iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN ENHANCING PERSONAL FINANCIAL MANAGEMENT

Thomas P K
Adjunct Faculty, CMS Business School,
JAIN (Deemed to be University), Bangalore
Pk.thomas@cms.ac.in

Shreya Kirty
Master of Business Administration, CMS Business School,
JAIN (Deemed to be University), Bangalore
Shreya_kirty24@cms.ac.in

ABSTRACT
This Study investigates the impact of AI on the effectiveness of Personal Financial Management (PFM). In order to do so, the researchers use a sample of 101 respondents based in Bangalore and conduct statistical analyses using measures such as Cronbach's Alpha, Pearson Correlation, and Multiple Regression Analysis. Based on their analyses, the researchers find that five dimensions of AI have a positive effect on the efficiency of PFM practices. These dimensions include AI-Based Budgeting, Predictive Analytics, Personalized Recommendations, Automated Savings, and Risk Detection. Of these, Predictive Financial Analytics and Personalized Recommendations had the strongest effects in terms of predicting PFM success, accounting for 67.5 percent and 64.0 percent of the variance respectively.

Keywords:
Artificial Intelligence, Personal Financial Management, Predictive Analytics, Financial Technology, Financial Behaviour.

1. INTRODUCTION
With the dynamic changes brought about by digitization, Artificial Intelligence (AI) has emerged as an innovation that is revolutionizing the way people manage their finances. Through AI technologies such as automated budgeting and financial forecasting, AI enhances individual capabilities of financial self-discipline through data driven financial decisions. With financial technology companies adopting intelligent systems to understand the spending pattern of their customers, make future financial predictions, and issue alerts, individuals are in a position to practice proactive finance management. However, this development has come about without adequate research into the effects that such innovations have on individual financial behaviour.
While many studies have examined applications of AI in financial institutions, especially in issues of credit risk management and organizational fraud detection, very little is known about the extent to which factors such as budgeting, prediction, personalization, automation, and security contribute towards individual PFM practices. This paper seeks to address this gap by considering all these five constructs together in their effects on PFM. In order to achieve the goal of the study, it will be carried out among urban dwellers in Bangalore city.

2. LITERATURE REVIEW
The integration of Artificial Intelligence (AI) into the landscape of personal finance has fundamentally shifted the paradigm of how individuals manage their daily monetary habits, moving from reactive tracking to proactive management. Central to this transformation is the concept of AI-based budgeting, where sophisticated algorithms automate the arduous task of categorizing expenses and monitoring spending patterns in real-time. Davenport and Ronanki (2018) highlight that these systems serve as advanced cognitive assistants that reduce the mental load on consumers. Furthermore, these tools function as "digital nudges," a concept popularized by Thaler and Sunstein (2008), which suggests that small, automated alerts and reminders can steer individuals toward more responsible spending behaviours without restricting their freedom of choice. By providing immediate feedback on budget deviations, AI minimizes the "pain of paying" and helps users maintain long-term financial discipline.
Building upon basic budgeting, Predictive Financial Analytics represents a significant leap in decision-support technology by lowering the cost and complexity of accurate forecasting. Agrawal et al. (2018) argue that the "simple economics" of AI lies in its ability to turn data into cheap and reliable predictions. In a personal finance

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

context, this allows users to anticipate future income fluctuations and upcoming expenses with high precision. This forward-looking capability is crucial because it reduces the inherent uncertainty of financial planning, enabling what Choi et al. (2020) describe as more logical and less impulsive financial choices. When users can "see" their future financial state through predictive modelling, they are less likely to fall victim to present bias, thereby aligning their current actions with future goals.

The emergence of Personalized Financial Recommendations further refines this experience by shifting from generic advice to tailored, algorithm-driven strategies. Traditional financial advice often suffers from human error or emotional bias; however, algorithm-based personalization significantly mitigates these risks. D'Acunto et al. (2019) observed that robo-advising and personalized prompts increase the participation of "non-expert" investors in the market by simplifying complex asset allocation. This is supported by the findings of Jung et al. (2018), who noted that tailored guidance not only increases user engagement with financial platforms but also fosters a deeper sense of long-term commitment. By delivering the right information at the right time, AI ensures that financial management is not just automated, but deeply relevant to the user's specific life stage and risk tolerance.

In addition to advice, the physical movement of capital has been revolutionized through Automated Savings and Investments. One of the greatest barriers to wealth accumulation is procrastination and inertia. Madrian and Shea (2001) famously demonstrated the power of default options in retirement savings, showing that automation can lead to significantly higher participation rates. Modern AI expands on this by using "sweep" technologies that analyze cash flow and automatically transfer surplus funds into savings or investment vehicles. Baker et al. (2020) emphasize that these structured investment systems are essential for reducing emotional trading—the tendency to buy high and sell low based on market panic—thereby helping individuals maintain the "steady hand" required for long-term financial success.

Finally, the sustainability of digital financial ecosystems relies heavily on Financial Risk Detection and security. As financial management becomes increasingly digitized, the threat of fraud and unauthorized access grows. AI-powered monitoring systems offer a proactive defense by identifying anomalous transaction patterns that would be invisible to the human eye. Bolton and Hand (2002) pioneered the discussion on statistical fraud detection, noting that machine learning can adapt to evolving fraud tactics in real-time. This capability, as explored by Ngai et al. (2011), is a cornerstone of digital trust; when users feel that their assets are being monitored by an intelligent, vigilant system, their confidence in utilizing digital financial platforms increases, leading to more consistent and effective personal financial management.

3. HYPOTHESES OF THE STUDY

The following hypotheses were developed to test the relationship between AI functions and PFM effectiveness:

- **H1:** AI-based budgeting help has a significant positive impact on PFM effectiveness.
- **H2:** Predictive financial analytics has a significant positive influence on PFM effectiveness.
- **H3:** Personalized financial recommendations significantly improve PFM effectiveness.
- **H4:** Automated savings and investment features have a significant positive impact on PFM effectiveness.
- **H5:** Financial risk detection and fraud alerts have a significant positive effect on PFM effectiveness.

4. RESEARCH METHODOLOGY

This study employs a comprehensive descriptive and analytical research design, utilizing a quantitative approach to investigate the influence of Artificial Intelligence on Personal Financial Management (PFM). By focusing on identifying patterns, correlations, and causal relationships, this methodology allows for an objective measurement of how specific AI functionalities—such as predictive analytics and automated budgeting—impact the overall effectiveness of a user's financial health within a substantial sample size.

The methodology underlying the study involves a two-tier process for collecting the necessary data through a combination of primary and secondary means. In particular, the primary data was collected using a web-based survey administered to the target population of residents of Bangalore. In addition, the secondary data was obtained by conducting an extensive literature review that included academic sources from peer-reviewed scholarly journals and publications on financial technology, as well as Master's theses.

The methodology used for sampling involved the use of convenience sampling that is a non-probability method of selecting participants who happen to be suitable for the research. This sampling technique was selected because of the intention of conducting the survey among Bangalore city residents who had advanced knowledge about technology. This sample represented different ages, incomes, and occupations. The sample size was 101 individuals, thus covering a wide range of respondents.

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

The main research tool was a questionnaire that was carefully formulated on the 5-point Likert Scale that ranges from Strongly Disagree (1) to Strongly Agree (5). The questionnaire was divided into two segments; the first segment dealt with the demographic background of respondents that was important to capture information regarding the ages, occupations, and awareness about AI tools. The second segment consisted of 25 statements aimed at measuring five key constructs of the study including AI-based budgeting, predictive analytics, personalized recommendations, savings automation, and risk/fraud detection.

Table 4.1 Descriptive Statistics of the Study Variables

Variables	N	Mean	SD	Min	Max
AI Based Budgeting	101	4.01	0.81	1.00	5.00
Predictive Analytics	101	4.09	0.77	1.00	5.00
Personalized Advice	101	4.11	0.87	1.00	5.00
Automated Features	101	4.07	0.83	1.00	5.00
Risk & Fraud detection	101	4.22	0.75	1.00	5.00
PFM Effectiveness	101	4.18	0.76	1.00	5.00

Interpretation

Descriptive statistics show that there is a strong agreement among Bangalore participants in relation to the importance of adopting AI for financial decision-making, with the mean values being above 4.00 for all measures. The category 'Financial Risk & Fraud Detection' proved to be the highest priority area in terms of its mean value (5.00) and smallest standard deviation (0.75). The category 'PFM Effectiveness' was next in importance, with a mean of 4.18. Small values of standard deviations from 0.75 to 0.87 speak about the uniformity of attitudes toward the use of AI technologies.

Table 4.2 Reliability Statistics of the Study Variables

Variables	Number of Items	Cronbach’s Alpha	Interpretation
AI Budgeting	4	0.930	Reliable
Predictive Analytics	4	0.939	Reliable
Personalized Advice	4	0.960	Reliable
Automated Features	4	0.947	Reliable
Risk & Fraud Detection	4	0.926	Reliable
PFM Effectiveness	4	0.942	Reliable

Interpretation

Through reliability test conducted using the Cronbach’s Alpha, it is clear that all six variables are statistically sound, showing a score which goes beyond the minimum value of 0.70 required in the social science field. Personalized Financial Advice shows the best reliability value of 0.960, while all others, including the dependent variable, PFM Effectiveness, have a value above 0.920. The very high levels imply that there is consistency between the questions used and interpretations made by respondents.

Table 4.3 Correlation Matrix of the Study Variables

Variables	V1	V2	V3	V4	V5	V6
V1: AI-Based Budgeting	1.000					
V2: Predictive Analytics	0.736	1.000				
V3: Personalized Advice	0.700	0.733	1.000			
V4: Automated Features	0.777	0.764	0.814	1.000		
V5: Risk & Fraud Detection	0.691	0.777	0.723	0.758	1.000	
V6: PFM Effectiveness	0.653	0.821	0.821	0.746	0.788	1.000

Interpretation

Pearson’s correlation matrix shows high and very high levels of positive correlation among all AI-enabled independent variables and PFM Effectiveness. Predictive Financial Analytics (r = 0.821) and Personalized Financial Advice (r = 0.800) have the highest effect, implying that the greater intelligence of the systems will improve user effectiveness. The presence of very high inter-variate correlation (0.691 – 0.814) indicates that those

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

users benefiting from one variable like personalized advice will be very keen on using other features like automation as well. In general, the high positive results show that the two technologies are developing together towards financial management success.

Table 4.4 Regression Analysis: Impact of AI-based budgeting on PFM effectiveness

Particulars	Coefficient	Standard Error	t-value	p-value	R²	Adjusted R²
Constant	1.7197	0.2917	5.896	0.000	0.427	0.421
AI based budgeting	0.6117	0.0712	8.590	0.000		

Interpretation
The regression analysis supports the hypothesis, revealing that AI-based budgeting significantly predicts PFM effectiveness with a coefficient of 0.6117 and a p-value of 0.000. With an R^2 of 0.427, this single predictor explains 42.7% of the variation in financial management success, confirming a substantial and statistically significant positive impact.

Table 4.5 Regression Analysis: Impact of Predictive Analytics on PFM effectiveness

Particulars	Coefficient	Standard Error	t-value	p-value	R²	Adjusted R²
Constant	0.8773	0.2343	3.745	0.000	0.675	0.671
Predictive Analytics	0.8066	0.0563	14.327	0.000		

Interpretation
Predictive financial analysis is highly effective in enhancing the efficiency of personal finance management, characterized by a highly significant positive coefficient (0.8066) at the 5% level. The explained variance accounted for is 67.5% ($R^2 = 0.675$), verifying that the theory postulates a powerful explanation of the phenomenon.

Table 4.6 Regression Analysis: Personalized financial recommendations improve PFM effectiveness

Particulars	Coefficient	Standard Error	t-value	p-value	R²	Adjusted R²
Constant	1.29999	0.2215	5.869	0.000	0.640	0.636
Personalized Recommendations	0.6999	0.0527	13.270	0.000		

Interpretation
Regression analysis confirms that Personalized Financial Recommendations significantly enhance PFM Effectiveness, with a coefficient of 0.6999 and a p-value of 0.000. The high R^2 value of 0.640 indicates that 64% of financial management success is explained by these tailored AI insights. With a strong t-value of 13.270, the hypothesis is fully supported, proving that individualization is a critical driver of improved financial performance.

Table 4.7 Regression Analysis: Automated savings and investment features impact PFM effectiveness

Particulars	Coefficient	Standard Error	t-value	p-value	R²	Adjusted R²
Constant	1.3898	0.2550	5.450	0.000	0.557	0.552
Automated Features	0.6838	0.0613	0.644	0.000	0.000	

Interpretation
The inclusion of such automation tools as automated transfers and robo-advisors positively affects the effectiveness of PFM (the coefficient equals 0.6838, $p < 0.05$). The R squared value is 0.557, which confirms the assumption that automation increases the effectiveness of financial management.

Table 4.8 Regression Analysis: Risk and Fraud Detection impacts PFM effectiveness

Particulars	Coefficient	Standard Error	t-value	p-value	R²	Adjusted R²
Constant	0.8119	0.2683	3.027	0.003	0.621	0.617
Risk and Fraud Detection	0.7980	0.0627	12.735	11.146	0.000	

International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

Interpretation

The regression results confirm a significant positive impact of Risk & Fraud Detection on PFM Effectiveness, with a high coefficient of 0.7980 and a p-value of 0.000. The R^2 value of 0.621 indicates that security features account for 62.1% of the variance in management success, underscored by a robust t-statistic of 12.735. Ultimately, the hypothesis is supported, highlighting that enhanced security and fraud alerts are critical drivers of financial management competence.

5. RESULTS AND DISCUSSION

The process of statistical analysis started off with a thorough assessment of the measures of central tendency and dispersion for the key variables of interest. As highlighted by descriptive statistics, "Financial Risk & Fraud Detection" secured the highest mean value (4.22). In other words, security and trust are considered as the core foundation of an AI-powered financial system. Not surprisingly, "Automated Savings & Investment" and "Predictive Financial Analytics" received the second and third highest mean values of 4.10 and 4.09, respectively, which implies a preference for predictive and effortless money management systems. All standard deviations were less than 1.0, thus reflecting the consistency in the responses of 101 participants with regards to the usefulness of the selected AI functions.

The crux of the research analysis was the use of Multiple Regression Analysis, aimed at exploring the degree to which independent functions of AI affect the level of overall efficiency of Personal Financial Management (PFM). In this regard, the results have yielded strong support for all five hypotheses. Of interest, "Predictive Financial Analytics" turned out to be the most important predictor, characterized by the highest beta coefficient (beta) of 0.8066 and accounting for 67.5% of PFM effectiveness variation (R^2 = 0.675). In other words, the capacity of an AI algorithm to make predictions on future finances seems to play the key role in encouraging better money-related behaviors among users. Next in line comes "Personalized Financial Recommendations," accounting for 64.0% variation (R^2 = 0.640).

This analysis of the results shows a substantial change in the behavior of customers from keeping financial information on paper to the use of what is known as "Delegated Financial Intelligence." Indeed, the presence of automation is strongly correlated with better results in the use of PFM tools, suggesting that consumers feel comfortable delegating decision-making to algorithms regarding "round up" saving and budget monitoring to counter mental obstacles like procrastination and present bias. At the same time, the high value of risk detection reveals that although automation and forecasting are responsible for the growth in personal finance, protection of digital assets, i.e., their security, still remains the psychological base for using them.

6. CONCLUSION

These results demonstrate that AI is not just another accessory in the field of personal finance, but a revolutionary element. The transition from manually entering data to managing information via an AI tool creates a new feeling of responsibility for one's finances and a greater tendency towards making decisions. With respect to the young and tech-savvy population of Bangalore, the importance of hierarchy is highlighted by the necessity of possessing certain characteristics: whereas reliable security and fraud protection are essential to users, the value of AI tools emerges when one takes into account their “intellectual” side. Namely, predictive abilities along with personalized recommendations are crucial.

In summary, this analysis shows that artificial intelligence can be considered an indispensable "cognitive resource," which efficiently links the intention to act and the actual action in finance. Through the automation of intricate procedures and delivery of immediate behavior prompts, this technology enables people to bypass cognitive constraints such as procrastination, lethargy, and emotional prejudice. In the future, artificial intelligence will undoubtedly expand its impact on the field of personal finance beyond mere transaction support to become a true partner for achieving improved financial health through enhanced precision and cognitive economy. This research lays a groundwork for financial organizations and FinTech businesses to focus on predictive and customized capabilities.

7. REFERENCES

1) Adinarayana Swamy, M. (2025). AI in financial services: Revolutionizing personalized banking and customer experience. *Journal of Computer Science and Technology Studies, 7*(5), 688–694. https://doi.org/10.32996/jcsts.2025.7.5.76
2) Sharma, A. (2025). Impact of AI on investment behaviour. *International Journal of Emerging Technologies and Innovative Research, 12*(5), c361–c366. http://www.jetir.org/papers/JETIR2505244.pdf

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

3) hanmuganathan, M. (2020). Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions. *Journal of Behavioral and Experimental Finance, 27*, 100297. https://doi.org/10.1016/j.jbef.2020.100297
4) Singh, G., et al. (2020). Application of artificial intelligence on behavioral finance. *ResearchGate*. https://www.researchgate.net/publication/339005894
5) Sangeetha, S., Sumi, S. S., & Jayalekshmi, S. R. (2026). AI driven personal finance management tools – A review. *International Journal of Novel Research and Development (IJNRD), 11*(3), c914–c919. https://ijnrd.org/papers/IJNRD2603300.pdf
6) Manasa, S., Shivashankar, S. K., Prasanna, P., & Mohan Kumar, H. P. (2023). AI based personal finance management system. *International Journal of Engineering Research & Technology (IJERT), 12*(5), 442–445. https://www.ijert.org/ai-based-personal-finance-management-system
7) **Ryu, H. S.** (2018). What makes users willing or hesitant to use Fintech? The moderating effect of user type. *Industrial Management & Data Systems*, *118*(3), 541-569. https://doi.org/10.1108/IMDS-07-2017-0325
8) Talasila, S. D. (2024). AI-driven personal finance management: Revolutionizing budgeting and financial planning. *International Research Journal of Engineering and Technology (IRJET), 11*(7), 890–894. https://www.irjet.net/archives/V11/i7/IRJET-V11I755.pdf
9) **Murinde, V., Rizopoulos, E., & Zachariadis, M.** (2022). The impact of the FinTech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis*, *81*, 102103. https://doi.org/10.1016/j.irfa.2022.102103
10) Bayakhmetova, A., Rudenko, L., Krylova, L., Suleimenova, B., Niyazbekova, S., & Nurpeisova, A. (2025). Artificial intelligence in financial behavior: Bibliometric ideas and new opportunities. *Journal of Risk and Financial Management, 18*(3), 159. https://doi.org/10.3390/jrfm18030159
11) Swathi, S. (2026). Impact of artificial intelligence on financial behavior of individual investors in emerging markets. *International Journal of Scientific Research in Engineering and Management (IJSREM), 10*(1), 81–85. https://ijsrem.com/download/impact-of-artificial-intelligence-on-financial-behavior-of-individual-investors-in-emerging-markets/
12) **Cao, L.** (2022). AI in finance: Challenges, techniques, and opportunities. *ACM Computing Surveys*, *55*(3), 1-38. https://doi.org/10.1145/3502289
13) **Giudici, P.** (2018). FinTech risk management: A research challenge. *Frontiers in Artificial Intelligence*, *1*, 1. https://doi.org/10.3389/frai.2018.00001
14) **Bank for International Settlements (BIS).** (2024). *Artificial intelligence in central banking and financial stability*. BIS Quarterly Review. https://www.bis.org/publ/qtrpdf/r_qt2403.htm
15) **Giudici, P.** (2018). FinTech risk management: A research challenge. *Frontiers in Artificial Intelligence*, *1*, 1. https://doi.org/10.3389/frai.2018.00001
16) **Suryono, R. R., Purwandari, B., & Budi, I.** (2020). Peer to peer lending problems and potential solutions: A systematic literature review. *Procedia Computer Science*, *161*, 204-214. https://doi.org/10.1016/j.procs.2019.11.116