

Article

Artificial Intelligence Applications and Financial Forecasting Accuracy in Banking Platforms: Evidence from Jordan

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Abstract

The continued digitalisation of banking systems has raised a demand for more reliable data-based decision-making, in particular when referring to financial forecasts as covered by e-banking applications. This research also investigates the usage of AI-based decision-making systems to facilitate forecasting effectiveness in Jordanian commercial banks. Field research was carried out and 390 employees, working at 14 commercial banks in Jordan, responded to an organised questionnaire. Although the minimum required sample size was 384 respondents, a total of 390 valid responses were collected and used in the final analysis, thereby exceeding the minimum sample requirement. This research concentrates on three dominant categories of AI applications, including expert systems (ES), machine learning (ML), and Robotic Process Automation (RPA), which together are analysed for their effect on forecasting results in the context of customer churn, debt repayment, as well as investment analysis. The results of the multiple regression analysis indicate that AI applications contribute to improvements in forecasting accuracy, with machine learning and RPA showing relatively stronger effects. Expert systems were found to support investment analysis and debt repayment forecasting; however, their influence on customer churn prediction was more limited. In general, the findings indicate that AI applications are not confined to routine automation but are increasingly used as decision-support tools that assist financial analysis and forecasting activities in banking systems.

Keywords: artificial intelligence; digital decision-making; banking platforms; machine learning; robotic process automation; financial forecasting accuracy; digital finance



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1. Introduction

The increasing digitalisation of financial services has brought a paradigm shift in the functioning and competencies offered by banks in an online environment ([Modiha, 2024](#)). The scope of banks has expanded from mere transactions to relying on highly sophisticated data analytics and artificial intelligence in decision-making and bank strategies in real-time. It is in this context that financial forecasting has become a crucial digital capability that helps banks in predicting customer behaviour and investment opportunities in a highly liquid online marketplace ([Rani et al., 2025](#); [De Silva et al., 2025](#); [Al-Hattami, 2025](#)).

Artificial intelligence technologies like machine learning, expert systems, and robotic process automation have become essential driving forces for data-driven forecasting in digital banking systems (Abu-Dabaseh et al., 2025). Through the processing of enormous amounts of financial data in both structured and unstructured forms, AI systems can uncover intricate patterns and further improve the accuracy of financial forecasting. Given the rapid nature of financial decisions required in digital financial settings, AI systems are now increasingly viewed not only as a set of automation resources but rather as a digital form of decision-making that changes the manner in which financial forecasting activities are conducted (Ade-Ibijola et al., 2025; Asemi et al., 2025).

Despite increased use of artificial intelligence in the banking and financial sector, the current literature has vastly focused either on technology acceptance, efficiency in operations, or generic performance results (Al-Okaily, 2025; Yuan et al., 2025). Although these studies are extremely useful, they lack clarity regarding the functionality of different uses of artificial intelligence as different digital functions. Moreover, these studies are fragmented in understanding the relative importance of expert systems, machine learning, or robotic automation in improving forecasting results in different financial aspects. This has been more evident in the emerging digital economies such as Jordan, where banks are transforming in an accelerated manner in the digital space but lack in data co-creation and system maturity (Al-Hattami, 2025).

It can be stated that the process of forecasting, as practiced in digital banking platforms, goes beyond the traditional budgetary forecasting process, encompassing predictive analysis related to customer churn, loan repayments, and investment outcomes. These analyses are important, contributing to the general financial stability, and also helping in intelligent management of business relations with customers (Mahmud et al., 2025). AI technology may support these processes as well, since it has the ability to integrate the historical data and transactions of these processes with AI-guided rules in order to create holistic analytical techniques (Liu, 2025). There is a lack of evidence related to the impact of specific AI technology on different dimensions of forecasting processes, especially related to commercial banks platforms within developing nations (Latif et al., 2025).

The research makes several contributions to the body of knowledge on AI-enabled financial decision-making within digital banking platforms. First, there is a theoretical contribution to knowledge as it conceptualises AI applications as an integrated digital capability as opposed to viewing them as discrete technological instruments. Second, there is an empirical contribution as it presents research findings on how different AI applications have varying effects on multiple domains of forecasting, with findings indicating how machine learning applications outperform expert systems and robotic process applications. Third, as research focuses on developing economies, there is an expansion of research boundaries as knowledge gained can be applicable to banks within transforming economies due to increased digital technologies. From a practical perspective, it can be noted that there are several implications that can be drawn from these findings, particularly for banking institutions that are seeking to improve their predictive capabilities using AI-based digital infrastructure. The knowledge that can be gleaned about specific strengths that can be leveraged based on various applications can lead to better decision-making at digital-based banks that are utilising digital banking platforms (Ade-Ibijola et al., 2025).

2. Theoretical Framework, Empirical Review, and Hypotheses Development

2.1. Literature Review

As a result of the accelerated adoption of digital banking platforms and online financial services, AI technology can be regarded as an integral basis of modern banking

systems (Singh et al., 2025). According to many studies (Abbas, 2025; Altarawneh et al., 2025; Latif et al., 2025; Elnakeeb & Elawadly, 2025) that in a digitally mediated financial setting, AI technologies can be integrated into decision-support systems. AI technology can be regarded as an automation process as well as a set of analytical methods, which help organisations process a considerable volume of financial data, extract forecasting information, and support instant decision-making.

Within digital banking platforms, AI-based solutions enable the integration of data associated with transactions, consumer behaviour, and market information in a way that is meaningful for financial forecasting (Ashrafuzzaman et al., 2025; Roy et al., 2025). Bringing these data elements together makes financial decisions faster, more reliable, and more accurate, variables that are particularly valuable in digital financial services, where market volatility is high, as well as information asymmetry, as pointed out by Dessaint et al. (2024) and Kumar et al. (2025). Accordingly, the role of artificial intelligence is central in digital banking processes for the creation of digital value through financial forecasting.

However, despite these developments, the literature on AI is perceived as a homogeneous concept, offering little insight into the way various applications of AI operate as unique digital decision-making abilities. This is even more evident in banking platforms, where the accuracy of forecasts is a function of the interplay between analytical intensity, automation, and data processing abilities.

In digitally enabled banking platforms, artificial intelligence applications operate as distinct digital decision capabilities rather than homogeneous technologies (Mirzaye & Mohiuddin, 2025). The role of each AI application for improved forecast accuracy can be different, depending on the depth of analysis behind, level of automation and ability to process real time data. Expert systems generally encode existing domain expertise and decision-making rules, machine learning allows for recognising patterns and learning predictive algorithms from big data sets whereas robotic process automation improves forecast reliability through reduction in execution errors and improved process consistency (Patrício et al., 2025). Accordingly, the impact of AI applications on financial forecasting accuracy is expected to vary across forecasting domains.

In digital banking applications, financial forecasting does not stop at budgeting and financial planning but rather also includes predictive analytics concerning customer churn, debt repayment and investment success. Precision of forecasting in these fields is crucial to maintain the competitive advantage, risk financial management, and to facilitate data-driven decision making (Eltweri et al., 2020, 2024; Faheem et al., 2024; Latif et al., 2025).

By predicting customer churn, banks can detect customers who are prone to disengagement and take proactive retention measures. Forecasting models based on machine learning have been indicated to lead to substantially more accurate customer churn prediction, by leveraging large-scale behavioural and transaction data (Dessaint et al., 2024; Thakkar et al., 2024). Likewise, predicting debt repayment aids credit risk management as banks are better able to evaluate the behaviour of borrowers and their chance for defaulting (Al Maruf et al., 2024; Metawa et al., 2025).

Investment analysis forecasting benefits from AI-enabled analytics by allowing banks to evaluate investment opportunities, assess risk-return profiles, and optimise resource allocation within digital financial ecosystems (Beniwal et al., 2024; Yang et al., 2025). Collectively, these forecasting dimensions highlight the strategic importance of AI as a digital decision capability within banking platforms (Utouh & Kitole, 2024). Prior studies highlight that secure financial big data infrastructures are essential for supporting advanced analytics and AI applications in digital accounting and financial systems (Faccia et al., 2021; Najem et al., 2025). Based on the above discussions, this study argues that artificial intelligence enabled financial forecasting represents a critical digital decision capability that enhances

forecasting accuracy in banking platforms. Accordingly, the following hypotheses are developed, as illustrated in Figure 1, the conceptual model explicitly incorporates robotic process automation as a core AI application alongside expert systems and machine learning.

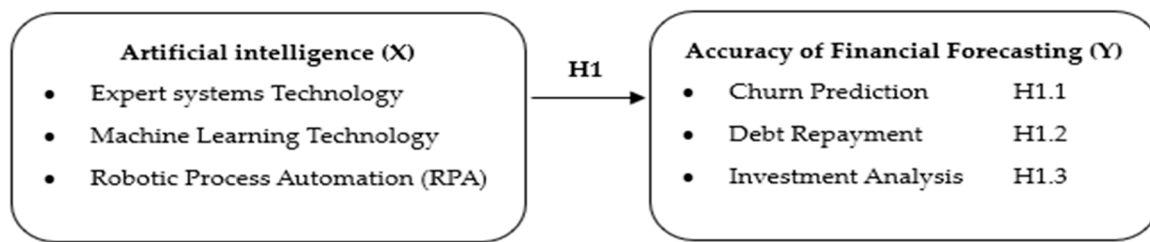


Figure 1. Conceptual model of AI applications (Expert Systems, Machine Learning, and Robotic Process Automation) and financial forecasting accuracy.

From a theoretical perspective, artificial intelligence applications can be conceptualised as organisational digital capabilities that enhance decision-making by improving information processing, prediction, and automation (Sjödin et al., 2023). However, the effectiveness of these capabilities is contingent upon their alignment with the nature of the task being supported. Structured, rule-based tasks are more amenable to expert systems, whereas dynamic and behaviour-driven prediction tasks benefit from adaptive and learning-based approaches. This task–technology fit perspective provides a unifying theoretical lens for examining how different AI applications influence distinct dimensions of financial forecasting accuracy.

2.2. Empirical Review and Hypotheses Development

2.2.1. Expert Systems Technology and Financial Forecasting

Building on the theoretical framing that conceptualises artificial intelligence as an organisational digital capability whose effectiveness depends on task–technology alignment, prior empirical studies suggest that expert systems are particularly effective in structured and rule-based decision environments (Yurin et al., 2018). In the context of financial services, expert systems have been widely applied to support credit assessment, compliance monitoring, and investment evaluation, where decision rules, thresholds, and codified knowledge play a central role. Existing empirical evidence indicates that such systems can enhance consistency and transparency in financial decision-making, thereby improving forecasting outcomes in domains characterised by stability and formalised processes.

Recent studies indicate that expert systems represent a critical digital decision-support capability in the banking sector by transforming expert knowledge, regulatory guidelines, and analytical rules into structured decision logic. Ahmed (2024) demonstrated that expert systems are particularly effective in the context of Islamic banks, where participatory financing decisions are characterised by complexity, uncertainty, and procedural intensity. Their findings showed that expert systems contribute to improving the evaluation of participatory financing requests by systematically analysing customer data, financial positions, and collateral requirements through rule-based reasoning, thereby reducing decision time and limiting subjective judgement. Consistent with broader expert system literature, these systems enhance decision accuracy and procedural consistency by storing and retrieving prior cases and expert knowledge in a standardised manner.

It can be said that expert systems are among the earliest applications of artificial intelligence in financial and accounting systems. Expert systems are developed to embody human expert knowledge in decision-making systems that simulate human expert decisions in certain conditions at commercial banks (MacCarthy & Jou, 2025; Duda et al., 2025). In

banking systems, expert systems help in forecasting by using preprogrammed rules in financial data to improve objectivity.

The studies by O. Abdullah et al. (2022) and Ahmed (2024) aimed to propose an expert system for evaluating participatory financing decisions in Islamic banks in light of the challenges facing this type of financing. The study adopted a descriptive-analytical approach by analysing the reality of participatory financing in Islamic banks and designing a proposed expert system based on a knowledge base that includes if-then rules, an inference engine, and a user interface. A practical case was applied through a questionnaire distributed to a sample of customers of an Islamic bank, totalling 390 questionnaires, of which 306 valid responses were used for analysis. The results revealed a clear need to apply an expert system in the field of participatory financing due to its role in reducing the time required for decision-making, simplifying procedures, limiting bias or subjective intervention, and improving the accuracy of financing decisions.

The study concluded that the proposed expert system is capable of efficiently supporting financing decisions in Islamic banks.

Also, recent studies indicate that expert systems represent a digital decision-support capability in the banking sector by transforming accumulated knowledge and analytical rules into structured decision logic. Cheng et al. (2024) demonstrated that expert systems contribute to predicting customer churn by analysing financial behaviour and linking it to clear retention rules, while Hassan et al. (2025) showed that these systems enhance the accuracy of debt repayment forecasting by reducing information asymmetry and supporting credit monitoring decisions. Moreover, Silva et al. (2024) and Kumar et al. (2025) found that expert systems improve the quality of investment analysis by integrating risk and return indicators within a consistent knowledge-based framework.

Evidence has also shown that expert systems have been useful in the domain of structured decisions, where decisions can be translated into rigid guidelines (van Ree, 2025; Pieszczyk & Daszykowski, 2025). Here, the use of expert systems has helped in enhancing the predictability of results with little scope for human bias.

However, the use of expert systems in dynamic forecasting, such as in the prediction of customer churn, is still in doubt. This is because the predictive model in expert systems is based on predefined rules, such that in environments where there is dynamically changing data, such as in the continuously changing behaviour of customers in finance, the predictive model in expert systems can be limited in its ability to predict accurately (Elnakeeb & Elawadly, 2025). In the light of the above discussion, the study develops the following hypotheses:

H1a. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Expert Systems on churn prediction in Jordanian commercial banks.*

H1b. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Expert Systems Technology on debt repayment prediction in Jordanian commercial banks.*

H1c. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Expert Systems Technology on investment analysis in Jordanian commercial banks.*

2.2.2. Machine Learning Technology and Predictive Analytics in Digital Banking Platform

Extending the theoretical perspective on task-technology fit, empirical research highlights machine learning as a data-driven and adaptive AI capability that is particularly suited to dynamic and behaviour-oriented forecasting tasks (Ghosh, 2025). Machine learning techniques enable the identification of complex, non-linear patterns within large datasets and continuously refine predictions based on new information (Tufail et al., 2023).

Prior studies demonstrate that these characteristics make machine learning especially relevant for financial forecasting contexts involving customer behaviour, risk dynamics, and uncertainty, thereby supporting more accurate and responsive predictive outcomes.

Machine learning is a more superior AI capability that implements data learning and improvement of predictive accuracy over time even without explicit programming. Machine learning algorithms are largely used for prediction tasks within digital banking platforms, as they are able to detect non-linear patterns and hidden data trends within a dataset (Ignacz et al., 2025; Islam et al., 2025; Kovacs et al., 2025).

It has been clear from the literature that machine learning can enhance the accuracy of the forecasting process with regard to financial tasks such as the evaluation of credit risks, predictions related to the behaviour of customers, as well as analysis of market trends (Abir et al., 2025; Safari & Ghaemi, 2025).

In his study, (Schmitt, 2024) explored the integration of Automated Explainable Machine Learning (Auto ML) in financial engineering, with a particular focus on its application in credit decision-making. This study demonstrates how combining Auto ML with X AI not only enhances the efficiency and accuracy of credit decisions but also fosters trust and collaboration between humans and AI systems. The findings underscore the potential of Auto ML to improve the transparency and accountability of AI-led financial decisions, in line with regulatory requirements and ethical considerations.

Recent empirical studies have demonstrated the effectiveness of machine learning techniques for complex predictive tasks in dynamic operational environments. For example, Jebbor et al. (2024) show how ML classifiers can be used to forecast supply chain disruptions using performance-aligned metrics, while Jebbor et al. (2025) provide a comprehensive synthesis of advanced digital technologies supporting predictive decision-making in complex systems. Although these studies are conducted outside the banking sector, they provide methodological grounding for the application of ML-based forecasting in similarly data-intensive and dynamic contexts.

A systematic (Vancsura et al., 2025) review of the literature explored the application of artificial intelligence and machine learning in financial market forecasting, focusing on four asset classes: equities, cryptocurrencies, commodities, and foreign exchange markets. Based on the PRISMA methodology, the results confirm the superiority of AI-based approaches, particularly neural networks, over traditional statistical methods in monitoring nonlinear and high-dimensional dynamics. However, the analysis also reveals several critical research gaps. Most notably, the limited integration of existing models into real or simulated trading strategies restricts their practical applicability. Furthermore, the sensitivity of commonly used metrics, such as the mean absolute error (MAPE), to volatility remains insufficiently studied, especially in highly volatile environments like cryptocurrency markets. Time stability is also a concern.

A study (Mistry, 2024) explored the pivotal role of machine learning in enhancing financial forecasting models, leading to improved customer service, risk management, and operational efficiency. The study's findings demonstrated that integrating machine learning into financial forecasting has revolutionised the way consumer banks operate. By leveraging machine learning models, banks can enhance fraud detection, personalise customer experiences, predict customer behaviour, make informed strategic decisions, and optimise interest rates and pricing. Machine learning in financial forecasting not only improves the accuracy and efficiency of forecasts but also enables banks to remain competitive in an increasingly data-driven sector. As machine learning technologies continue to evolve, we anticipate the emergence of even more innovative applications in financial forecasting, which will fundamentally transform the retail banking sector.

The contemporary literature emphasises that machine learning is among the most effective artificial intelligence technologies for financial forecasting due to its ability to analyse large-scale data and detect non-linear patterns. Lin and Chen (2024), supported by the findings of González (2025), showed that machine learning models achieve higher accuracy in predicting customer churn compared to traditional methods. Additionally, Lee and Park (2021) and R. K. Abdullah et al. (2025) demonstrated that machine learning enhances creditworthiness assessment and reduces default risk. J. Müller et al. (2024) and Metha (2025) further confirmed that machine learning models contribute to improved investment return forecasting and support asset allocation decisions.

Machine learning has been proven to perform better than traditional rule-based systems in making forecasts of customer churn rate and bad debt repayments within banking systems, especially when there are ample amounts of data (Okeke et al., 2024; Owolabi et al., 2024; Thakkar et al., 2024). This puts machine learning in key roles as important enabling information technology in improving the forecasting capabilities of digital banking platforms financial services (AlQudah et al., 2025). Based on these discussions, this study develops the following hypotheses:

H2a. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Machine Learning Technology on churn prediction in Jordanian commercial banks.*

H2b. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Machine Learning Technology on debt repayment prediction in Jordanian commercial banks.*

H2c. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Machine Learning Technology on investment analysis in Jordanian commercial banks.*

2.2.3. Robotic Process Automation and Financial Forecasting in Banking Platforms

From the same theoretical standpoint, robotic process automation represents an AI-enabled capability that enhances forecasting performance indirectly through process efficiency, accuracy, and data reliability (Afrin et al., 2024). Empirical studies suggest that by automating routine and repetitive accounting and reporting tasks, RPA reduces human error, improves data timeliness, and ensures greater consistency in information inputs used for forecasting models. As a result, RPA strengthens the operational foundation upon which financial forecasting and analytical decision-making are built.

Robotic Process Automation (RPA) differentiates itself among other Artificial Intelligence applications in focusing more on automating repetitive rules-based tasks rather than predictive analytics. In digital banking environments, RPA is largely used to automate data extraction, validation, reporting, and transaction processing operations, thereby improving efficiency and minimising human error (Sousa & Rocha, 2021; Alassuli, 2025).

RPA increases the quality of data on consistency, timeliness and integrity but these are important issues in accuracy predictions' determinants, as prediction-based prerequisites for data is significant ingredients (Rai, 2022; Aljamal et al., 2025). Community dynamics predicting the flow of resources, in an electronic financial ecosystem, RPA is significant as prediction systems depend on a continuous stream of data. Latest research on banking analysed the utilities of fusion of RPA to enhance forecasting accuracy through eliminating delays and errors in handling data manually (Alassuli et al., 2025). RPA is thus an enabler of the digital infrastructure functionality in bank systems.

This study (Okoro et al., 2025) presents the roles, benefits, challenges, and future paths for implementing robotic process automation (RPA) in banking and financial institutions. Based on pilot studies and industry reports, we analyse how RPA streamlines back-office operations, accelerates customer onboarding and loan processing, and improves data

accuracy and regulatory compliance. We also address obstacles such as legacy system integration, high upfront costs, security vulnerabilities, and workforce adjustment challenges. Furthermore, we explore emerging trends, including the integration of RPA with cognitive automation and artificial intelligence (AI) to handle complex and semi-structured tasks. The study's findings indicate that while RPA delivers significant operational gains and prepares organisations for digital transformation, its full potential is only realised when implemented as part of a broader process improvement strategy.

A literature review was conducted to [Delagrammatikas et al. \(2025\)](#) examine current use cases of robotic process automation (RPA) in the banking and insurance sectors, analysing how these technologies can be leveraged to enhance corporate efficiency and performance. Based on recent academic publications and case studies published between 2017 and 2025, the review identifies key implementation areas such as onboarding new customers, claims processing, compliance reporting, and underwriting automation. The findings highlight significant improvements in processing speed, error reduction, and resource utilisation, along with the development of effective performance metrics. The study concludes by identifying key success factors, performance measurement methods, and challenges in implementing RPA, providing valuable insights for both practitioners and researchers seeking to understand the role of automation in the transformation of financial services.

Studies indicate that robotic process automation plays a supportive role in financial forecasting by improving data quality, reducing operational errors, and accelerating processing speed. [H. H. Müller and Schäfer \(2024\)](#), showed that RPA contributes to improved customer data management, thereby supporting customer churn prediction. Furthermore, [Nguyen \(2024\)](#) found that process automation enhances the accuracy of monitoring financial obligations and strengthens debt repayment forecasting. [Alcázar-Blanco et al. \(2024\)](#) and [Ben Youssef et al. \(2025\)](#) also demonstrated that RPA improves data reliability and accelerates the execution of investment decisions within banks. Based on these discussions, this study develops the following hypotheses:

H3a. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Robotic Process Automation Technology on churn prediction in Jordanian commercial banks.*

H3b. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Robotic Process Automation Technology on debt repayment prediction in Jordanian commercial banks.*

H3c. *There is a statistically significant effect at the significance level ($\alpha < 0.05$) of Robotic Process Automation Technology on investment analysis in Jordanian commercial banks*

3. Methodology and Methods

3.1. Sampling and Data Collection

This research adopts a quantitative descriptive analytical design that aims to explore how applications based on artificial intelligence can play a role as digital decision-making capabilities for enhancing financial forecast accuracy on banking platforms ([Hair et al., 2021](#)). The design for this research is appropriate for studying relationships between capability enhancements facilitated by digital technology and decision-making outcomes within digital financial environments.

The empirical environment is the banking sector in Jordan. This sector has been undergoing rapid digital change through the use of AI analytics, automation, and advanced information systems. Focusing on such an environment allows for the presentation of em-

pirical findings from a developing digital banking environment, beyond the highly mature environments investigated by many existing studies on digital banking and e-commerce.

The target population consists of workers in the 14 commercial banks operating in Jordan; their approximate total number is set at 13,921 employees. The employees are directly and indirectly involved in financial analysis and other banking decision-making tasks related to risk assessment and accounting.

A probability method of sampling was employed to ensure that the final results are well represented. Taking into consideration the guidelines for the size of the sample and the size of the population, the study employed a minimum of 384 respondents to ensure the 95% confidence level survey requirements are met. To prevent the problem of non-response, 430 questionnaires were used, and 390 valid responses were obtained for analysis. The size of the sample used in the study is sufficient for multivariable analysis and improves the generalisability of the results (Sekaran & Bougie, 2016). Table 1 presents the demographics of the study's population.

Table 1. Demographic and Professional Characteristics of the Sample (n = 390).

Variable	Category	Frequency	Percentage
Age	Younger than 25 years	35	9
	25–34 years	130	33.3
	35–44 years	110	28.2
	45–54 years	75	19.2
	55 years and above	40	10.3
Educational Qualification	Bachelor's degree	210	53.8
	Higher diploma	55	14.1
	Master's degree	95	24.4
	Doctorate degree	30	7.7
Work Experience	Less than 5 years	60	15.4
	5 to under 10 years	105	26.9
	10 to under 15 years	95	24.4
	15 to under 20 years	70	17.9
	20 years and above	60	15.4
Total		390	100

The population that the study mostly comprises is early-to-mid-career professionals who have relevant educational qualifications and experience, ensuring that the responses provided on AI-powered forecasting in the bank platforms are authentic.

Data were collected using a structured questionnaire designed to capture respondents' perceptions of AI applications and financial forecasting accuracy within their respective banking platforms. The questionnaire consisted of two main sections.

The first section gathered demographic and professional information, including age, educational qualification, and work experience. The second section measured the study variables, comprising artificial intelligence applications and financial forecasting accuracy.

3.2. Variables and Measurement

This study examines the impact of artificial intelligence applications including expert systems, machine learning, and robotic process automation on the accuracy of financial forecasting in banking platforms, measured across customer churn prediction, debt repayment prediction, and investment analysis. All constructs are operationalised using multi-item perceptual scales adapted from prior digital finance and information systems literature, with reliability and diagnostic tests conducted to ensure measurement robustness. The variables, their operational definitions, measurement methods, data sources, and supporting references are summarised in Table 2.

Table 2. Variables measurement.

Construct	Variable Type	Dimensions/Indicators	Measurement	Scale	Source
Artificial Intelligence Applications (AI)	Independent	Expert Systems Technology	Mean score of multiple questionnaire items capturing rule-based decision support and knowledge encoding	5-point Likert (1 = strongly disagree to 5 = strongly agree)	Ahmed (2024); O. Abdullah et al. (2022); (Cheng et al., 2024)
		Machine Learning Technology	Mean score of items capturing predictive analytics, pattern recognition, and adaptive learning	5-point Likert	Gupta et al. (2022); Cheng et al. (2024); González (2025)
		Robotic Process Automation (RPA) Technology	Mean score of items measuring automation, data processing speed, and error reduction	5-point Likert	Afrin et al. (2024); Sousa and Rocha (2021); Okoro et al. (2025)
Financial Forecasting Accuracy	Dependent	Customer Churn Prediction	Mean score of items capturing accuracy of predicting customer disengagement	5-point Likert	Faritha Banu et al. (2022); Dessaint et al. (2024); Thakkar et al. (2024)
		Debt Repayment Prediction	Mean score of items assessing accuracy of predicting loan repayment behaviour	5-point Likert	Thakar et al. (2024); Okeke et al. (2024); Owolabi et al. (2024)
		Investment Analysis	Mean score of items measuring accuracy of investment outcome forecasting	5-point Likert	Beniwal et al. (2024); Yang et al. (2025)

Cronbach's alpha coefficients were calculated to estimate the internal consistency of the measurement scales. The results indicate that all variables exceeded the recommended minimum of 0.70, demonstrating satisfactory reliability and internal consistency (Sekaran & Bougie, 2016). Table 3 shows the Cronbach's alpha values for the study variables.

Table 3. Sample Measurement Items and Constructs.

Construct	Measurement Focus
Expert Systems Technology	Rule-based decision support, consistency of financial evaluation, reduction in subjectivity
Machine Learning Technology	Predictive analytics, pattern recognition, adaptive learning from financial data
RPA Technology	Automation of routine tasks, data accuracy, processing speed
Churn Prediction Accuracy	Accuracy of predicting customer disengagement
Debt Repayment Prediction	Accuracy of forecasting loan repayment behaviour
Investment Analysis Accuracy	Accuracy of forecasting investment outcomes

Face validity was ensured by adapting measurement items from prior studies and by reviewing the instrument with domain experts in banking and accounting before distribution in Table 3.

The reliability coefficients in Table 4 indicate that the measurement items consistently capture the underlying constructs and are suitable for subsequent statistical analysis.

Table 4. Reliability Statistics of Study Constructs.

Variables	Cronbach's α
Artificial Intelligence Applications	
Expert Systems Technology	0.70
Machine Learning Technology	0.79
Robotic Process Automation (RPA) Technology	0.78
Financial Forecasting Accuracy	
Customer Churn Prediction	0.81
Debt Repayment Prediction	0.86
Investment Analysis	0.76

3.3. Normality Assessment

To evaluate whether the distribution of the variables approximates normality, skewness and kurtosis values were examined for each independent and dependent variable. Although the normality of residuals (errors), rather than the variables themselves which is the primary assumption in regression, inspecting skewness and kurtosis provides useful descriptive insight into the distributional properties of the data (Williams et al., 2013).

As shown in Table 5, all skewness and kurtosis values fall within commonly accepted thresholds (e.g., skewness within ± 2), indicating approximate normality of the variable distributions (Byrne, 2010). Although regression requires the normality of residuals rather than predictors, at this stage descriptive distributional checking can help ensure the data behave without extreme departures from normality.

Table 5. Normality Assessment through Skewness and Kurtosis.

Variable	Skewness	Kurtosis
Expert Systems Technology	−0.441	0.425
Machine Learning Technology	0.163	−0.130
Robotic Process Automation (RPA) Technology	−0.413	0.348
Artificial Intelligence Applications	−0.179	0.201
Churn Prediction	0.096	0.378
Debt Repayment Prediction	−0.133	−0.042
Investment Analysis	−0.322	−0.128
Accuracy of Financial Forecasting	−0.027	0.119

3.4. Multicollinearity Assessment

Multicollinearity refers to a situation in which two or more independent variables are highly correlated, which can inflate standard errors and distort the interpretation of regression coefficients (IBM, 2025). To detect multicollinearity, Tolerance and Variance Inflation Factor (VIF) statistics are used. A Tolerance value greater than 0.1 and a VIF value less than 10 are generally considered acceptable indicators of low multicollinearity (Hair et al., 2021).

The results in Table 6 indicate that all independent variables are within acceptable limits for both Tolerance and VIF, suggesting that multicollinearity is not a significant concern in the model (VIFs below 10). This confirms the appropriateness of including these predictors in the regression analysis without undue distortion of coefficient estimates.

Table 6. Multicollinearity Statistics of Independent Variables.

Variable	Tolerance	VIF
Expert Systems Technology	0.351	2.846
Machine Learning Technology	0.279	3.583
Robotic Process Automation (RPA) Technology	0.296	3.383

To further explore the relationships among the study variables, Pearson correlation coefficients were calculated. This step helps to identify the strength and direction of associations between different AI technologies (Expert Systems, Machine Learning, and RPA) and financial forecasting outcomes (Churn Prediction, Debt Repayment Prediction, Investment Analysis). Understanding these correlations is essential in the context of this study, as it provides preliminary insight into how AI applications may influence financial forecasting accuracy and informs the interpretation of subsequent regression results.

As indicated in the correlation matrix, Table 7 indicate all independent variables and financial forecasting outcomes show significant positive correlations at the 0.01 level. The highest observed correlation is 0.797 between Machine Learning Technology and

Investment Analysis, while no correlation exceeds 0.80. This indicates that, although the variables are moderately to strongly related, there is no extremely high correlation that could threaten the stability of the regression coefficients. In other words, the predictors are sufficiently independent from each other to be included in the regression model without risking multicollinearity problems. These findings justify the inclusion of all AI technology variables as predictors in the subsequent multiple regression analysis.

Table 7. Pearson Correlation Coefficients Among AI Technologies and Financial Forecasting Outcomes.

	1	2	3	4	5	6
1. Expert Systems Technology	1					
2. Machine Learning Technology	0.774 **	1				
3. Robotic Process Automation (RPA) Technology	0.759 **	0.714 **	1			
4. Churn Prediction	0.602 **	0.743 **	0.708 **	1		
5. Debt Repayment Prediction	0.792 **	0.759 **	0.764 **	0.689 **	1	
6. Investment Analysis	0.738 **	0.797 **	0.726 **	0.707 **	0.707 **	1

** Correlation is significant at the 0.01 level (2-tailed).

4. Analysis and Findings

4.1. Descriptive Analysis

This study examines the relation between artificial Intelligence represented by (Expert Systems Technology, Machine Learning Technology, Robotic Process Automation (RPA) Technology) as an independent variable and the accuracy of financial forecasting represented by (Customer churn prediction, Debt repayment prediction, Investment analysis) as dependent variables: Evidence from Jordan

4.1.1. The Independent Variable: Artificial Intelligence Applications

Table 8 displays the descriptive statistics for the variable Artificial Intelligence Applications, highlighting the mean scores and standard deviations across three key domains: Expert Systems Technology, Machine Learning Technology, and Robotic Process Automation (RPA) Technology. These domains are arranged in descending order based on their mean scores, providing a comparative perspective on the extent of AI application within each area.

Table 8. Means and Standard Deviations of Artificial Intelligence Applications in Descending Order.

Rank	N	Domain	Mean	Std. Deviation	Level
1	1	Expert Systems Technology	3.77	0.56	high
2	3	Robotic Process Automation (RPA) Technology	3.73	0.65	high
3	2	Machine Learning Technology	3.68	0.66	high
		Artificial Intelligence Applications	3.73	0.58	high

As shown in the results, the highest mean value ($M = 3.77$, $SD = 0.56$) was reported for Expert Systems Technology which indicates that this AI technology is most widely used of the three domains included in this study. Technology (Robotics Process Automation, RPA) followed Technology with a mean of 3.73 ($SD = 0.65$), while Machine Learning Technology had just registered slightly less with a mean of 3.68 ($SD = 0.66$). On average, the combined mean for Artificial Intelligence Applications was 3.73 ($M = 0.58$), thus pointing to a high level of AI implementation across the examined technologies.

4.1.2. The Dependent Variable: Accuracy of Financial Forecasting

Table 9 shows the descriptive statistics of the dependence variable, Accuracy in Financial Forecasting for three domains: Investment Analysis, Debt Redemption Predictions and Churn Prediction. Mean values and standard deviations for each domain by decreasing mean value are presented in the data. This configuration provides a more transparent look at what regions have the highest perceived accuracy.

Table 9. Means and standard deviations of Accuracy of Financial Forecasting, ranked in a descending order.

Rank	N	Domain	Mean	Std. Deviation	Level
1	3	Investment Analysis	3.78	0.62	High
2	2	Debt Repayment Prediction	3.58	0.60	moderate
3	1	Churn Prediction	3.48	0.73	moderate
Accuracy of Financial Forecasting			3.61	0.59	moderate

As shown in the table, the highest mean score was observed in the domain of Investment Analysis ($M = 3.78$, $SD = 0.62$), indicating a high level of accuracy in financial forecasting within this area. Debt Repayment Prediction and Churn Prediction followed with moderate levels of accuracy, having mean scores of 3.58 and 3.48, respectively. Overall, the general mean for financial forecasting accuracy across the three domains was 3.61 ($SD = 0.59$), suggesting a moderate level of forecasting accuracy in the sampled data.

4.2. Hypotheses Testing

To test the first AI Applications and Financial Forecasting Accuracy, multiple regression analysis was performed to assess the impact of artificial intelligence accounting applications—specifically Expert Systems Technology, Machine Learning Technology, and Robotic Process Automation (RPA) Technology—on the accuracy of financial forecasting across three domains: Churn Prediction, Debt Repayment Prediction, and Investment Analysis in Jordanian commercial banks. The results of this analysis are presented in Table 10, which displays the unstandardised and standardised coefficients, *t*-values, and significance levels for each independent variable.

Table 10. Multiple Regression Analysis of the Impact of AI Accounting Applications on Financial Forecasting Accuracy in Jordanian Commercial Banks.

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Constant	0.145	0.074		1.960	0.051
	Expert Systems Technology	0.193	0.032	0.182	5.955	0.000
	Machine Learning Technology	0.365	0.030	0.410	11.989	0.000
	Robotic Process Automation (RPA) Technology	0.375	0.030	0.411	12.370	0.000
	R = 0.935	R ² = 0.874		F = 891.559	p = 0.000	

The regression analysis results show a statistically significant effect of artificial intelligence accounting applications on the accuracy of financial forecasting in Jordanian commercial banks. The overall regression model was found to be statistically significant ($F = 891.559$, $p < 0.001$), with a high explanatory power ($R^2 = 0.874$), suggesting that approximately 87.4% of the variance in financial forecasting accuracy is explained by the three AI technologies examined.

All three AI technologies demonstrated statistically significant positive effects on forecasting accuracy:

- Expert Systems Technology had a moderate positive effect ($B = 0.193$, $t = 5.955$, $p < 0.001$).
- Machine Learning Technology showed a strong positive impact ($B = 0.365$, $t = 11.989$, $p < 0.001$).
- Robotic Process Automation (RPA) Technology was the strongest predictor ($B = 0.375$, $t = 12.370$, $p < 0.001$).

These findings confirm the hypothesis (H1) and show that the use of AI technologies greatly increases accuracy in financial forecasting in the banking industry. Among them, RPA and Machine Learning appear to be the most influential contributors.

Hypothesis H1a. *AI Applications and Churn Prediction.*

To test AI Applications and Churn Prediction, a multiple regression analysis was performed to examine the impact of artificial intelligence accounting applications including Expert Systems Technology, Machine Learning Technology, and Robotic Process Automation (RPA) Technology on churn prediction in Jordanian banks. Table 11 below summarises the regression results, displaying the unstandardised and standardised coefficients, t-values and significance levels for each independent variable.

Table 11. Multiple Regression Analysis of the Effect of AI Accounting Applications on Churn Prediction in Jordanian Commercial Banks.

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Constant	0.131	0.121		1.083	0.279
	Expert Systems Technology	−0.365	0.053	−0.276	−6.878	0.000
	Machine Learning Technology	0.750	0.050	0.678	15.040	0.000
	Robotic Process Automation (RPA) Technology	0.527	0.050	0.465	10.608	0.000
	R = 0.884	R ² = 0.781		F = 458.399	p = 0.000	

The regression results provide partial support for Hypothesis H1a, indicating a statistically significant but negative effect of Expert Systems Technology on churn prediction in Jordanian commercial banks. The model is highly significant ($F = 458.399$, $p < 0.001$), with an R^2 value of 0.781, meaning that 78.1% of the variance in churn prediction is explained by the three AI technologies included in the model. Specifically:

- Expert Systems Technology had a significant negative impact on churn prediction ($B = -0.365$, $t = -6.878$, $p < 0.001$), indicating that its utilisation may not have value added to useful or can hinder accurate churn forecasting in this setting.
- Machine Learning Technology had the strongest significant positive impact ($B = 0.750$, $t = 15.040$, $p < 0.001$), suggesting that this technology is desirable for predicting customer churn.
- Robotic Process Automation (RPA) Technology also had a significantly positive influence ($B = 0.527$, $t = 10.608$, $p < 0.001$), such that its importance in churn prediction was further confirmed.

In general, the results support our hypotheses with critical influence of Machine Learning and RPA on increasing churn prediction accuracy whereas for Expert systems its performance may need to be re-examined or improved under practical application.

Hypothesis H1b. *AI Applications and Debt Repayment Prediction.*

To examine AI Applications and Debt Repayment Prediction, a multiple regression analysis was carried out to assess the impact of artificial intelligence accounting applica-

tions, including Expert Systems Technology, Machine Learning Technology, and Robotic Process Automation (RPA) Technology on debt repayment prediction in Jordanian banks. Table 12 presents the regression outcomes, including the unstandardised and standardised coefficients, t-values and levels of significance for each independent variable.

Table 12. Multiple Regression Analysis of the Effect of AI Accounting Applications on Debt Repayment Prediction in Jordanian Commercial Banks.

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
1	(Constant)	B	Std. Error	Beta		
	Expert Systems Technology	0.201	0.116		1.738	0.083
	Machine Learning Technology	0.459	0.051	0.423	9.036	0.000
	Robotic Process Automation (RPA) Technology	0.190	0.048	0.209	3.975	0.000
		0.254	0.048	0.272	5.334	0.000
R = 0.838		R ² = 0.702		F = 303.392	p = 0.000	

The results of the regression analysis provide strong empirical support for Hypothesis H1b confirming that artificial intelligence accounting applications significantly affect debt repayment prediction in Jordanian commercial banks. The overall model is statistically significant ($F = 303.392$, $p < 0.001$), and the R^2 value of 0.702 indicates that 70.2% of the variance in debt repayment prediction is explained by the three AI technologies included in the analysis.

Each of the AI technologies showed a significant positive impact:

- The impact of Expert Systems Technology was also the most significant ($B = 0.459$, $t = 9.036$, $p < 0.001$), which demonstrated its remarkable effect on debt repayment prediction-on improvement.
- Robotic Process Automation Technology exhibited a significant positive effect on investment analysis accuracy ($B = 0.254$, $p < 0.01$), indicating that automation and process efficiency contribute to improved forecasting outcomes.
- Machine Learning Technology demonstrated a positive and statistically significant effect on customer churn prediction accuracy ($B = 0.190$, $t = 3.975$, $p < 0.001$).

The constant, however, was not significant ($p = 0.083$), but this does not affect the significance of all other independent variables. In general, the findings are consistent with the proposition and demonstrate that AI technologies particularly Expert Systems and RPA are relevant to improve the debt repayment prediction accuracy in banking.

Hypothesis H1c. *AI Applications and Investment Analysis.*

To examine the effect of artificial intelligence applications on investment analysis, a multiple regression analysis was conducted using Expert Systems Technology, Machine Learning Technology, and Robotic Process Automation (RPA) Technology as independent variables. The results of the analysis are reported in Table 13.

Table 13. Multiple Regression Analysis of the Effect of AI Accounting Applications on Investment Analysis in Jordanian Commercial Banks.

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
1	(Constant)	B	Std. Error	Beta		
	Expert Systems Technology	0.102	0.099		1.034	0.302
	Machine Learning Technology	0.485	0.043	0.436	11.216	0.000
	Robotic Process Automation (RPA) Technology	0.154	0.041	0.166	3.803	0.000
		0.344	0.040	0.360	8.507	0.000
R = 0.892		R ² = 0.795		F = 499.491	p = 0.000	

The regression model is statistically significant ($F = 499.491, p < 0.001$) and explains a substantial proportion of the variance in investment analysis performance ($R^2 = 0.795$), indicating that approximately 79.5% of the variation in investment analysis can be explained by the AI technologies examined.

All three AI application variables exerted positive and statistically significant effects on investment analysis. Expert Systems Technology emerged as the strongest predictor ($B = 0.485, t = 11.216, p < 0.001$), highlighting the importance of rule-based decision support and structured knowledge processing in investment-related evaluations. Robotic Process Automation Technology also demonstrated a strong positive effect ($B = 0.344, t = 8.507, p < 0.001$), reflecting its role in automating investment-related processes and improving analytical efficiency. Machine Learning Technology had a positive and significant, though comparatively smaller, effect on investment analysis ($B = 0.154, t = 3.803, p < 0.001$), indicating its contribution to predictive and data-driven investment decision-making.

Overall, the findings provide strong empirical support for Hypothesis H1c, confirming that artificial intelligence applications play a significant role in enhancing investment analysis in Jordanian commercial banks.

5. Discussion

The research focuses on examining the functionality of applications involving artificial intelligence to enhance the precision of forecasts on banking platforms. Findings from the research confirm strong evidence to attest to the fact that applications involving artificial intelligence are crucial to determining data-driven forecasts on banking platforms. In fact, the findings support the fact that applications involving expert systems, machine learning applications, as well as robotic process automation applications, positively influence forecasts.

The study aims to transform financial forecasting using Artificial Intelligence (AI) to improve forecasting accuracy within banking systems. Results of the study Validate strong evidence in proving that applications using AI are vital for the process of determining data driven projections on banking systems. This summary is consistent with the results which indicate that both expert systems applications, machine learning applications, and robotic process automation applications have a positive impact on forecasting.

At a general level, AIs explain in great part the variance of financial forecasting precision. The data accords with previous evidences, put the AI analytics deep learning in enhancing overall prediction power in the digital finance domain (Latif et al., 2025; Kumar et al., 2025). The evidence also that the model holds a substantial level of explanatory authority strengthens the hypothesis that AI apps should be considered as complementary skills being cascaded in a banking system rather than an independent technology. Earlier studies on commercial banks show that the efficient anticipation of liquidity risk is a determinant for sustained financial performance, demonstrating the significance of accurate forecasting and decision making based on data in banking systems (Eltweri et al., 2024).

An essential insight here is the differentiated impact of AI applications on forecasting. The variables of machine learning and RPA are identified to be the most influential factors in determining the quality of forecasting. This finding confirms the growing need for machine learning and RPA in today's online banking world. The results of machine learning are well aligned with previous studies that have established that learning-based methods have outperformed other approaches in processing nonlinear patterns to adapt to changing patterns of finance (Abir et al., 2025; Safari & Ghaemi, 2025).

The crucial role of robotic process automation emphasises its indirect contribution to the forecasting function. Even though it does not contribute to predictive insights per se, there is an enhancement of forecasting results due to the improved quality of data and

timeliness of analysis inputs through the integration of RPA. The existing literature portrays the incorporation of RPA to complement analytical AI in the digital financial environment of banks to ensure accurate forecasting results with minimised human error (Rai, 2022; Alassuli, 2025).

The credibility of digital forecasting systems also depends on the transparency and assurance of underlying IT processes, as extended audit reporting has been shown to enhance trust and reputational confidence in technology-enabled environments (Faccia et al., 2020). The accuracy of AI-based forecasting techniques is also predicated on the security and integrity of large volumes of financial data, as weak safeguards regarding data privacy and protection can, in turn, compromise the trustworthiness of analytical outputs and automated decision processing (Faccia et al., 2021). A good financial planning in digital banking settings depends as well on strong risk management and control systems, due to the fact that a lack of risks governance in e-business models might decrease the trustiness of technology-based decision processes (Eltweri et al., 2020).

However, the results for expert systems are more complex. The expert system has a positive impact on debt repayment prediction and investment analysis, but it has a negative relationship with customer churn prediction. The reason behind this complexity might be attributed to the nature of expert systems, which are useful in decision-making problems requiring a well-structured environment where decision rules are stable. In such a scenario, expert systems perform well with their analytical capabilities. However, customer churn prediction involves behaviour, which remains dynamic. Hence, expert systems require adaptive learning for effective decision making (Elnakeeb & Elawadly, 2025; Dessaint et al., 2024).

The negative relationship observed between Expert Systems Technology and customer churn prediction warrants careful interpretation. Unlike machine learning approaches, expert systems rely on predefined rules and static decision logic, which are most effective in structured and stable decision environments. Customer churn, however, is a highly dynamic and behaviour-driven phenomenon influenced by evolving preferences, service experiences, and external conditions. In such contexts, rigid rule-based systems may fail to capture emerging patterns in customer behaviour, potentially leading to delayed or inaccurate churn signals. Moreover, excessive reliance on predefined thresholds may oversimplify complex behavioural drivers and crowd out adaptive learning mechanisms, thereby reducing forecasting effectiveness.

In addition to the theoretical explanation, further diagnostic checks were conducted to assess whether the negative coefficient for Expert Systems Technology reflects a statistical artefact. Variance Inflation Factor (VIF) values were examined and, while higher than ideal, remained below commonly accepted thresholds, indicating that severe multicollinearity is unlikely. The sign reversal observed for Expert Systems Technology is therefore consistent with a suppression effect, whereby overlapping explanatory variance with more adaptive AI technologies (particularly machine learning) alters the direction of the coefficient in the multivariate model. Importantly, the bivariate relationship between Expert Systems Technology and churn prediction remained positive, suggesting that the negative coefficient emerges only when controlling for other AI applications. This supports retaining the current model specification and interpreting the result as conditional rather than contradictory.

This interpretation is consistent with the study's finding that expert systems positively influence debt repayment prediction and investment analysis, characterised by greater structural stability, formal rules, and quantifiable criteria. The contrasting effects across forecasting domains highlight that the effectiveness of AI applications is contingent upon their alignment with the nature of the prediction task. Rather than indicating a failure of

expert systems, the negative coefficient underscores the importance of task–technology fit when deploying AI-based decision-support tools in banking platforms.

Theoretically, the results above can be considered to contribute to the electronic commerce and digital finance bodies of knowledge because they indicate that applications of AI should be distinguished and should not be considered equal or similar applications from the point of view of performance forecasting. In that regard, by creating a differentiation among the learning capabilities provided by AI (machine learning), process-enabling capabilities provided by AI (robotic process automation), and rule-based reasoning systems (expert systems), the study explains AI's impact on forecasting on a remote platform.

The results also have significant managerial implications for banks in the digital transformation context. Instead of focusing on general approaches for adopting artificial intelligence, it is more important for banks to align artificial intelligence applications with individual forecasting tasks. Research in machine learning intelligence is set to deliver significant returns in tasks that relate to the behaviour of customers as well as credit risks, while robotic process automation can be leveraged to improve the accuracy of forecasting processes through stronger data governance processes. Even expert systems are still applicable in stable decision domains, including the evaluation of investments and structured credit analysis, while their weaknesses in dynamic domains are paramount in consideration. Lastly, the emphasis on the Jordanian banking system also helps the inclusion of empirical evidence from an emerging digital banking system where institutional limitations and system advancement potentially impact the results of AI implementation. Findings include that even in such situations, the use of AI-driven decision-making abilities still has the potential to increase forecasting precision when effectively incorporated into existing banking systems, making the study relevant to the evolving state of digital finance studies initiated by previous studies aiming to promote the use of AI-driven forecasting in advanced fintech environments (Latif et al., 2025). In conclusion, it can be summarised that the importance of artificial intelligence as it improves financial forecast capabilities is mentioned as it does not only make financial forecasts more accurate as a result of automation but also changes the architecture of financial decision-making as a whole in banking platforms.

6. Conclusions

The study aims to investigate the extent to which artificial intelligence applications can enhance financial forecast accuracy as a form of digital decision-making capabilities within banking systems

Using the evidence collected from commercial banks in Jordan, the research finds that these technologies have demonstrated an ability to greatly improve forecast accuracy relative to critical financial areas, such as customer churn prediction, debt payment prediction, and investment analysis.

Findings indicate that the impact of AI applications across different aspects of forecasting is not uniform. Machine learning and robotic process automation are established to be the most effective AI applications in this context, which is attributed to their capabilities for adaptive learning, handling a vast amount of data, and process efficiency in a digitally enabled environment of finance. However, expert systems, which are efficient in the systematic forecast related to investment analysis and debt repayment, are less effective in behaviour-centric domains such as customer churn forecast.

From a theoretical perspective, it has made contributions to both electronic commerce and digital finance studies by conceptualising applications of AI as distinct decision capabilities, as opposed to viewing it as a homogenous tool in these two fields. The paper has theoretically demonstrated how various applications of AI have different effects on forecasting errors.

In practice, the implication of the findings is that the strategy ought to go beyond the adoption of AI and target investments aiming at the suitable use of AI to accomplish forecasting. Improvement of the analytics of machine learning, the use of RPS to improve the data reliability, and the judicious use of expert systems to improve decision-making entries can be effective.

Although this study offers important insights into the matter, it also has several limitations that should be considered. The use of survey data and the specific banking environment may contribute to generalisation issues in this study. Future studies could further develop this line of research by conducting longitudinal studies that use actual data for performance measures in AI-powered forecasting applications across digital finance environments.

Despite the contributions of this study, several limitations should be acknowledged. First, the study relies on self-reported survey data collected from a single source at a single point in time. As a result, the findings may be subject to common method bias, which can arise when both independent and dependent variables are measured using the same instrument. Although procedural remedies were applied during survey design, future research could employ multi-source data or longitudinal designs to further mitigate this concern.

Second, financial forecasting accuracy in this study is measured using respondents' perceptions rather than objective performance metrics. While perceptual measures are appropriate for capturing managerial assessments of system effectiveness, they may not fully reflect realised forecasting accuracy based on actual financial outcomes. Future studies are therefore encouraged to incorporate objective indicators such as forecast error rates, historical performance data, or system-generated prediction logs to validate and extend the findings.

Finally, the cross-sectional design limits the ability to capture learning effects and dynamic changes in AI system performance over time. Longitudinal research could provide deeper insights into how AI applications evolve and how their impact on financial forecasting accuracy changes as organisations gain experience with these technologies.

A particularly important avenue for future research concerns the use of objective, performance-based data to assess the impact of artificial intelligence applications on financial forecasting outcomes. While this study relies on managerial perceptions of forecasting accuracy, future studies should employ actual forecasting performance measures, such as forecast error rates, realised investment returns, loan default outcomes, or system-generated prediction logs. The use of objective data would allow for a more precise evaluation of AI effectiveness and strengthen causal inference regarding the performance implications of AI-enabled decision-support systems in banking.

In conclusion, the experiment confirms the importance of artificial intelligence in improving the accuracy of financial forecasting and its role in establishing the foundation of the digital transformation of the financial sector.

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