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Ai-Enabled Risk Management in Fintech: The Mediating Role of Managerial Leadership

Anum Salman¹, Usman Hameed², Sadia saeed³, Surayya Jamal⁴, Kousar Khoso⁵, Alaa Mohammad Hourani⁶, Muhammad Imran Majeed⁷

¹Hailey College of Commerce, University of the Punjab. Email: anumsalman@gmail.com

²Professor of Law, University of Lahore. Email: usman.hameed@law.uol.edu.pk

³Superior University Lahore, Pakistan. Assistant Professor (Law) and PhD Scholar at UKM Malaysia. Email: Sadia.saeed@superior.edu.pk

⁴Assistant Professor at Department of Management Sciences, Qurtuba University of Science and Information Technology Peshawar, Pakistan. Email: surayyajml@gmail.com

⁵Executive MBA In health Management from Liaquat University of Medical and Health Sciences Lumhs Jamshoro, Pakistan. Email: kousarsattar.khan@gmail.com

⁶Financial Technology Department, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan. Email: Ahorani@ammanu.edu.jo <https://orcid.org/0000-0003-3630-3145>

⁷Assistant Professor PhD Project Management, CMgr FCMI (UK) NBS, The University of Faisalabad Email: imranmajeed.nbs@tuf.edu.pk

Corresponding Author: Sadia saeed

ABSTRACT

Artificial intelligence (AI) provides fintech companies with the capability to identify fraud, track transactions and evaluate financial risks. But having AI tools doesn't mean that alerts are understood, escalated or acted upon properly. This paper aims to investigate if there is a mediating effect of managerial leadership between AI-enhanced risk management capability and RM effectiveness in Pakistani fintech firms. Managerial leadership is exhibited in practices that can be observed, such as: delegating responsibility for alerts; providing support for staff; reviewing exceptions; and leading risk responses. The professionals who work in risk management, compliance, fraud prevention, cyber security and other related fintech roles were the target of a quantitative, three-wave survey. The aim is to get around 350 full, matched responses from adults who have relevant experience of at least three months. At Time 1 the questionnaire will measure AI capability, managerial leadership and managerial effectiveness as baseline; at Time 2 the questionnaire will measure managerial leadership; at Time 3 the effectiveness of the management of risks. The proposed instrument has five items for each construct that are rated on a 5-point Likert scale. The responses will be analysed by descriptive statistics, scale-reliability and confirmatory factor analysis, as well as adjusted path analysis. This indirect association will be computed using 5,000 bootstrap resamples, except for the cases where the respondents are clustered in the same firm, where statistical inference will be adjusted. The intended analysis is illustrated with data in numerical tables; there are 350 artificial records. The values are hypothetical and not reflective of the actual values of Pakistani fintech organizations and need not be used to fail or pass the hypotheses. In this sense, the study did not have any empirical results at this stage. After collecting actual data, the analysis will identify whether there is a direct relationship between AI capability and subsequent effectiveness and whether managerial leadership is a lens that explains this relationship. The study aims to shed light on how the analytical tools are integrated with managerial control in fintech organizations and to acknowledge that an observational design does not necessarily allow the establishment of causation.

Keywords: Artificial Intelligence; Fintech; Risk Management; Managerial Leadership; Mediation; Pakistan.

1. Introduction

Artificial Intelligence (AI) is becoming increasingly adopted by Financial Technology (fintech) companies in the areas of transaction analysis, fraud detection, cyber security threat identification and credit risk scoring. These systems can analyze information quicker than the manual review process. However, technological capability is not necessarily correlated to improved risk decisions (Zada et al., 2024). The benefits of AI that financial firms in the UK saw are identified as analytical insights, anti-money-laundering activity and fraud

prevention. Data privacy and data quality and model complexity were also noted as concerns by the respondents (Bank of England & Financial Conduct Authority, 2024). In the case of fintech companies, the issue is how signals from AI become timely and accountable responses (Chatterjee et al., 2023).

The ability of an organization to obtain reliable data, deploy suitable analytical tools and make the outputs of the analysis available to staff members responsible for risk assessment is what is meant by the term AI enabled risk management capability. Mikalef and Gupta (2021) demonstrated that organizational AI capability depends on a mix of resources and not technology acquisition. Based on the evidence from commercial banks, one can argue that the development of fintech can also contribute to a decrease in risk-taking, which comes from the ability to manage risk better (Li et al., 2022). But bank results do not imply how the same relationship exists in other types of organizations that are involved in financial services, such as fintech organizations, where the products and risk processes could be different (Goyal et al., 2025).

With AI come governance responsibilities. Automated alerts might be inaccurate, incomplete or hard to understand; external tools provided to the firm may bring external dependencies that are not under the firm's control. Financial Stability Board (FSB 2024) outlines three areas of potential weaknesses in AI-enabled finance: model risk, data governance, and cyber risk and third-party dependencies. It is proposing organizational governance and senior management practices for responsible AI adoption in its consultation report for 2026 (FSB, 2026). Similarly, the AI Risk Management Framework emphasizes governing and managing AI risks throughout a system's life cycle (Tabassi, 2023). In reality, a suspicious transaction will need to be reviewed by a human, have a path of escalation, and a decision on what to do, should be made. These steps are partially dependent on what managers expect, monitor and support (Aldboush & Ferdous, 2023; Bholat & Susskind, 2021).

It can be hypothesized that managerial leadership can serve as a potential mediating variable between AI capability and the effectiveness of risk management. In this instance, leadership is in the sense of what is actually being done: clarifying responsibilities for alerts created by AI, training staff, reviewing exceptions, challenging unreliable alerts, and ensuring that serious concerns are raised. In their research, Mahmood et al. (2024) did find a mediating effect between AI and organizational performance in various industries, but not within the context of fintech risk functions. AI has also been found to enhance business-process governance and risk management in financial enterprises (Cheng et al., 2025). These studies only establish the plausibility of the pathway, but fail to measure the mediating effect of leadership between AI capability and risk management effectiveness in the context of fintech firms in Pakistan (Ashta & Herrmann, 2021).

Thus, this study aims to explore the direct and indirect relationship between AI risk management capability and subsequent risk management effectiveness through managerial leadership, using a quantitative approach. It suggests that valuable AI risk information can incentivize managers to adopt more effective oversight and response regimes that could further enhance risk identification, escalation and action. These will be measured at three points taking into account initial leadership and effectiveness. The research will provide insights into the organizational context in which fintech companies could leverage AI to aid responsible risk taking (Baba et al., 2023).

1.1 Statement of the Problem

AI is becoming a common tool for financial risk identification in fintech companies, but it is not sufficient by itself to achieve successful financial risk management. AI alerts need to be followed by managers who must take ownership, give instructions to employees and ensure appropriate action. While existing studies show a correlation between AI and digital leadership and organizational performance, there is less evidence linking the role of leadership with AI capability and risk management effectiveness in fintech companies (Mahmood et al., 2024). This is especially significant given the model, data and third-party risks that can emerge with the use of AI (Financial Stability Board, 2024). Accordingly, this research investigates the mediating role of managerial leadership in the link between risk management capability with AI and risk management effectiveness in the Pakistani fintech companies.

1.2 Research Objectives

1. To examine the relationship between AI-enabled risk management capability and risk management effectiveness in Pakistani fintech organizations.
2. To assess the relationship between AI-enabled risk management capability and managerial leadership.
3. To determine whether managerial leadership mediates the relationship between AI-enabled risk management capability and risk management effectiveness.

1.3 Research Hypotheses

H1: AI-enabled risk management capability is positively associated with risk management effectiveness.

H2: AI-enabled risk management capability is positively associated with managerial leadership.

H3: Managerial leadership positively mediates the relationship between AI-enabled risk management capability and risk management effectiveness.

2. Literature Review

2.1 AI-Enabled Capability and Risk Management

AI capability is the ability of an organization to integrate technology and make it useful with usable data, the right people and processes to transform analysis into action. If an employee is unable to understand the alerts or if the data being entered is incomplete, then a firm may invest in fraud-detection software without gaining much benefit. Mikalef and Gupta (2021) created and validated a scale to assess organizational AI capability, which was found to be positively correlated with organizational creativity and performance. Their results corroborate the need to consider capability as a kind of resource package instead of simply a yes-or-no indicator of use of AI. In this context, AI's role in risk management revolves around access to, integration with and use of AI tools for fintech risk assessment (Anshari et al., 2021).

Large amounts of transactions can be monitored for suspicious activity and pattern changes by using AI. In a report by the Bank of England and Financial Conduct Authority (2024), financial firms mentioned fraud detection, cyber security and analytical insights as applications/capabilities that they think would be beneficial. But accuracy of the data and models used by AI is key, and misleading alerts can undermine decisions even with widespread use. Based on data provided by commercial banks in China, Li et al. (2022) reported that the development of fintech was correlated with a decrease in the risk-taking behavior of financial institutions, at least partly because of the enhanced risk management capability of financial institutions. This finding implies investigation, as banks are not the same size and processes as fintech companies, so it is not guaranteed that it will happen in Pakistan. This research focuses on the relationship between the effectiveness of identification, escalation and response in fintech risk functions and stronger AI capability (Doupou et al., 2023).

2.2 AI Capability and Managerial Leadership

Technology has the ability to impact the information that is available to the manager, but the manager decides how this information gets into their work. Leaders can define who reviews risk scores/alerts; how to ensure that uncertainty is addressed; when a case should escalate. They can train and allocate resources if they receive alerts of which staff capacity has been exceeded. Managerial leadership is thus manifested in actions to ensure accountability and consistency of AI-supported work. The AI Risk Management Framework includes governance as a component, alongside mapping, measuring and managing AI risks (Tabassi, 2023). In the case of the Financial Stability Board, its proposed practices highlight also organizational governance and senior management in the context of adoption of AI (Financial Stability Board, 2026).

The aim of these frameworks is to elaborate on the reasons why leadership should be included in a research of AI risk processes, but none of them prove that AI capability leads to a change in leadership behavior. In a multi-industry study, Mahmood et al. (2024) found that digital leadership serves as a mediator in the relationships between AI, digital transformation and organizational performance. Their result was wide organizational performance; this study is on the risk management. It suggests that the availability of accessible AI data and information could be linked to greater managerial involvement in AI, and that managerial involvement can also impact AI adoption. The measurement of baseline leadership will help to account for that possibility (Mikalef & Gupta, 2021).

2.3 Managerial Leadership and Risk Management Effectiveness

Effective risk management is not a process of just determining a potential issue. Steps to strengthen by a manager: Assign responsibility, review missed/false alerts, support staff judgment, and modify procedures as risk level changes. On the other hand, ambiguity of authority can result in technically correct alerts that are not properly acted upon. According to Crisanto et al. (2024), governance, expertise, model risk management and data governance are some areas that should be considered when it comes to financial institutions' use of AI. For Chinese financial companies, Cheng et al. (2025) discovered that business-process governance was also a factor of the link between AI technology and firm performance. They show the importance of organizations, but do not directly examine and test the role played by managerial leadership in risk management effectiveness in the context of fintech. This study investigates whether leadership after AI capability is related to subsequent risk effectiveness accounting for baseline risk effectiveness. Observational

survey data alone cannot establish a causal mechanism, however; a positive indirect association would support the proposed mediation (Pattnaik et al., 2024).

4. Methodology

3.1 Research Design

The study aimed to conduct a quantitative and three-wave survey of AI in risk management of Fintech firms in Pakistan. It explored the independent variable (AI-based risk management capability), the mediator (managerial leadership) and the dependent variable (risk management effectiveness). Time 1 was used to assess AI capability and baseline leadership and effectiveness measures (Mahmood et al., 2024); Time 2 to measure leadership and Time 3 to measure effectiveness. This sequence was designed to determine the sequence of measurement and to correct for differences which were present at the start of the study. The design was observational so it was not capable of finding causal relationships.

3.2 Population

The population targeted was the adult working population in the fintech organizations of Pakistan. It contained professionals in the fields of risk management, fraud prevention, compliance, cyber security and credit assessment and related activities. Qualified participants needed to have 3+ months' experience with the organization's risk processes. They were also required to have a certain amount of knowledge about the AI tools used in their work unit to reply to the questionnaire. Tools and activities with intended risk responsibilities were not included in the intended sampling frame for those without relevant risk responsibilities or knowledge of those tools.

3.3 Sampling and Sample Size

For this study, purposive sampling was chosen as the sampling method to ensure access to professionals who have direct experience with fintech risk processes. The recruitment was organized in payment services, digital lending, and insurance/wealth technology and risk/compliance technology companies. The number of complete responses that were matched across all three waves was approximately 350. More participants were planned for Time 1 as some may not fill out the later surveys. A mediation power analysis was used to determine the target, and the size of the sample obtained was to be reported once it was collected.

3.4 Research Instrument

A questionnaire was constructed in a structured manner to assess the three main constructs. It contained five proposed items each for AI-enabled risk management capability, managerial leadership and risk management effectiveness. The responses were measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). It is built on research on organizational AI capability and AI risk governance (Mikalef & Gupta, 2021; Tabassi, 2023). Prior to the main survey, the questionnaire was drafted for expert review and a small group of around 25-30 eligible professionals was asked to test the questionnaire.

3.5 Data Collection

The data collection was organized into three surveys with the aim of collecting the data in approximately 4 weeks. The Time 1 survey was designed to record consent, eligibility, respondent characteristics, AI capability, baseline leadership and baseline effectiveness. The Time 2 survey was conducted to assess managerial leadership and the Time 3 survey assessed subsequent risk management effectiveness. A confidential participant code was identified to connect responses across the three waves without including names in the data analysis file. The participation was voluntary and the questionnaire contained no customer records or confidential information about transactions.

3.6 Data Analysis

An analysis plan was supplied for checking for duplicate responses, missing data and incomplete matches between waves of the survey. The frequencies, means and standard deviations were chosen as the most appropriate measures to report the characteristics of respondents and main variables. Internal consistency and confirmatory factor analysis were set as the criteria to test the reliability and separation of the three measures. The direct relationships were to be tested using path analysis and an indirect effect was to be tested using 5,000 bootstrap resamples with a 95% confidence interval. Baseline leadership, baseline effectiveness and appropriate characteristics of the respondent or firm were controlled for, and the same organisation's responses will be used in inferential statistics.

5. Data Analysis

Table 1. Demographic and Professional Characteristics (N = 350)

Characteristic	Category	n	%
Age	18–29 years	142	40.6
Age	30–39 years	110	31.4
Age	40–49 years	77	22.0
Age	50 years or above	21	6.0
Gender	Male	200	57.1
Gender	Female	139	39.7
Gender	Another description/prefer not to say	11	3.1
Job function	Risk management or fraud prevention	113	32.3
Job function	Compliance	83	23.7
Job function	Cybersecurity or technology	72	20.6
Job function	Credit assessment or related operations	82	23.4
Fintech service	Payments or digital wallets	80	22.9
Fintech service	Digital lending	120	34.3
Fintech service	Insurance or wealth technology	80	22.9
Fintech service	Risk, compliance or infrastructure technology	70	20.0
Relevant work experience	Less than 1 year	59	16.9
Relevant work experience	1–3 years	107	30.6
Relevant work experience	4–6 years	106	30.3
Relevant work experience	7 years or more	78	22.3

For this hypothetical example, the records were randomly assigned to 35 different firms of 10, totaling 350 records. The most numerous age group was 18-29 years (40.6%) and 57.1% of the records were identified as male. The top service category for digital lending was 120 records or 34.3%. The most common job function was risk management/fraud prevention (32.3%). These figures refer only to artificial records and should be replaced by the characteristics of the respondents observed.

Table 2. Scale Reliability and Measurement Statistics

Construct	Items	Cronbach's α	Composite reliability	Average variance extracted	Loading range
AI capability, Time 1	5	.894	.895	.630	.760–.818
Managerial leadership, Time 2	5	.890	.891	.619	.778–.793
Risk management effectiveness, Time 3	5	.895	.895	.630	.772–.821

Cronbach's alpha values for the illustrative five scales ranged from .890 to .895. They have composite reliabilities between .891 and .895. The average variance extracted was in the range of .619 to .630 and the estimated one-factor loadings ranged from .760 to .821. The alpha of simulated leadership and effectiveness scales were .897 and .891, respectively, at baseline. These statistics are based on the artificial responses and are not indications of the reliability or the validity of the questionnaire used with real participants.

Table 3. Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3
1. AI capability, Time 1	2.992	1.047	1.000		
2. Managerial leadership, Time 2	2.982	1.028	.294	1.000	

3. Risk management effectiveness, Time 3 2.979 1.036 .316 .461 1.000

Note. Construct means were calculated from five items scored from 1 to 5.

The simulated average scores for AI capability, leadership and effectiveness were 2.992, 2.982 and 2.979 respectively. The difference between each construct and the standard deviation was around scale point one. A positive correlation was found between AI capability and managerial leadership ($r = .294$). There was a positive correlation between leadership and effectiveness ($r = .461$), and between AI capability and effectiveness ($r = .316$). These unadjusted associations were not adjusted for baseline scores or respondents within firms.

Table 4. Inferential Tests of the Proposed Paths

Model and path	Standardised β	Firm-adjusted SE	95% CI	p
Model A: AI capability $\rightarrow$ managerial leadership (a)	.194	.050	[.092, .297]	< .001
Model B: AI capability $\rightarrow$ effectiveness, total association (c)	.205	.055	[.094, .316]	< .001
Model C: Managerial leadership $\rightarrow$ effectiveness (b)	.305	.049	[.205, .405]	< .001
Model C: AI capability $\rightarrow$ effectiveness, direct association (c')	.146	.053	[.037, .254]	.010

Higher subsequent leadership scores ($\beta = .194$) were correlated with greater AI in Model A. The total association between AI capability and the subsequent effectiveness of risk management was positive for Model B ($\beta = .205$). Leadership continued to be positively related to effectiveness when the other variables were added to the model ($\beta = .305$) in Model C. The positive link between the ability and effectiveness of AI also persisted ($\beta = .146$). Positive confidence intervals were obtained for all four simulated paths following adjustments for baseline measures and the characteristics listed.

Table 5. Bootstrap Test of Managerial Leadership as a Mediator

Effect	Estimate	SE	95% CI	Illustrative interpretation
Indirect association through leadership (a $\times$ b)	.059	.018	[.024, .096]	Positive interval excludes zero
Direct association (c')	.146	.053	[.037, .254]	Positive association remains
Total association (c)	.205	.055	[.094, .316]	Positive overall association

The indirect association was of the order of .059, which was about the product of paths a and b. A 95% confidence interval for the population mean μ , based on the 5,000-resample bootstrap, was [.024, .096]. There was no zero in this interval and the result obtained by the simulation was positive, which satisfied the specified condition for H3. The remaining direct association was .146, which was less than the total association of .205. These are only illustrative of mediation testing and do not provide an actual mediation in Pakistani fintech companies.

Table 6. Research Objectives and Hypothesis Tests

Research objective	Hypothesis	Illustrative test result	Illustrative decision
Examine the AI capability–effectiveness relationship	H1: AI capability is positively associated with effectiveness	Total $\beta = .205$, 95% CI [.094, .316]	Supported in simulated data
Assess the AI capability–leadership relationship	H2: AI capability is positively associated with leadership	$\beta = .194$, 95% CI [.092, .297]	Supported in simulated data

Test managerial leadership as a mediator	H3: Leadership positively mediates the relationship	Indirect effect = .059, 95% bootstrap CI [.024, .096]	Supported in simulated data
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The adjusted total association was linked to objective 1 to explore H1. Objective 2 was paired with the timeline from AI capability to later leadership to explore H2. The bootstrapped indirect association was resorted to for the analysis of H3, which was matched to Objective 3. Positive estimates with confidence intervals that did not include zero were made for each illustrative decision. All of these decisions should be taken and reported as an actual study finding after it is analyzed.

5. Findings

The illustrative analysis applied 350 simulated, matched records of the surveys across 35 hypothetical fintech companies. Of these records, 40.6% were marked as being in the 18-29 age group, 34.3% were in digital lending and 32.3% were in risk management or fraud prevention. The simulated gender distribution consisted of 200 male coded records (57.1%), 139 female coded records (39.7%) and 11 records in another category (3.1%). Of the 78 records with experience, 22.3% had 7+ years of experience in the same field (7 categories). These numbers are illustrative and do not reflect the actual number of professionals that were surveyed.

In this example, the three five item scales demonstrated internal consistency, with Cronbach's alpha of .894 for AI-enabled risk management capability, .890 for managerial leadership and .895 for risk management effectiveness. The composite reliability estimates fell between .891 and .895, and the average variance extracted estimates were .619 and .630. These statistics merely show how measurement quality can be represented and are not a validation of the questionnaire for the study proposed.

The simulated mean scores were 2.992 for the capability with AI; 2.982 for managerial leadership; and 2.979 for effectiveness in risk management, on a five-point scale. Positive bivariate correlations were found: AI capability and managerial leadership, $r = .294$; AI capability and risk management effectiveness, $r = .316$; managerial leadership and risk management effectiveness, $r = .461$. These correlations were for relationships without adjustment. Uncertainty-adjusted models also featured baseline leadership, baseline effectiveness, age, relevant work experience and fintech service.

The estimated association between AI capability and subsequent leadership was positive ($\beta = .194$, 95% CI [.092, .297]) and was found to be within a reasonable range to support the illustrative criterion set in H2. In the total-association model, AI capability was significantly and positively related to subsequent risk management effectiveness ($\beta = .205$, 95% CI [.094, .316]) meeting the criterion for H1. The coefficient for leadership entered the effectiveness model was positive ($\beta = .305$, 95% CI [.205, .405]) and the direct coefficient for AI capability was also positive ($\beta = .146$, 95% CI [.037, .254]). The indirect association through leadership was estimated as .059 and the interval bounds were [.024, .096] after 5,000 resampling of the firm level level bootstrap. This interval of data did not include zero, so the simulated analysis satisfied criterion H3. Combined these example showed positive direct and indirect associations. None of these coefficients or hypothesis decisions were findings of the Pakistani fintech organizations as no real participant data was provided.

6. Discussion

The illustrative results demonstrate the interpretation of the proposed model in the case of actual data that yield a similar pattern. There was an adjusted positive relationship between AI capability and risk management effectiveness, and the relationship persisted with a smaller, positive value after managerial leadership was added in (Financial Stability Board, 2024). There are two potential routes for this contribution: either via the availability and timeliness of risk information that the AI tools can provide, or indirectly through organizing the use of that information by managers. The ratio of 0.059/0.205 of the indirect estimate to the simulated total estimate is not a causal ratio of improvement, however, and was about 29%. It is a description of artificial-recorded coefficients (Cheng et al., 2025).

This interpretation aligns with the ownership of AI tools vs an organizational AI capability. Supporting a conceptualization of AI capability, Mikalef and Gupta (2021) argue that it is a result of resources, and this is where a software acquisition would not necessarily be able to make for better decision-making. In the financial services sector, Li et al. (2022) demonstrated that risk management played a role in the link between the development of fintech and bank risk-taking. They lack any evidence that comes from the banks

and provide context, not evidence of a relationship within the Pakistani fintech companies (Financial Stability Board, 2026). The simulated leadership pathway is also found to be compatible with Mahmood et al. (2024) who argued that digital leadership serves as a mediating mechanism in a study on AI, digital transformation and organizational performance in different industries. The difference in the present model is the definition of outcome, which is specifically defined as the effectiveness of the risk management program (Crisanto et al., 2024).

AI-generated alerts demand decisions regarding verification, management and escalation, which is where managerial leadership plays a vital role in the proposed model. Managers can explain when and how an alert should be challenged, include appropriate training, and review mistakes and identify process weaknesses. Cheng et al. (2025) demonstrated how business-process governance is associated with the relationship between AI and performance in Chinese financial companies (Benitez et al., 2022). When financial institutions adopt AI, the governance of AI and the quality of expertise and data are identified as key areas of concern by Crisanto et al. (2024). It is noteworthy that these sources do not provide any evidence of the applicability of the illustrative coefficients to Pakistan, but they do indicate that such a mechanism as studying managerial practices is possible. The Bank of England and Financial Conduct Authority (2024) found concerns within financial firms in the UK about the cost of using AI, data privacy, and data quality and model complexity. Tabassi (2023) also included governance in the scope AI risk management. There is no evidence that the simulated mediation works in Pakistan from either source (Sachan et al., 2024).

An important alternative explanation for the model is that good leaders may have adopted better AI tools prior to the first wave of the survey. Adding baseline leadership and effectiveness somewhat diminishes the ambiguity but doesn't remove the unmeasured variations among companies. Results from self-reported effectiveness can also vary with incident records and/or customer results or independent audits. The Financial Stability Board (2024) also listed among the risks that may not balance the operational advantages, the model risk, the cyber risk and third party risk, and recommended governance practices for responsible adoption in its 2026 consultation report. Therefore, a positive survey association doesn't imply that a specific AI system is safe or correct. Substantive conclusions must be drawn following actual matched responses, measurement checks and, where possible, independent performance indicators (Tian et al., 2024).

7. Conclusion

In this paper, the researchers suggested a quantitative analysis to explore if managerial leadership acts as a mediating variable between AI use in risk management and risk management effectiveness in Pakistani fintech firms. The above numerical tables were used to illustrate the intended analysis using 350 artificially generated records. In that specific example, the association between AI capability and later leadership and effectiveness was positive, and the 95% confidence interval for the indirect association via leadership did not contain zero. The patterns presented are illustrative of the ways the three hypotheses could be evaluated, but they do not imply that any of the hypotheses are supported by real fintech professionals. This draft did not receive any participant responses, nor were there any organizational records or observed risk outcomes.

The contribution of the study is related to the conceptualization of the three components of the AI capability, managerial action, and risk outcomes as distinct parts of the same process. AI can detect patterns and generate alerts, but it's important to note that it is not enough; organizations must also have individuals who can analyze these alerts, determine who is responsible for addressing them, and coordinate the necessary response. Managerial leadership offers a possible explanation of how technical capacity is connected to routine risk practice. Meanwhile, leadership can come before investing in AI, and both can be a reflection of the organisation's resources. A three-wave survey of baseline leadership and effectiveness can provide cross-wave support for the proposed test while not eliminating all other possible explanations.

The model asks the participants to focus on the circumstances in which AI information would be valuable: reliable data, clear decision ownership, understanding of the tools by staff, and error review and escalation procedures. These measures align with today's guidelines for AI risk governance, but the benefits of these measures cannot be quantified for specific companies through the simulated analysis (Tabassi, 2023; Financial Stability Board, 2026). Fintech companies should test their AI models in addition to the actions taken by humankind based on the results. An effective risk management is not synonymous with a high level of use of tools, a requirement that means that it would be necessary to assess the quality and timeliness of the responses.

The next step is to gather authentic answers from qualified professionals, record recruitment and attrition, test the measurement model, and estimate the proposed paths, using suitable adjustment for firm clustering.

Future work should ideally include a comparison of perceptions of effectiveness with incident or audit indicators at an aggregated level, if possible. The proposed design will allow for reporting of both positive and null associations in a transparent manner. Observed estimates: The final findings, discussion and conclusion should then be revised to include any unsupported hypotheses. This example concludes numerically until such evidence is available, it is only a demonstration of analytical reporting and not a conclusion about the fintech sector in Pakistan.

8. Recommendations

8.1 Develop Managers' AI Risk Skills

Managers need to be ready to interpret the AI-generated risks and alerts. Knowing the limitations of the model, false alarms, data privacy, and need for human review should be covered in training. Managers should practice making decisions about verifying or escalating an output. This training should include the involvement of risk, compliance and technical specialists, with their respective areas of expertise being reflected in the decisions. Decision quality be used as a metric in assessing the impact of training, not assumed by the mere presence of the training course.

8.2 Define Accountability and Escalation Procedures

For each AI-assisted risk process it is important to define who is responsible for looking at alerts, who gives authority to act and who documents the conclusion. Escalation procedure must be written and clearly outline those cases that need urgent senior review and routine cases. Managers need to ensure that staff are aware of these duties prior to an incident. Any exceptions or un-resolved alert records should be documented for delays investigation. If an external provider was to provide an AI tool they would also make responsibility more apparent through these procedures.

8.3 Monitor Data and Model Quality

Fintech companies should evaluate if the data used in AI risk tools is accurate, relevant and complete. They should check on misclassified cases, false alarms, and how the model performs over time. If a tool is delivered by a third party, managers should create arrangements for information provided to them by the third party regarding what they are able to provide about the tool and updates. The findings of these reviews should be recorded by risk and technical teams. Alert volume is not the criteria for judging the usefulness of a tool or the decisions you make based on the alerts.

8.4 Connect Technical and Risk Teams

It is important that AI specialists and risk professionals work together to review the use of AI model output in their day-to-day work. Staff should be afforded the opportunity to clarify cases and discuss any alerts that were not as they saw them or did not match their assessment at regular meetings. It can be used by managers to enhance guidance, training and review processes. Technical changes should be communicated to those employees who may be required to take action on alerts. This co-ordination would help to maintain the linkage between system design and risk decisions.

8.5 Evaluate Effectiveness With Actual Outcomes

Evaluation should assess the timeliness and quality of risk responses as well as staff perceptions in the future. Firms should review incidents, resolutions, and audit observations (where possible and feasible) as they relate to incidents. The number of subjects completing each survey wave should be reported, and an analysis should be conducted to determine if attrition resulted in a change of findings. Real observations and appropriate adjustments for differences between firms should be used in the proposed mediation, as should the retesting of the proposed mediation. Only after the numerical study, recommendations should be finalized, based on the results obtained.

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