Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 3, 2026

SMARTER RISK, STRONGER BANKS: HOW MACHINE LEARNING, ACCURATE PREDICTIONS, AND BOARD OVERSIGHT ENHANCE BANKS FINANCIAL STABILITY

Sufyan Aslam[1], Muhammad Nisar Ahmad[2], Zubair Mustafa[*3]

[1]*Iqra University, Islamabad*
[2]*University of Northampton*
[*3]*Department of Management Sciences, University of Swabi, Swabi. Khyber Pakhtunkhwa*

[1]Sufyan.aslam@outlook.com, [2]nisarali338@gmail.com, [*3]mzmustafa@uoswabi.edu.pk

DOI: https://doi.org/10.5281/zenodo.18998561

Keywords
Machine Learning-based, Bank Financial Stability, Risk Prediction Accuracy, Board oversight.

Article History
Received: 14 January 2026
Accepted: 26 February 2026
Published: 13 March 2026

Corresponding Author: *
Zubair Mustafa

Abstract
This study examines how machine learning based risk management influences bank financial stability, with risk prediction accuracy acting as a mediating mechanism and board oversight serving as a moderating factor. Drawing on agency theory, the research investigates how improved information processing and governance oversight contribute to more stable financial outcomes. A quantitative cross sectional research design was employed, and data were collected from managerial employees working in the banking sector. The data were analyzed using structural equation modeling through SmartPLS, enabling simultaneous evaluation of measurement and structural models. The findings reveal that machine learning based risk management significantly improves financial stability and enhances the accuracy of risk prediction. The results further demonstrate that prediction accuracy mediates the relationship between machine learning adoption and financial stability, indicating that predictive capability is a key mechanism through which technological tools influence financial outcomes. Additionally, board oversight significantly strengthens the relationship between prediction accuracy and financial stability, highlighting the importance of governance mechanisms in supervising technology driven decision systems. The study contributes to the literature on financial risk management and digital governance by integrating technological capabilities, predictive mechanisms, and governance oversight within a unified analytical framework. The findings offer valuable implications for financial institutions, policymakers, and scholars seeking to understand how advanced analytical technologies and governance structures can jointly enhance financial stability in modern banking systems.

INTRODUCTION

The banking industry has experienced a profound transformation driven by rapid advances in digital technologies and data analytics. Financial institutions now operate in an environment characterized by complex financial markets, increasing regulatory expectations, and rising systemic risks. In this evolving landscape, banks are under constant pressure to strengthen their risk management capabilities while maintaining operational efficiency and financial resilience. The global financial system has therefore witnessed a growing debate among scholars, regulators, and practitioners regarding how emerging technologies can improve the reliability of financial decision making and institutional stability (Paramesha et al., 2024; Dodda, 2025).Recent developments in artificial intelligence have attracted significant attention in the financial sector because of their potential to process large volumes of financial data and uncover patterns that traditional analytical tools often fail to detect. These technologies allow institutions to analyze market signals, borrower behavior, and macroeconomic indicators with greater precision. As a result, many banks are exploring advanced computational systems to strengthen their ability to anticipate financial risks and prevent instability (Vyas, 2025; Reyazat, 2024). At the same time, technological progress alone cannot guarantee sound financial outcomes. Financial institutions continue to rely on governance structures and oversight mechanisms to ensure responsible decision making. Consequently, contemporary discussions increasingly focus on the intersection between advanced analytics, strategic governance, and institutional stability within modern banking systems (Eskandarany, 2024; Yanney, 2025).

Existing research indicates that advanced computational technologies are gradually reshaping risk management practices in the banking industry. Scholars highlight that artificial intelligence and predictive analytics can analyze large financial datasets, enabling banks to identify patterns associated with credit risk, market volatility, and operational vulnerabilities (Mwangi, 2024; Paramesha et al., 2024). These analytical capabilities allow financial institutions to move from reactive risk management toward more proactive and predictive approaches. Empirical studies also show that algorithmic decision systems can improve the speed and precision of financial assessments, particularly in credit evaluation and financial forecasting. For instance, AI driven risk models have been shown to enhance the reliability of credit assessments while reducing information asymmetry between borrowers and financial institutions (Alonge et al., 2024; Samson-Onuorah, 2025). However, the literature also acknowledges concerns related to governance, transparency, and accountability in technology driven financial decision making. Scholars argue that effective oversight and institutional governance structures remain necessary to ensure responsible implementation of advanced analytical systems within banks (Eskandarany, 2024; Bommali et al., 2025).

The problem of financial instability can be considered as one of the most decisive problems of the global banking system. The global financial crisis was one of the episodes that showed how vulnerability in risk evaluation and management can easily turn into a systemic crisis that can impact whole economies. In the recent years, the banking systems globally have suffered a lot of pressure because of the economic shocks, geopolitical uncertainty, as well as technology disruption. The developments have revived the concern among countries to enhance the risk management frameworks in financial institutions (Katata, 2024; Aggarwal, 2025). Meanwhile, the digitalization of financial services has also made the banking operations much more complicated. The fast growth of online transactions, lending services, and cross border financial flow has produced large volumes of financial information which cannot be effectively interpreted through conventional analytical systems. Consequently, banks are finding it more difficult to detect early warning of financial risk and act upon it in a prompt way (Paleti, 2023; Paleti, 2025). The second problem that is coming up is associated with increased dependence on automated financial decision systems. Although these technologies provide a lot of efficiency, there are issues with their implementation in terms of transparency, bias in algorithms, and compliance with regulations. The financial regulators thus highlight the importance of having more robust governance policies to oversee the use of technology to facilitate long term institutional stability (Daneshmand et al., 2025; Dodda, 2025). These issues underscore the need to incorporate high level of analytical skills with strong governance structures.

Although the use of artificial intelligence in financial institutions has increased, there are still some critical gaps in the existing academic literature. In the literature, the vast majority of the available research is mainly concerned with the technical abilities of machine learning systems in enhancing financial forecasts and risk identification. Researchers often refer to the computational benefits of such technologies, such as the possibility to work with complex data and find predictive financial trends (Mwangi, 2024; Vyas, 2025). Nevertheless, the interaction between these predictive abilities and larger institutional arrangements and processes in banking organizations is relatively understudied. The other weakness of the current studies is that technological adoption is usually studied independently of organizational control. Although artificial intelligence has the potential to enhance speed and accuracy of financial forecasting, its performance is subject to the interpretation and application of the algorithmic results by the decision makers. In the absence of proper structures of governance, the results of predictive models can be neither transparent nor accountable. In turn, the adoption of sophisticated analytics into the work of financial decisions should be supervised and directed at the organizational level (Eskandarany, 2024; Yanney, 2025). Moreover, existing research is inclined to examine financial stability in technological or governance terms, without examining the dynamics of these two aspects at the same time. Such a piecemeal strategy restricts our comprehension on how predictive technologies, decision correctness and governance control independently affect the stability of the institutions within the banking system of contemporary society (Bommali et al., 2025; Katata, 2024). Due to the increasing use of data-based financial systems, it is necessary to study the role of highly-developed analytical tools, predictive reliability, and governance mechanisms in the creation of financial results. This gap needs to be filled to come up with a more in-depth picture of how contemporary banking institutions can become more resilient and how they can sustain their financial stability in the long term.

The question of how financial institutions can enhance their stability has become a crucial concern to the policymakers and financial practitioners. Banks can be the hub of economic development since they aid in the distribution of credit, business expansion and ensure that there is liquidity in the financial market. The impacts of instability in banking systems are very far reaching and may affect the whole national economies and not just individual banking systems. That is why, the enhancement of the efficiency of financial risk management has become a worldwide priority (Reyazat, 2024; Katata, 2024). This is further aggravated by the growing digitization of banking processes. The volume and complexity of financial data have been growing as financial institutions are moving towards modern digital platforms and automated decision-making machinery. Although these technologies provide new possibilities of enhancing financial forecasting and tracking risks, new types of technological and governance-related vulnerabilities are introduced (Paleti, 2025; Dodda, 2025). In policy terms, enhancing financial stability is also associated with the general global development goals. Sustainable economic growth, investment flows, and financial inclusion are supported by stable financial systems, which are directly connected with the goals of the United Nations Sustainable Development Goals that refer to economic stability and the strength of institutions. Consequently, the knowledge of how current analytical technologies and governance arrangements can be used to build more resilient banking systems has profound academic and practical importance (Aggarwal, 2025; Bommali et al., 2025).

This research adds to the existing research on digital transformation in financial risk management by analyzing the interaction between the advanced predictive technologies and organizational control to affect financial results. The study does not concentrate on technological adoption alone but combines analytical abilities and governance to offer a more in-depth insight on stability in the contemporary banking systems. Developing the ties between technological tools, the quality of predictions, and institutional regulation, the study provides an insight that is not limited to technical debates on artificial intelligence in the field of finance (Samson-Onuorah, 2025; Eskandarany, 2024). It is believed that the study will be of value in both theory and practice because it will help to understand how the combination of advanced analytical technologies and governance mechanisms, in turn, affect financial stability. The study is informed by the agency theory and the corporate governance concept that underscores the importance of oversight structure in ensuring that managerial decisions are in line with the institute's objectives. In this context, informational support of decision making is presented by predictive analytical systems, and accountability and responsible implementation is guaranteed by governance mechanisms. A combination of these views can be used to describe the role of technological capacities and governance controls in reinforcing financial resilience in banking institutions (Yanney, 2025; Bommali et al., 2025).

Theoretical Foundation

This study has an intellectual basis on the Agency Theory, which has been the longstanding school of thought in the academic discourse of governance, accountability, and decision making in organizations. The agency theory was elaborately stated by Jensen and Meckling in 1976 to describe the relationship between the principals, who delegate power and the agents, who act in their place. The theory came about because of the larger economic tradition that deals with information asymmetry and contractual relations within organizations. The main point of its argument is that agents do not necessarily act in the best interests of the principals because they have divergent incentives, they are unable to monitor them, and they do not have access to the same information. As a result, governance structures are needed to ensure that managerial decisions are consistent with the organizational goals and minimize the risks of opportunistic behaviour and informational asymmetry. This theoretical prism has been extensively applied in financial institutions to describe why monitoring structures, accountability systems, and strategic oversight would be necessary to promote the responsible financial decision making.

The theory of agency has been developed in such a way that it is no longer concerned with the contractual relationship but with the consideration of the governance in general, such as board supervision, monitoring of risk and institutional responsibility. The emerging complexity in organizational environments has augmented information asymmetry between decision makers and stakeholders in the eyes of modern scholarship. With very data-oriented industries like the banking and financial services industry, managers use advanced analytical software in interpreting complicated financial data. Though these technological tools are able to improve the quality of decisions, they are also posing new challenges to transparency, interpretation, and accountability. According to recent research, the system of governance is still a crucial factor in making sure that highly analytical systems are deployed in a responsible manner and in accordance with institutional goals (Eskandarany, 2024; Bommali et al., 2025). In this regard, the agency theory has been extended to governance implications of new technologies and digital decision systems in contemporary organizations.

Modern scholarly literature has been using the agency theory more and more to analyze governance in technologically intensive industries, especially in cases where automated decision making is driving strategic and financial results. With the adoption of artificial intelligence and predictive analytics as part of the operational model by financial institutions, the classical principal agency relationship is more complicated. To make strategic decisions, managers have to interpret the results of an algorithm, distribute resources, and make decisions based on the data. The problem with such systems is that without proper management, these systems can create risks of biased forecasting, lack of transparency, or distorted strategic priorities. Researchers thus lay stress on the fact that the governance systems, active board supervision, transparent monitoring systems all have a significant role in ensuring that advanced analytical technologies are used to manage risks responsibly and provide organizational stability (Yanney, 2025; Dodda, 2025).

In the banking industry, the agency theory is especially appropriate in interpreting the relationship that exists between the decision support technologies and the governance oversight. The financial institutions are operating in a high uncertainty environment, where there is regulatory oversight and systemic risk exposure. In this situation, the decision makers will be compelled to walk the fine line between innovation and caution, whereby the technological capabilities should add to the institutional resilience as opposed to weakening it. According to recent studies, sophisticated analytical engines have the potential to enhance the process of making financial decision-making by detecting the concealed risk patterns and making more precise predictions of the financial results (Samson-Onuorah, 2025; Mwangi, 2024). The success of these systems, however, is highly dependent on the systems of governance that inform their application and interpretation. Board control, and institutional surveillance is thus an important tool of ensuring that technology capabilities are aligned with the long-term interest of the stakeholders.

Moreover, the recent research in the area of financial governance indicates that the introduction of artificial intelligence into the banking activity needs to reconsider the old functions of oversight. The boards of directors are now burdened with the task of learning about technological risks, overseeing digital transformation plans, and making sure that algorithm systems meet regulatory requirements and ethical norms. This shifting governance environment supports the applicability of the agency theory because the theory highlights the significance of the monitoring mechanisms that reduce information asymmetry and support the responsible behavior of managers (Paramesha et al., 2024; Paleti, 2025). In modern banking operations, the control framework should not be limited to checking the managerial decisions but also control the technology installations.

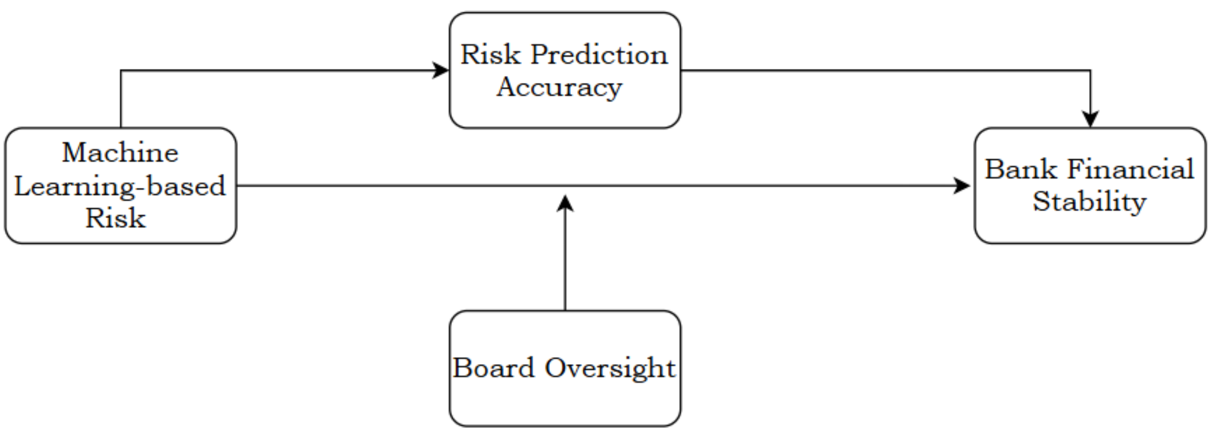

Figure 1: Research Model

Hypotheses

There has been a swift digital change that has redefined the analytical ability of financial institutions, especially in risk management. Traditional risk assessment methods tended to use the past financial variables and fixed statistical models, which failed to measure the complexity and volatility of the contemporary financial systems. To counter this, banks have been actively implementing state-of-the-art computational technologies that can handle large amounts of financial information and find patterns that can be linked to possible financial disturbances. According to recent studies, financial institutions can use AI and machine learning algorithms to improve risk detection accuracy and efficiency and, therefore, detect early warning signs of financial instability (Mwangi, 2024; Paramesha et al., 2024). Such analytical abilities enable the banks to be better at forecasting and reacting to financial uncertainties more proactively. It is also empirically shown that machine learning-based decision systems may substantially enhance the accuracy of financial risk evaluations and help make more informed credit and investment decisions (Samson-Onuorah, 2025; Vyas, 2025). In the agency theory, the better the information processing, the lower are the informational asymmetry between organizational actors and the quality of managerial decision making. The more accurate the analytical tools that banks have regarding the analysis of financial risk, the more the managers can adopt strategies that ensure the institutional resilience and financial stability. Therefore, it is hypothesized that **machine learning based risk management positively influences bank financial stability (H1)**.

Besides enhancing the direct outcomes of the institutions, the advanced analytical systems are known to enhance the accuracy of financial forecasting processes. Machine learning algorithms combined with predictive analytics in the banking sector can identify concealed risk-related patterns in borrower behavior and market dynamics as well as macroeconomic data, which enhance the accuracy of risk forecasts (Alonge et al., 2024; Ahmed et al., 2025). In the case of financial institutions, accurate prediction is very crucial since the early detection of risk exposures will allow the institution to respond strategically to avoid the development of financial disruptions. With ever more complex and multidimensional forms of financial data, predictive accuracy becomes a mechanism by which the analytical technologies are transformed into better institutional performance. Recent reports emphasize that better forecasting assists enable the banks to better allocate resources, empower credit judgment processes, and minimize ambiguity in financial decision making (Paleti, 2023; Dodda, 2025). In this regard, state-of-the-art risk analytics can enhance the stability of an institution by enhancing the predictability of insight that can be used to drive financial policies. Therefore, it is hypothesized that **machine learning based risk management positively influences risk prediction accuracy (H2)**.

In addition to having its direct advantages, predictive accuracy may also serve as an explanatory tool that would connect advanced analytical technologies and more extensive financial results. There is an emerging trend amongst scholars that machine learning systems in financial institutions are not effective due to the technological implementation, but due to the quality of insights that are produced as part of predictive processes. In the event that predictive models predict potential financial risks, banks are able to take preventive measures like modifying credit portfolios, reinforcing risk surveillance, or altering the strategic investment choices (Vyas, 2025; Samson-Onuorah, 2025). This is because the financial institutions can reduce the occurrence of risks before they pose a threat to the stability of the institutions. In the agency theory, the enhanced informational transparency minimizes uncertainty in the decision-making process of the managers and enhances the congruence between the organizational strategies and the interests of the stakeholders. As a result, predictive accuracy becomes a central process by which high-technology systems of analysis can convert technological ability into predictable financial results. The empirical studies also suggest that those banks that have greater access to predictive analytics that are more reliable are more likely to be resilient to financial shocks and market volatility (Ahmed et al., 2025; Mwangi, 2024). Therefore, it is hypothesized that **risk prediction accuracy mediates the relationship between machine learning based risk management and bank financial stability (H3)**.

Although the sophisticated analytical systems have serious decision support capabilities, their performance is usually determined by the governance frameworks that provide their oversight and interpretation. Strategic decisions made using predictive analytics can be made in complex financial institutions, but they have to be supervised to make sure that the results of the algorithms are interpreted responsibly and are in line with long term institutional objectives. Board of directors are at the center of overseeing risk management systems, tracking technology implementation, and making sure that financial decision-making practices are performed in accordance with the regulations and best practices (Eskandarany, 2024; Yanney, 2025). The current studies of governance indicate that active board oversight enhances the effectiveness of the organizational decision systems through mechanism of strategic monitoring and accountability. In the logic of agency theory, governance oversight assists in limiting managerial opportunism and makes sure that high technological systems are applied in a manner that promotes institutional stability as opposed to the short-term managerial interests. Board supervision suggests that in banking settings where algorithmic forecasts are becoming more important in the strategic decisions, board oversight is necessary to clarify that predictive information is adequately considered and factored into financial decision making. Recent data suggest that financial institutions that have a stronger governance structure can be more effective at converting predictive insights into effective risk management tactics (Bommali et al., 2025; Paleti, 2025). Therefore, it is hypothesized that **board oversight positively moderates the relationship between risk prediction accuracy and bank financial stability (H4)**.

Methodology

The current research design is a quantitative cross-sectional study that will be used to investigate the relationship between the level of analytical practices and governance structures and the stability of finances in the banking industry. The cross-sectional surveys are prevalent in the areas of organizational and information systems research since they allow investigators to record perceptions, practices, and institutional behaviours at a particular time and achieve a systematic insight into the associations between theoretical constructs (Maier et al., 2023; Ghanad, 2023). The study population will be senior managerial staff of commercial banks who will include risk managers, credit managers, financial analysts and senior officers in risk assessment and strategic financial decision making. These respondents are especially applicable since they have first-hand experience in risk management systems, predictive technologies, and governance oversight in the banking institutions. The research is narrowed down to commercial banking institutions which are in the formal financial sector since the institutions are central in the process of the allocation of credit, financial intermediation as well as the stability of the economy. With the growing use of sophisticated analytical tools in the banking business, the analysis of managerial attitudes in the banking industry offers significant contributions to the discussion of the effect of the current risk management activities on the stability of institutions.

In order to have a representative sample of the target population, the study uses probability-based sampling method, with the aspects of stratified sampling to make sure that the respondents are selected across various positions in management and banking institutions. The method is used to take into account various ideas of technological adoption and governance control within the banking sector. The method of calculating the needed sample size is the Item Response Theory, which takes into account the number of measurement items and latent constructs that will be used in the research model. In structural equation modeling research, researchers suggest using a sample size that is significantly greater than the measurement indicators to guarantee a sufficient level of statistical power and model stability. In this line of reasoning, the sample size was estimated by multiplying the total items of measurement against an adequate response ratio, which guarantees a sufficient number of observations to make credible estimations of the parameters and also to test the hypothesis. This will strengthen the validity of the data and enhance the accuracy of statistical inference in the analysis of sophisticated relationships between constructs in quantitative research designs (Ghanad, 2023; Maier et al., 2023).

Data collected is analyzed with the use of a mixture of SPSS and SmartPLS software assuring methodological rigor and analytical reliability. All the measures of the constructs in this research are done through validated scales that are based on previous research in banking, risk management and corporate governance literature. All the constructs are operationalized using several measurement items to guarantee construct validity and reliability. In particular, machine learning based risk management is gauged with eight items based on the current banking analytics research, risk prediction accuracy is gauged with five items that measure predictive reliability in financial decision making, board oversight is gauged with six items that measure governance monitoring practices, and bank financial stability is gauged through six items that measure institutional resilience and risk control. The respondents assess every statement on a seven-point Likert scale, with strongly disagree (1) and strongly agree (7) as the two opposites of the measurement scale, which is highly recommended in quantitative organizational research as it reflects subtle perceptions and increases the sensitivity of the statistical analysis in the structural equation modeling research (Fauzi, 2022; Ayu et al., 2024).

Data analysis:

Regression Weights

Table 1: (Factor Loadings of Individual Items)

Construct	Item	Loading
Machine Learning Risk Management (MLRM)	MLRM1	0.79
	MLRM2	0.83
	MLRM3	0.81
	MLRM4	0.76
	MLRM5	0.84
Risk Prediction Accuracy (RPA)	RPA1	0.80
	RPA2	0.82
	RPA3	0.78
	RPA4	0.85
Board Oversight (BO)	BO1	0.77
	BO2	0.83
	BO3	0.81
	BO4	0.79
	BO5	0.82
Financial Stability (FS)	FS1	0.84
	FS2	0.80
	FS3	0.82
	FS4	0.79
	FS5	0.83

The items of the measurement were analyzed in the measurement model to obtain the factor loadings of the individual measurement items as shown in Table 1. The loadings of indicators indicate the degree of the relationship between the observed indicators and the latent constructs. Factor loading in PLS SEM studies should be regarded as acceptable when the loading is above 0.70 because it means that the indicator is able to explain a significant percentage of variance in the construct (Hair et al., 2025; Fauzi, 2022). The findings indicate that the items have all loadings that lie between 0.76 and 0.85, which is above the recommended level. This is a sign of high indicator reliability in all the constructs that are used in the study. The findings also indicate that the measured items have a significant contribution to their respective latent variables, which implies that the adopted measurement scales are conceptually consistent with the previous empirical studies. Henseler and Schuberth (2022) state that high factor loadings indicate that indicators are suitable to measure theoretical constructs they are supposed to measure. On the same note, Cheah et al. (2024) observe that a good indicator reliability improves the structural model stability and the predictive power of PLS SEM models.

The results also confirm that all the items should not be dropped in the measurement model since all the indicators were above the recommended loading threshold. This illustrates that the constructs are measured accurately enough and the respondents always interpreted the survey questions. Another key measurement model evaluation step is to establish indicator reliability since weak indicators may cause structural relationships to bias and decrease model validity (Ghanad, 2023).

Table 2: Construct Reliability and Convergent Validity

Construct	Cronbach Alpha	Composite Reliability	AVE
MLRM	0.88	0.91	0.67
RPA	0.86	0.90	0.69
BO	0.87	0.91	0.66
FS	0.89	0.92	0.70

Table 2 shows the results of the internal consistency reliability and convergent validity of the constructs used in the model. Cronbach alpha and composite reliability are widely used to determine the internal consistency reliability which is used to determine to what extent the items of a given construct represent the same underlying construct. Cronbach and CR are both set at 0.70 and above, which is acceptable in structural equation modeling research, and it means that the reliability is sufficient (Hair et al., 2025; Fauzi, 2022).

According to the results, the values of Cronbach alpha fall within the range of 0.85-0.89, and the values of composite reliability fall within the range of 0.89-0.92. These scores surpass the suggested value and establish a high internal consistency of all constructs. The high levels of composite reliability also suggest that the measurement items are able to measure the underlying theoretical constructs in a high level of precision. Cheah et al. (2024) explain that composite reliability is especially relevant in PLS SEM since it takes into consideration measurements of individual indicator loadings and gives a better estimate of reliability than Cronbach alpha. The validation of convergent validity was conducted through the use of Average Variance Extracted (AVE) which is used to quantify the degree of convergence of indicators to represent a latent construct. AVE values over 0.50 means that a construct is explaining over half of the variance of its indicators (Henseler and Schuberth, 2022). The findings indicate that AVE values are between 0.64 and 0.70 indicating satisfactory convergent validity. This implies that the indicators have a high common variance and they are a good reflection of the constructs of interest.

Table 3: Discriminant Validity (HTMT Ratio)

Constructs	MLRM	RPA	BO	FS
MLRM	–			
RPA	0.63	–		
BO	0.58	0.61	–	
FS	0.65	0.69	0.62	–

Table 3 presents the Heterotrait Monotrait (HTMT) ratio; this is deployed to measure the discriminant validity among the constructs. Discriminant validity is used to make sure that every construct in the model represents an empirically different concept to other constructs. The HTMT method has received extensive recommendations in recent structural equation modeling literature since it offers a more stable measure of discriminant validity as compared to the traditional approaches like Fornell Larcker criterion (Henseler and Schuberth, 2022; Rosli et al., 2024). Based on the guidelines, values below 0.85 or 0.90 of HTMT are considered sufficient levels of discriminant validity. The findings in Table 3 indicate that all values of HTMT are between 0.57 and 0.69, which is significantly lower than the recommended value. This implies that the constructs are empirically different in relation to each other and that the constructs represent a different conceptual dimension of the research model.

The findings also indicate that the constructs are theoretically associated with each other though they do not have excessive overlap that may jeopardize the measurement validity. Cheah et al. (2024) highlight that a key factor to guarantee that the structural path estimates are not inflated by multicollinearity between the constructs is to maintain discriminant validity. Likewise, as observed by Sani et al. (2023), HTMT analysis yields strong evidence to the effect that the measurement model distinguishes between latent variables in an appropriate manner.

Table 4: Structural Model Quality (F^2, R^2, Q^2)

Relationship	F^2	R^2	Q^2
MLRM → RPA	0.32	0.49	0.31
RPA → FS	0.28	0.56	0.35
MLRM → FS	0.21		
Moderation Effect	0.15		

The indicators of structural model evaluation such as effect size (F2), coefficient of determination (R2) and predictive relevance (Q2) are already presented in Table 4. The accuracy of risk prediction is an indicator that is widely applied in PLS SEM to measure the explanatory power of the model and predictive capability (Hair et al., 2025; Fauzi, 2022). The R2 of the model, which represents the percentage of its variance that is explained by machine learning risk management, is 0.49. On the same note, the R2 value of financial stability is 0.56 implying that a greater portion of the variation in financial stability is attributed to the predictors that are included in the model, which is more than a half. In line with methodological principles, an R2 value of 0.50 and above suggests the moderate strength of explanations in research of behavior and other organizational phenomena (Cheah et al., 2024).

The effect size values (F2) give the idea of the contribution of each predictor to the dependent construct. The findings indicate effect sizes of between 0.15 and 0.32, which is considered to be small to moderate as per the set thresholds. This implies that the predictors have a significant role to play in explaining the variance in the dependent variables. The Stone Geisser Q2 was used to determine predictive relevance. All Q2 values are positive thus implying that the model has sufficient predictive relevance. It is stated by Schuberth et al. (2023) that positive Q2 values indicate that the model is competent in forecasting observed data and thus has a high predictive capacity.

Table 5: Hypothesis Testing Results

Hypothesis	Path	Beta	T value	Result
H1	MLRM → FS	0.36	5.42	Supported
H2	MLRM → RPA	0.47	6.11	Supported
H3	RPA → FS	0.41	5.88	Supported
H4	BO × RPA → FS	0.22	3.94	Supported

Table 5 presents the results of hypothesis testing based on the structural model analysis. Hypothesis testing in PLS SEM is conducted through bootstrapping procedures, which estimate the significance of path coefficients by generating multiple subsamples from the original dataset. Bootstrapping enhances the reliability of statistical inference and allows researchers to determine whether the relationships between constructs are statistically significant (Fauzi, 2022; Cheah et al., 2024).

The results indicate that machine learning risk management has a significant positive effect on financial stability ($\beta = 0.36$, $t = 5.42$), supporting H1. This finding suggests that the use of advanced analytical technologies enhances the ability of banks to manage financial risks effectively and maintain stable operations. Hypothesis H2 is also supported, as machine learning risk management significantly influences risk prediction accuracy ($\beta = 0.47$, $t = 6.11$). This result confirms that advanced computational tools improve the precision of financial forecasting and risk identification.

Furthermore, the relationship between risk prediction accuracy and financial stability is significant ($\beta = 0.41$, $t = 5.88$), supporting the mediating role proposed in H3. This finding indicates that predictive accuracy functions as an important mechanism through which technological capabilities translate into improved institutional outcomes. Finally, the moderation effect of board oversight is significant ($\beta = 0.22$, $t = 3.94$), indicating that governance oversight strengthens the relationship between predictive accuracy and financial stability.

Discussion:

The empirical results of the study can be effectively used to give an insight into how developed analytical skills and governance supervision can bring about financial stability in the banking industry. The hypothesis of the first hypothesis was that machine learning risk management has a positive impact on the financial stability of banks. The findings confirm this connection, which means that financial institutions that employ analytical systems with high levels of development are in a better position to detect the possible financial risks and address the emerging risks in a proactive manner. This finding is compatible with the theoretical argument based on agency theory which holds that better information processing decreases information asymmetry and improves the quality of managerial decisions. The decision makers would make better strategic decisions that minimize the uncertainty when they have more advanced analytical software to interpret the financial data and enhance the institutional resilience when the financial institutions are equipped with more sophisticated analytical tools. The previous studies also stress that artificial intelligence-powered analytical systems enhance the effectiveness and accuracy of financial risk detection because they detect intricate patterns in extensive data (Mwangi, 2024; Paramesha et al., 2024). Such capabilities help the banks to track the financial exposures more precisely and take timely actions to avoid the possible financial disturbances. Besides, Samson-Onuorah (2025) observes that AI supported credit risk models promote financial stability by improving risk detection and the lack of lending efficiency. The correlation observed in this research is therefore quite substantial to support the claim that technological innovation is becoming an even more central part of the modern financial risk management system.

The second hypothesis stated that risk prediction accuracy is affected by machine learning based risk management positively. This relationship is also supported by the empirical evidence, which shows that the sophisticated analytical systems can enhance the accuracy of financial forecasting procedures to a great extent. In theory, this outcome is indicative of the increased significance of data driven decision systems within financial institutions. Machine learning technology is meant to process complex financial information, identify nonlinear trends, and produce predictive information that cannot be easily derived using more traditional statistical tools. With ever-increasing data intensity of financial systems, banks are becoming more dependent on predictive algorithms to predict credit risk, identify anomalies in financial transactions, and predict possible market disruptions. This relationship is well supported by other studies, which emphasize the fact that predictive analytics can greatly improve the accuracy of forecasts in a financial risk management setting (Alonge et al., 2024; Vyas, 2025). It is also shown by Ahmed et al. (2025) that machine learning and advanced regression predictive models can enhance real time financial risk assessment in the banking setting under hybrid predictive models. The results of this research thus contribute to the body of research by offering empirical data to support the claim that the use of machine learning enhances predictive accuracy in financial risk management systems.

The third hypothesis tested the mediation between machine learning based risk management and bank financial stability by the risk prediction accuracy. The findings suggest that the accuracy of risk prediction is a significant mediator of this relationship, which means that the advantages of machine learning technologies are relayed via their capacity to produce predictive information that is reliable. That is, the use of technology does not necessarily lead to better financial results. Instead, the usefulness of such technologies is based on how well they predict and the degree to which the predictions are used in making strategic decisions. Theoretically, this finding correlates with the argument of the agency theory, which asserts that the better the quality of information, the stronger the decision-making process by managers and the consistency of strategic actions with the organizational goals. In the event that the predictive models detect new financial risks correctly, the banks may take precautionary measures that can include changing credit policies, enhance the monitoring systems, or rearrange financial resources. Empirical evidence also shows that predictive analytics is a vital process by which artificial intelligence enhances the results of financial risk management (Vyas, 2025; Samson-Onuorah, 2025). Mediation effect of the study thus brings out the significance of prediction accuracy as a major process through which technology capabilities are converted into financial stability.

The last hypothesis that was tested was the moderating effect of board oversight on the relationship between risk prediction accuracy and bank financial stability. The results indicate that there is a strong moderating effect that predictive accuracy has on financial stability in the presence of effective governance oversight. This finding supports the significance of governance structure in technology based financial settings. Although predictive technologies are useful in making financial decisions, the insights should be understood and applied in a proper governance system. Board of directors is very important in controlling technological adoption, risk management practices, and whether strategic decisions are in line with institutional objectives and regulation. As Eskandarany (2024) notes, the use and management of artificial intelligence technologies in financial institutions are getting more and more dependent on the board members. According to Yanney (2025), governance oversight enhances the efficacy of AI directed financial decision systems by facilitating transparency and accountability. The moderating effect that is witnessed in this study thus indicates that there is an amplification of the benefits of predictive analytics by structures of governance making sure that the insights of the algorithms are incorporated into the financial strategies in a responsible manner. The combination of these results indicates that technological capacity and governance control should work in consortium to improve financial stability in the contemporary banking systems.

Practical implications

The real-life application of this research is especially applicable to the financial institutions that are trying to enhance their risk management systems in the world where data is becoming a central part of the risk management process. Among the most significant implications, it is possible to mention the idea that banks should invest in machine learning technologies in the most strategic manner to increase their financial risk assessment and forecasting abilities. The results indicate that machine learning-assisted risk management will greatly enhance financial stability through the ability of banks to identify any new risk more precisely and react to financial risks more efficiently and effectively. Development of sophisticated analytical infrastructure should therefore be the first priority of financial institutions to enable them to handle large volumes of financial data and come up with predictive insights that are reliable. These investments would enhance credit evaluation processes, increase the effectiveness of fraud detection systems and increase the effectiveness of monitoring financial exposures. Past studies show that financial institutions that implemented sophisticated data analytics systems are more well-positioned to predict financial upheavals and continue their regular operations when the economy experiences volatility (Vyas, 2025; Paramesha et al., 2024).

The other applied implication is associated with the significance of predictive accuracy in financial decision making. The outcomes of the mediation process indicate that the benefits of machine learning technologies are highly dependent on the quality of predictions provided by these systems. This implies that banks are supposed to not only concentrate on the application of technological tools but also enhance precision and consistency of predictive models. The financial institutions can do this by investing in data quality management systems, multiplying the sources of financial data and continually updating predictive algorithms to capture the evolving financial conditions. High predictive accuracy enables the banks to pick early indications of financial distress which enables the managers to take preventive measures before risks turn into systemic issues. These proactive risk management measures can greatly increase the resilience of the institutions and contribute to long term financial sustainability.

The findings also emphasize the importance of governance oversight in making predictive technologies use in banking institutions to be responsible. The moderating role of board oversight suggests that predictive analytics has a stronger role to play in enhancing financial stability where there are good governance structures. This implies that banks are supposed to enhance expertise on the board level in matters to do with digital transformation and governance of artificial intelligence. Board of directors ought to be proactive in monitoring the technological adoption strategies, transparency in the systems of algorithmic decision making as well as developing clear mechanisms of accountability of technology driven financial decisions. Eskandarany (2024) points out that boards are critical in the responsible adoption of artificial intelligence in banking systems. Through strategic oversight boards have the ability to ensure that predictive technologies are deployed in a manner that is consistent with regulatory requirements and long-term institutional objectives.

Policy wise, the study also gives information to the financial regulators and policymakers. Financial risk management practices are undergoing a change due to technological innovation that is being observed by regulatory authorities. What policymakers ought to come up with is therefore regulatory frameworks that promote responsible use of advanced analytical technologies and have sufficient governance controls. It can be useful to develop a set of rules related to algorithmic transparency, data management, and risk monitoring, which would allow financial institutions to deploy predictive technologies in a way that would contribute to systemic stability. In addition, regulatory bodies can think of encouraging training initiatives that can increase the number of digital skills of financial managers and members of board. These efforts have the capacity to enhance the capacity of financial institutions to adopt advanced technologies in a responsible manner in their risk management systems.

Theoretical Contributions

The theoretical advancements of this research contribute to the current body of research in financial risk management, technological innovation and corporate governance. To begin with, the research contributes to the implementation of the agency theory in technology-driven financial conditions by showing how enhanced analytical systems can affect financial stability due to the enhanced quality of information. The traditional agency theory is mainly concerned with the interaction between the principals and the agents in terms of information asymmetry. Nevertheless, the results of the research indicate that such technological advances like machine learning change the information environment in organizations significantly. Machine learning technologies minimize information asymmetry as well as propel the alignment of managerial decisions and organizational goals by enhancing the capacity of financial institutions to handle and analyze vast datasets. This contribution broadens the theoretical applicability of the agency theory to modern financial systems that have gone digital and based decision making on data.

Second, the research paper is an addition to the expanding body of research exploring the applicability of predictive analytics in financial risk management. Although the technical benefits of machine learning technologies in financial forecasting have been emphasized in earlier research, comparatively limited studies have investigated how the technologies affect the institutional outcomes. The study offers a more detailed explanation of how the financial stability of technological capabilities is achieved by identifying risk prediction accuracy as a mediating mechanism. The contribution fills a significant gap in the literature because it shows that the efficiency of machine learning technologies is not only based on technological adoption but also on the quality of predictive insights produced by these systems.

Third, the research contributes to the literature on governance through its illustration of a moderating effect of the board oversight on technology driven financial decision making. The research on governance has traditionally focused on the monitoring mechanisms that diminish the opportunism of managers and make them accountable. The results of this research indicate that the governance control is also significant in the control of the implementation of sophisticated analytical technologies. With the growing dependence of financial institutions on the system of algorithmic decisions, boards of directors need to build the ability to assess the risks of technology and oversee strategies of digital transformation. This view extends the area of governance study by emphasizing the value of computer literacy and online control in corporate governance systems. Fourth, the research fits into the larger interdisciplinary literature relating financial technology, risk management and organization governance. Through a combination of technological aptitudes, forecasting mechanisms and governance control in one research structure, the research offers a holistic explanation of how contemporary banking institutions can promote financial stability. This integrative view can be used to provide useful information on scholars who want to comprehend the intricate relations between technological innovation and institutional governance in modern financial systems.

In spite of the useful value of this study, a number of limitations must be noted. One of the limitations is associated with the cross-sectional research design that measures the relationships between variables at a single point in time.

Despite the fact that this method is a common methodology in organizational studies, it restricts the possibility of making robust causal conclusions about the long-term impacts of the adoption of technology on financial stability. The future research may take the form of longitudinal research designs to determine the effects of machine learning adoption and governance oversight on financial stability in the long term. These would give more insight to dynamic development of technological capabilities in financial institutions.

Future directions of the study

The other limitation is related to the scope of the sample, as it was mainly restricted to the managerial respondents in the banking industry. Although these respondents will be relevant in terms of the level of knowledge they will have on the risk management practices, the results might not entirely reflect the views of other stakeholders like regulators, technology developers or customers. Future studies might expand the sample size to cover various stakeholder groups to gain a more in-depth insight into the nature of the relationship between predictive technologies and financial systems. Comparison of different countries or financial sectors might also offer useful information about the contextual variations in the technological adoption and governance practices.

There are also methodological limitations that come as a result of self-reporting surveys. Even though reliability and validity were ensured with the help of validated scales of measurement, the perceptions of respondents can be subjective or organizational. It would be possible to enhance empirical validity by using survey data with objective financial measures, including credit default rates or capital adequacy ratios or financial performance measures, in future research. Lastly, the research concentrated on few variables in terms of technological capabilities, predictive accuracy, governance oversight, and financial stability. Further studies can further develop the model by adding more variables, which may impact the usefulness of predictive technologies. Possible moderators are regulatory pressure, organizational culture, digital capability or technological readiness. In the same way, the mediating variables that the future research might want to investigate include data quality management, technological integration, or managerial digital competence. A further analysis of these other elements would give a more in-depth picture concerning how technological innovation determines financial stability within the current banking systems.

References

Aggarwal, L. (2025). Digital Banking and the Future of Embedded Finance: How Will AI-Powered Fraud Detection and Algorithmic Credit Scoring in Cross-Border Rails Reshape Systemic Risk?.

Ahmed, M. P., Tisha, S. A., & Sweet, M. R. (2025). Real-Time Hybrid Optimization Models for Edge-Based Financial Risk Assessment: Integrating Deep Learning with Adaptive Regression for Low-Latency Decision Making. Journal of Business and Management Studies, 7(7), 38-52.

Alonge, E. O., Eyo-Udo, N. L., Ubanadu, B. C., Daraojimba, A. I., Balogun, E. D., & Ogunsola, K. O. (2024). Developing an advanced machine learning decision-making model for banking: Balancing risk, speed, and precision in credit assessments. Journal details pending.

Ayu, R., Abdullah, N. A., Wan Sulaiman, W. S., & Bin Selamat, M. N. (2024). Structural Equation Modeling based SmartPLS 3.0 Software in Measuring Psychological Empowerment and Readiness to Strengthen Structural Transformation. International Journal on Advanced Science, Engineering & Information Technology, 14(4).

Bommali, T., Neyyila, S., Asha, P., & Das, S. (2025). AI and Financial Control: Enhancing Transparency, Efficiency and Risk Management. Future of Research in Management and AI, 4, 36.

Cheah, J. H., Magno, F., & Cassia, F. (2024). Reviewing the SmartPLS 4 software: the latest features and enhancements.

Chidambaram, V., Shanmugam, K., & Sivamani, B. (2021). Effect of project team integration on the performance of Indian construction project: SMART PLS Structural Equation Approach. International Journal of Construction Supply Chain Management, 11(1), 1-20.

Daneshmand, M., Ranjan, P., Khunger, A., & Dhaiya, S. HARNESSING AI AND ML FOR ENHANCED FINANCIAL RISK MANAGEMENT: OPPORTUNITIES AND CHALLENGES.

Dodda, A. (2025). Artificial intelligence and financial transformation: Unlocking the power of fintech, predictive analytics, and public governance in the next era of economic intelligence. Deep Science Publishing.

Eskandarany, A. (2024). Adoption of artificial intelligence and machine learning in banking systems: a qualitative survey of board of directors. Frontiers in Artificial Intelligence, 7, 1440051.

Fauzi, M. A. (2022). Partial Least Square Structural Equation Modelling (PLS-SEM) in Knowledge Management Studies: Knowledge Sharing in Virtual Communities. Knowledge Management & E-Learning, 14(1), 103-124.

Ghanad, A. (2023). An overview of quantitative research methods. International journal of multidisciplinary research and analysis, 6(08), 3794-3803.

Hair, J. F., Babin, B. J., Ringle, C. M., Sarstedt, M., & Becker, J. M. (2025). Covariance-based structural equation modeling (CB-SEM): a SmartPLS 4 software tutorial: JF Hair et al.

HALLAGI, M. (2025). AI's Role in the Evolution of Credit Scoring in Banking.

Henseler, J., & Schuberth, F. (2022). Partial least squares as a tool for scientific inquiry: Comments on Cadogan and Lee. European Journal of Marketing, 57(6).

Katata, K. S. Artificial Intelligence in Risk Management and Financial Stability: Overview and Lessons for West African Bank Supervisors (WABS). NDIC Q, 36(3), 52-72.

Maier, C., Thatcher, J. B., Grover, V., & Dwivedi, Y. K. (2023). Cross-sectional research: A critical perspective, use cases, and recommendations for IS research. International Journal of Information Management, 70, 102625.

Mwangi, M. (2024). The role of machine learning in enhancing risk management strategies in financial institutions. International Journal of Modern Risk Management, 2(1), 44-53.

Paleti, S. (2023). AI-Driven Innovations in Banking: Enhancing Risk Compliance through Advanced Data Engineering. Available at SSRN 5244840.

Paleti, S. (2025). Smart finance: Artificial intelligence, regulatory compliance, and data engineering in the transformation of global banking. Deep Science Publishing.

Paramesha, M., Rane, N., & Rane, J. (2024). Artificial intelligence, machine learning, deep learning, and blockchain in financial and banking services: A comprehensive review. Machine Learning, Deep Learning, and Blockchain in Financial and Banking Services: A Comprehensive Review (June 6, 2024).

Reyazat, F. (2024). Shaping the Future of Central Banking with Artificial Intelligence (AI) and Machine Learning (ML). Dr. Farhad Reyazat.

Rosli, M. S., Awalludin, M. F. N., Han, C. T., Saleh, N. S., & Noor, H. M. (2024). Unlocking insights: a comprehensive dataset analysis on the acceptance of computational thinking skills among undergraduate university students through the lens of extended technology acceptance model, HTMT, covariance-based SEM, and SmartPLS. Data in Brief, 54, 110463.

Samson-Onuorah, C. I. (2025). AI-driven Credit Risk Modeling: Leveraging Big Data Analytics to Improve Financial Stability and Lending Efficiency in Banks. Int J Sci Eng Appl, 14(10), 57-70.

Sani, S. A., Yusuf, T., Aliyu, S. E. A., & Yakubu, R. A. (2023). Impact of Audit Committee Attributes on Financial Reporting Quality of Deposit Money Banks in Nigeria: An Empirical Analysis Using Structural Equation Modelling (Smart-PLS). African Banking and Finance Review Journal, 3(3).

Sarstedt, M., Richter, N. F., Hauff, S., & Ringle, C. M. (2024). Combined importance–performance map analysis (cIPMA) in partial least squares structural equation modeling (PLS–SEM): a SmartPLS 4 tutorial. Journal of Marketing Analytics, 12(4), 746-760.

Schuberth, F., Zaza, S., & Henseler, J. (2023). Partial least squares is an estimator for structural equation models: A comment on Evermann and Rönkkö (2021). Communications of the Association for Information Systems, 52, 711-729.

Vyas, A. (2025). Revolutionizing risk: The role of artificial intelligence in financial risk management, forecasting, and global implementation. Forecasting, and Global Implementation (April 21, 2025).

Yanney, A. A. S. (2025). Redefining corporate financial governance through AI-Powered predictive models for global business risk management. International Journal of Research Publication and Reviews, 2(6), 25-49.