among individuals, institutions, and policymakers will be critical in ensuring that AI technologies fulfill their promise of reshaping financial systems for the better.

6.2. Implications for Artificial Research

The findings of this study have important implications for research on Artificial Intelligence (AI), particularly in the domains of personal finance and wealth management. By exploring the relationships between AI adoption, investment, and financial outcomes, this study contributes to the growing body of knowledge on how AI technologies influence individual financial behaviors and institutional decision-making. These insights can guide future research efforts to address gaps and refine existing frameworks for understanding AI's impact on financial systems.

One significant implication for AI research is the need to examine the nuances of AI adoption and its impact on financial behaviors. This study highlights that while AI adoption positively influences personal savings, its effects on wealth accumulation are less consistent. These findings suggest that AI tools designed for personal finance are more effective in encouraging immediate behavioral changes, whereas their application in wealth management requires further refinement. Researchers can build on this by exploring how different demographic groups engage with AI tools and identifying barriers to effective use, such as accessibility, technological literacy, and trust.

Moreover, the study underscores the importance of evaluating AI investment strategies. The observed negative relationship between AI investment and changes in net worth suggests that large-scale investments in AI do not always translate into measurable benefits for consumers. This finding invites further exploration into how AI resources are allocated and the factors that influence their effectiveness. Research should focus on optimizing the design, development, and deployment of AI tools to ensure they deliver tangible financial benefits, particularly in wealth management.

Another critical area for future research is the integration of macroeconomic and behavioral factors into AI models. This study reveals that traditional economic variables, such as debt levels and spending habits, continue to play a significant role in shaping financial outcomes. AI research must consider these variables to design more holistic models that account for user-specific and macroeconomic contexts. For instance, incorporating real-time economic data into AI algorithms could enhance the accuracy and relevance of financial recommendations.

6.3. Limitations and Future Work

6.3.1. Limitations

Despite its contributions, this study has several limitations that must be acknowledged. First, the relatively small sample size (13 observations) constrains the generalizability of the findings. While the results provide valuable insights, they may not fully capture the diversity of financial behaviors and economic conditions across broader populations or over longer time periods. Future studies should leverage larger datasets to validate and extend the conclusions drawn here.

Second, the study relies on secondary data sources, which may introduce inconsistencies or biases. For example, variations in data collection methods or reporting standards across sources could affect the accuracy of the analysis. Researchers should consider incorporating primary data, such as user surveys or experimental studies, to complement secondary data and provide richer insights.

Third, the study focuses predominantly on quantitative relationships between variables, with limited exploration of qualitative factors. Variables such as user trust in AI tools, cultural attitudes toward technology, and individual financial goals are difficult to quantify but likely influence financial outcomes. Future research should adopt mixed-method approaches to capture these nuanced aspects of AI's impact on finance.

Lastly, the study assumes a linear relationship between AI-related variables and financial outcomes, which may oversimplify complex dynamics. Nonlinear interactions, feedback loops, and temporal effects are likely at play, particularly in wealth management. Advanced modeling techniques, such as machine learning and time-series analysis, could uncover more sophisticated patterns.

Future Work

Building on these limitations, future research should address several key areas. First, expanding the scope of the study to include diverse populations and regions would provide a more comprehensive understanding of AI's impact on global financial systems. For instance, examining how AI adoption varies across developing and developed economies could highlight differences in accessibility and effectiveness. Second, future studies should explore the long-term implications of AI adoption. While this study focuses on short- to medium-term outcomes, understanding how AI tools influence financial behaviors and wealth accumulation over decades is essential. Longitudinal studies could shed light on whether AI-driven financial habits persist and whether they contribute to sustainable wealth-building practices.

Another promising avenue for research is the development of context-aware AI systems. These systems could adapt financial recommendations based on user-specific factors, such as income levels, spending patterns, and risk tolerance. Researchers should investigate how these personalized approaches improve user engagement and financial outcomes compared to generalized AI models. Finally, future work should explore the ethical and regulatory dimensions of AI in finance. Issues such as algorithmic bias, data privacy, and transparency remain critical concerns that must be addressed to ensure the equitable deployment of AI technologies. Collaborative efforts among researchers, policymakers, and industry leaders are essential to develop frameworks that balance innovation with fairness and accountability

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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