Integrating artificial intelligence into risk management frameworks: a mixed-methods analysis of the Palestinian banking sector

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Abstract

Purpose – This study aims to investigate the impact of artificial intelligence (AI) on risk management practices within Palestinian banks, specifically examining its application in credit, market and operational risk domains. The research assesses the extent to which AI enhances risk mitigation effectiveness within the unique economic and regulatory context of Palestine.

Design/methodology/approach – The study used an explanatory sequential mixed-methods design. The initial quantitative phase involved surveying 80 internal auditors, selected via simple random sampling from a population of 95. This was followed by a qualitative phase comprising in-depth interviews with 23 purposively selected participants to contextualize and elaborate on the quantitative findings. Data were analyzed using statistical methods and deductive thematic analysis, guided theoretically by the DeLone and McLean (D&M) IS Success Model (2003).

Findings – Findings demonstrate AI's effectiveness in enhancing credit and operational risk management through improved decision-making accuracy, process automation and real-time anomaly detection. However, its potential contribution to market risk management is significantly constrained by infrastructural limitations, shortages in specialized expertise and competing strategic priorities, thereby underscoring the critical influence of contextual factors on successful AI adoption.

Research limitations/implications – The study acknowledges certain limitations. Primary reliance on internal auditors, while offering crucial oversight, may not capture the full experiential range; future work could benefit from including risk managers, IT specialists and senior management. The unique Palestinian politico-economic context necessarily limits direct generalizability, though identified themes regarding infrastructure, skills and strategy likely resonate with other emerging economies. Building on this study, future research

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should explore the longitudinal evolution of AI's impact as infrastructure and skills develop. Comparative cross-country studies within diverse emerging markets would further elucidate national context influences. Integrating deeper analysis of organizational culture, change management and specific ethical considerations related to AI decision-making in risk management represents another fruitful avenue. Exploring the specific impact of different AI techniques (e.g. machine learning vs deep learning) across risk domains would also yield valuable insights. Such research will deepen the understanding of how AI can be effectively and responsibly leveraged to foster resilient global financial systems.

Practical implications – The findings yield significant practical implications for stakeholders within the Palestinian banking sector and, by extension, for other emerging economies confronting similar challenges. First, AI's differential impact underscores the imperative for banks to adopt a nuanced, risk-specific integration strategy. For credit and operational risks, where AI is effective, institutions should optimize existing systems and ensure robust governance frameworks upholding transparency, accountability and regulatory compliance. Second, identified infrastructural and human capital deficiencies, pivotal impediments in market risk management, necessitate strategic investment in data infrastructure (especially real-time capabilities) and specialized expertise through training, recruitment and partnerships. Third, regulatory bodies should consider developing adaptive governance frameworks, balancing innovation with financial stability and ethics. Incorporating standards like ISO/IEC 42001:2023, with flexibility for local contexts, can guide responsible AI adoption. Finally, a phased, context-sensitive implementation, aligned with continuous evaluation of system performance and organizational readiness, is advocated over wholesale adoption to enhance long-term success and resilience, empowering leaders to maximize AI's potential within resource-constrained and volatile environments.

Originality/value – This study advances understanding of AI in finance by providing empirical evidence on its differentiated impact across credit, market and operational risks within the Palestinian banking sector, a context marked by institutional and regulatory challenges. Theoretically, it extends the DeLone and McLean IS Success Model to AI-driven risk management. Practically, it offers actionable guidance on human capital, technological infrastructure and governance, fostering sustainable, context-sensitive AI-enabled risk management in emerging economies.

Keywords Artificial intelligence (AI), Risk management, Banking, Palestine, Credit risk, Operational risk, Market risk, Mixed-methods research, DeLone and McLean IS success model

Paper type Research paper

1. Introduction

The escalating complexity and volatility of the global financial landscape necessitate advanced risk management practices. As a strategic imperative, risk management involves systematic identification, analysis, evaluation and mitigation of potential financial threats, including credit, market, operational and liquidity risks – to safeguard organizational assets and earnings, thereby underpinning financial objectives and fostering operational resilience, particularly within uncertain operating contexts (Tanbour *et al.*, 2024). *Indeed*, as a cornerstone of financial stability and long-term sustainability (Miliūnaitė and Žigienė, 2023a, 2023b), it integrates systematic strategies, policies and controls, enabling institutions to proactively anticipate and navigate potential threats while maintaining risk exposure within predefined tolerance levels, thus bolstering institutional resilience amid dynamic market conditions (Rana *et al.*, 2023a, 2023b).

In parallel with these developments, Artificial Intelligence (AI) has emerged as a transformative force, offering banks unprecedented capabilities to enhance predictive accuracy, streamline decision-making and bolster financial stability through advanced predictive analytics, machine learning and process automation. Consequently, integrating AI-driven solutions for optimizing credit assessment, fraud detection, operational risk mitigation and responsiveness to market volatility is rapidly becoming standard practice worldwide (Xu *et al.*, 2024a, 2024b; Rana *et al.*, 2023a, 2023b; Miliūnaitė and Žigienė, 2023a, 2023b).

However, despite the significant global expansion of research and practical applications of Artificial Intelligence (AI) in banking and financial risk management, a substantial knowledge gap remains regarding its practical applicability and effectiveness in fragile environments affected by conflict or political constraints. The Palestinian banking sector represents a salient case in this regard, operating within a complex environment characterized by heightened credit risk, macroeconomic volatility, restrictive regulatory and logistical barriers that limit access to international financial markets and structural deficits resulting from prolonged political and economic constraints (Palestinian Monetary Authority, 2023). Under such compounded challenges, traditional risk management frameworks are often inadequate for ensuring institutional sustainability and operational resilience.

Therefore, the impetus for this study stems from the critical need to understand the practical applicability and effectiveness of AI in financial risk management within environments marked by severe geopolitical and economic constraints. While the extant literature documents AI's potential to enhance predictive analytics, risk detection and decision-making in stable economic settings (Rana *et al.*, 2023a, 2023b), its practical impact and the unique implementation challenges in fragile financial environments remain considerably underexplored. *This research, consequently, addresses this lacuna by providing* a rigorous, evidence-based analysis of how AI adoption intersects with local institutional, economic and political realities to strengthen risk management frameworks in conflict-affected contexts.

Accordingly, the central research problem addressed in this study is: to what extent can AI enhance the effectiveness of risk management in Palestinian banks, particularly in the domains of credit, market, and operational risk, within their unique institutional, economic and political context? To solve this problem, the study is guided by the following research questions:

RQ1. To what extent does AI contribute to improving credit risk management in Palestinian banks?

RQ2. How can AI enhance the effectiveness of market risk management under constrained economic conditions?

RQ3. To what degree does AI improve operational risk management in Palestinian banks?

RQ4. What are the key challenges and limitations impeding the adoption of AI in risk management within the Palestinian context?

Building on these questions, the study pursues the following objectives:

- To investigate the impact of AI on risk management practices in Palestinian banks, with a particular focus on credit, market and operational risk domains.
- To assess the extent to which AI enhances the effectiveness of risk mitigation within Palestine's unique economic and regulatory context.
- To provide an in-depth analysis of how AI adoption can be strategically tailored to reinforce risk management frameworks, leveraging AI's predictive, analytical and automation capabilities in a manner that is responsive to local contextual specificities.

This study importantly addresses a critical research lacuna concerning the practical impact and implementation feasibility of Artificial Intelligence (AI) within fragile banking environments. While existing literature has explored AI's role in stable economies, its performance amidst significant institutional and infrastructural constraints remains underexplored. *Consequently,* *this research systematically investigates* AI's differentiated impact across credit, operational and market risk management within the Palestinian banking sector, a prototypical case of a complex and volatile milieu.

To achieve this objective, an explanatory sequential mixed-methods design was used. The initial quantitative phase comprised a survey of 80 internal auditors, selected via simple random sampling from a population of 95 to ensure representativeness. Following rigorous validation of the instrument's psychometric properties (e.g. Cronbach's alpha, factor analysis), a qualitative phase was conducted, involving in-depth interviews with 23 purposively selected experts to provide explanatory depth for the quantitative results and explore underlying contextual factors.

The findings subsequently reveal a pronounced and domain-specific impact of AI. A significant positive influence on credit and operational risk management was empirically confirmed, a result driven by enhanced predictive accuracy, operational efficiencies via automation and robust anomaly detection. *Conversely,* AI's contribution to market risk management was found to be significantly constrained by identifiable contextual impediments, namely, infrastructural deficits, a scarcity of specialized expertise and competing strategic priorities.

Ultimately, the principal contribution of this study is two-fold. First, it furnishes actionable, evidence-based insights for policymakers and financial sector stakeholders, informing the development of technology-driven strategies designed to bolster institutional resilience and support sustainable growth in Palestine. Second, it offers critical theoretical and practical guidance for other financial systems confronting analogous challenges globally. *Crucially, the research underscores that* realizing AI's full potential necessitates not only technological acquisition but also targeted, concurrent investments in infrastructure, human capital and strategic alignment.

While corroborating existing literature on AI's transformative potential (Brown, 2024; Kamisetty, 2024a, 2024b; Xu *et al.*, 2024a, 2024b), this study critically underscores the necessity of domain-specific evaluation. It demonstrates that AI's practical effectiveness is profoundly mediated by contextual factors, particularly the unique economic and regulatory landscape characterizing the Palestinian banking sector. *Furthermore, this research directly addresses* the limited understanding of AI performance under political instability and infrastructural constraints prevalent in conflict-affected or emerging economies. Palestine, with its less-researched financial ecosystem and distinct politico-economic conditions, provides an opposite context to explore this interplay.

This study, therefore, delivers distinct and impactful contributions to the evolving discourse on Artificial Intelligence (AI) in finance, particularly within the underrepresented context of the Global South. Empirically, it provides a nuanced examination of AI's differential effects on credit, market and operational risks in the Palestinian banking sector, revealing that AI's effectiveness is deeply contingent on local institutional, infrastructural and socio-political conditions. Theoretically, the study extends the DeLone and McLean IS Success Model (2003) to the novel domain of AI-driven risk management, highlighting the mediating roles of system quality, information quality and organizational readiness. Practically and policy-wise, it offers actionable guidance on human capital development, technological infrastructure enhancement and context-sensitive governance frameworks, equipping banks in resource-constrained environments to implement AI responsibly and sustainably while fostering resilient, forward-looking risk management practices.

The Palestinian banking sector, indeed, presents a compelling yet demonstrably under-explored context for investigating the implementation and impact of Artificial Intelligence (AI) in financial risk management. Despite global recognition of AI's transformative potential – evident in predictive analytics, fraud detection and operational automation – limited empirical research has assessed its performance within fragile and resource-constrained environments (Xu *et al.*, 2024a, 2024b; Rana *et al.*, 2023a, 2023b). Palestinian banks must navigate a confluence of systemic challenges, including heightened credit risk, macroeconomic instability, deficient infrastructure and restricted access to digital ecosystems due to prevailing political and regulatory impediments (Hurani *et al.*, 2024). These conditions not only amplify traditional risk exposures but also simultaneously obstruct the practical adoption of advanced AI technologies.

Moreover, technological capacity within the Palestinian market remains markedly uneven. Internet connectivity, for example, varies from 2G in Gaza to 3G/4G in parts of the West Bank, while AI readiness is nascent, with a mere 0.09% of startups reportedly leveraging AI in 2021 (Shihadeh, 2024). Banking institutions also confront significant barriers related to entrenched legacy systems, inadequate cybersecurity frameworks and constrained digital literacy among both customers and staff (Hurani *et al.*, 2024). These collective constraints underscore the urgent need for context-sensitive analysis to understand not only if AI can improve risk management outcomes, but also how specific integration pathways and organizational readiness conditions mediate its effectiveness.

This study, consequently, directly addresses a critical research lacuna. It provides much-needed empirical evidence on AI's differentiated effects across credit, market and operational risk within the Palestinian banking sector – a case scarcely analyzed in the extant literature. *In so doing, this research contributes* to both academic knowledge and policy formulation by elucidating how the viability of AI adoption is profoundly shaped by institutional fragility and technological lag. These insights hold considerable relevance for other emerging or conflict-affected economies confronting analogous challenges.

The paper is structured as follows: Section 1 reviews relevant literature and presents hypotheses. Section 2 outlines the methodology. Section 3 details findings. Section 4 provides conclusions and implications.

2. Literature review

2.1 Navigating the artificial intelligence revolution in banking: theoretical underpinnings and regulatory landscapes

In alignment with the DeLone and McLean Information Systems Success Model (D&M model, 2003), this study conceptualizes artificial intelligence (AI) as a strategic information system pivotal to enhancing the effectiveness of financial risk management within banking institutions. Specifically, predictive AI is emphasized as the dominant form used in the Palestinian banking context, owing to its robust capability to process complex data sets, detect anomalies and support data-driven decision-making. Methodologies such as Random Forest, Gradient boosting and support vector machines have been widely adopted for applications including credit scoring, fraud detection and real-time risk monitoring (Kalyani and Gupta, 2023; Alomari *et al.*, 2023).

Furthermore, the explainability of these models – a domain known as Explainable AI (XAI) – is particularly critical within highly regulated financial environments, where transparency and auditability are indispensable (Chang *et al.*, 2024; Xiao and Ke, 2021). Such AI systems contribute directly to enhancing system quality (i.e. algorithmic performance and reliability), information quality (i.e. the relevance, accuracy and timeliness of risk insights) and ultimately, net benefits (i.e. reduced credit default rates, improved regulatory compliance and enhanced internal control efficiency), consistent with the core dimensions delineated by DeLone and McLean (Tanbour *et al.*, 2025a).

To ensure the responsible deployment of AI in high-risk domains such as banking, this research also draws upon ISO/IEC 42001:2023 – the inaugural international standard for AI Management Systems (AIMS). This standard furnishes a comprehensive governance framework designed to ensure transparency, accountability and fairness throughout the AI lifecycle, with particular emphasis on requisite human oversight, ethical risk mitigation strategies and adherence to regulatory mandates (ISO, 2023). Given the fragile regulatory and economic landscape prevalent in Palestine, the adoption of such frameworks is crucial for maximizing the transformative potential of AI while concurrently minimizing systemic vulnerabilities (Tanbour *et al.*, 2025b).

A critical distinction must be drawn between the general adoption of Artificial Intelligence (AI) for routine banking operations – such as customer service automation or personalized marketing – and its specialized deployment within core risk management functions. While the former primarily targets operational efficiency and customer engagement, the latter is explicitly concerned with enhancing risk identification, assessment, mitigation and compliance within highly regulated financial environments. This research narrows its analytical scope to this latter domain, investigating how AI-driven risk analytics and intelligent monitoring systems fortify internal control structures and support evidence-based decision-making under conditions of uncertainty (Kapate *et al.*, 2025).

The adoption of Artificial Intelligence (AI) in financial decision-making introduces significant ethical and regulatory challenges that demand rigorous attention to ensure trustworthiness and compliance. Foremost among these is the risk of algorithmic bias, wherein AI models may perpetuate or even amplify existing social and economic disparities due to biases inherent in their training data (Raji and Buolamwini, 2019). The principle of explain ability (or interpretability) is therefore paramount; stakeholders must be able to comprehend and justify AI-driven decisions, particularly in high-stakes applications such as credit risk assessment (Morley *et al.*, 2020). Furthermore, robust accountability mechanisms must be clearly delineated to assign responsibility for errors or adverse outcomes emanating from AI systems.

International standards, notably ISO/IEC 42001:2023, furnish a structured governance framework designed to mitigate these risks by mandating transparency, fairness and requisite human oversight throughout the entire AI lifecycle. For Palestinian banking institutions, the incorporation of such ethical and regulatory safeguards is not merely advisable but essential for the responsible and effective deployment of AI (Jobin *et al.*, 2019).

Thus, AI is not merely treated as a technical artifact but is positioned as a governance-enabling infrastructure. This infrastructure supports adaptive, ethical and resilient risk management practices meticulously tailored to the unique exigencies of banking systems within emerging markets (Dwivedi *et al.*, 2011; Rashwan and Alhelou, 2022).

A clearer distinction must also be made regarding the specialized application of Artificial Intelligence (AI) across different risk domains:

- In *credit risk management*, AI techniques such as logistic regression, decision trees and neural networks are extensively used for sophisticated credit scoring, loan default prediction and granular customer segmentation.
- In *operational risk*, AI contributes significantly to the detection of anomalous transactions, insider threats and process inefficiencies through the application of advanced pattern recognition and process mining algorithms.
- Within the domain of *cybersecurity risk*, AI is leveraged via real-time threat intelligence platforms, anomaly-based intrusion detection systems and behavioral biometrics to fortify institutional resilience against phishing, malware and unauthorized access.

Across each of these domains, AI's predictive, adaptive and real-time analytical capabilities enable banking institutions to anticipate, prevent and respond to multifaceted risks with substantially greater precision and alacrity (Mubarroq *et al.*, 2025).

In this study, Artificial Intelligence (AI) usage within the Palestinian banking sector is operationalized and categorized across three primary functions: predominantly predictive and decision-supportive, with diagnostic applications now emerging:

(1) *Predictive usage:* This is evidenced by the deployment of machine learning models, notably Random Forest and Gradient Boosting, for credit scoring and fraud detection. This application aligns with standard practice in sectors such as finance and health care, where real-time risk forecasting is critical (Rehan, 2023).

(2) *Decision-supportive usage:* This function is illustrated by AI-driven systems that augment managerial decision-making through data-rich dashboards and automated recommendations. This parallels the role of clinical decision-support systems, which guide resource allocation and ensure compliance in medical settings (Tanbour *et al.*, 2025a).

(3) *Diagnostic usage:* While less mature in the Palestinian context, this application is gaining traction through the adoption of explainable AI (XAI) methodologies. These methods facilitate root-cause analysis and enhance the auditability of automated decisions and identified risk events (Černevičienė and Kabašinskas, 2024).

2.2 Framing bank risk management in the context of mitigation strategies and the role of artificial intelligence

Bank risk management constitutes a comprehensive and systematic framework designed to identify, analyze and implement measures to mitigate the adverse effects of various risks on financial institutions (COSO, 2017). Within this framework, mitigation strategies are primarily classified into several key mechanisms, two of which are particularly relevant here (Tanbour *et al.*, 2025c):

(1) *Risk reduction:* This mechanism involves the implementation of technical and organizational controls and procedures designed to either lower the probability of a risk event occurring or reduce its potential impact. Examples include enhancing internal control systems, improving data quality and leveraging advanced analytical tools.

(2) Risk transfer: This strategy entails contractually shifting a portion of the risk to an external party. Common methods include purchasing insurance policies or outsourcing specialized services, thereby reducing the direct financial or operational burden on the institution.

In this context, the adoption of Artificial Intelligence (AI) serves as a strategic enabler that significantly enhances the efficacy of these mitigation strategies. It facilitates this through advanced predictive modeling, big data analytics and early risk detection capabilities (BIS, 2025). Specifically, AI-driven machine learning and deep learning techniques enable more accurate risk classification and real-time monitoring of anomalous patterns, thereby directly supporting risk reduction through proactive intervention.

Furthermore, AI can also contribute to improving risk transfer processes. This is achieved by enhancing the transparency and efficiency of smart contracts and by enabling interactive insurance systems that leverage real-time data analytics, which can reduce operational costs and fortify rapid response capabilities (Financial Stability Board, 2024a, 2024b).

Moreover, AI not only strengthens traditional risk management mechanisms but also integrates sustainability considerations into banking practices. Recent studies emphasize the application of AI in green finance, showing that it can support decision-making, enhance compliance monitoring and address ethical concerns, while simultaneously aligning risk mitigation efforts with environmentally responsible investment practices (Hassanein and Tharwat, 2024).

Accordingly, AI should not be viewed as a standalone solution but rather as an integral and synergistic component within a holistic risk management ecosystem. It operates in concert with multiple mitigation strategies, collectively contributing to the enhancement of institutional stability, resilience and sustainable financial performance amid complex and dynamic challenges.

2.3 Framing artificial intelligence-driven risk management within global financial governance and emerging economy dynamics

The integration of Artificial Intelligence (AI) into finance is now a central topic of international regulatory and academic debate. Recent reports from leading institutions such as the Basel Committee on Banking Supervision and the Financial Stability Board (FSB) have underscored a fundamental tension: while AI offers unprecedented opportunities for improving banking efficiency and decision-making, it also presents novel systemic risks, including algorithmic opacity, model risk and heightened reliance on third-party infrastructure (Basel Committee on Banking Supervision, 2024; Financial Stability Board, 2024a). This evolving discourse underscores the imperative of embedding AI adoption within robust governance frameworks that ensure accountability, fairness and transparency.

In response, the Basel Committee's May 2024 report advocates enhanced supervisory coordination and data governance to address vulnerabilities arising from the digitalization of finance (Basel Committee on Banking Supervision, 2024). Similarly, the Financial Stability Board (2024a) cautions that without robust oversight, AI systems could exacerbate cyber risk, market fragmentation and operational disruptions, especially in jurisdictions with less mature regulatory frameworks.

Within the accounting and financial reporting literature, this concern is echoed by Sreseli and Kadagishvili (2024), who argue that integrating AI into reporting systems necessitates a fundamental rethinking of the ethical and procedural dimensions of transparency, disclosure and auditability. Their systematic review highlights a critical gap in current governance models, particularly in emerging markets where institutional readiness often lags technological capabilities.

These international frameworks and scholarly findings directly affirm the relevance of this study's context. Palestinian banks, operating under geopolitical constraints, fragmented infrastructure and regulatory fragility, represent a prototypical case for examining the nuanced interplay between AI adoption and institutional risk resilience. Unlike research situated in technologically mature economies, this study offers critical insights into the preconditions under which AI can effectively function as a strategic enabler for risk governance in vulnerable financial ecosystems.

This study, therefore, contributes directly to this evolving global discourse by furnishing a contextually embedded, evidence-based analysis that resonates with international regulatory trajectories. It addresses a multifaceted gap in literature by integrating geopolitical, regulatory and institutional dimensions into its analytical framework, thereby enriching both the information systems and financial governance scholarship with insights specifically tailored to emerging economies.

2.4 Institutional and infrastructural dimensions of artificial intelligence adoption

To deepen the understanding of Artificial Intelligence (AI) adoption within Palestinian banks, a critical analysis of the underlying barriers and enablers in relation to broader institutional and infrastructural themes is essential.

Among the most prominent *barriers* is the underdeveloped digital infrastructure. This encompasses limited data integration capabilities, inadequate legacy IT systems and a lack of real-time data access – all of which directly constrain the deployment of sophisticated AI models. Organizational resistance also presents a significant impediment; entrenched hierarchical structures, a deficit in digital leadership, and apprehensions regarding workforce displacement often hinder the internal acceptance of AI-driven innovations. Furthermore, regulatory uncertainty, particularly the absence of tailored national guidelines or supervisory frameworks for AI in finance, generates hesitancy among decision-makers due to concerns over compliance, liability and ethical risks (Hurani *et al.*, 2024).

Conversely, several *enablers* create fertile ground for AI diffusion. These include strategic digital transformation agendas at the national level, such as initiatives launched by the Palestinian Monetary Authority (PMA) that incentivize technological modernization. International partnerships and donor-funded programs furnish crucial technical support and capacity-building for AI experimentation. Additionally, rising competitive pressures within the banking sector, amplified by evolving customer expectations and regional FinTech advancements, act as a powerful catalyst for adoption.

By situating these countervailing factors within broader institutional dynamics, this study offers a nuanced understanding of how AI adoption unfolds within a fragile yet evolving financial ecosystem (Palestinian Monetary Authority, 2023).

2.5 Theoretical framework: the DeLone and McLean IS success model

This study uses the DeLone and McLean (D&M) Information Systems (IS) Success Model (DeLone and McLean, 2003) as its theoretical foundation. This widely validated framework offers a robust structure for evaluating the multifaceted success of information systems, making it highly suitable for assessing the effectiveness and impact of Artificial Intelligence (AI) within bank risk management. The D&M model posits that IS success emerges from the interplay of core dimensions: System Quality, Information Quality, Service Quality, (Intention to) Use/Usage, User Satisfaction and ultimately, Net Benefits.

Conceptually, AI is treated here as an advanced IS, distinguished by its capacity to process vast, complex data sets (big data) and execute sophisticated analytics. Within the Palestinian banking sector, these capabilities offer the potential to significantly enhance credit, operational and market risk management through improved predictive accuracy, refined fraud detection and more informed decision-making (Dwivedi *et al.*, 2011). Applying the D&M dimensions to AI risk management systems in this context yields the following operationalization:

- *System quality:* This dimension addresses the core technical performance and reliability of the deployed AI risk management systems. It encompasses critical factors like algorithmic sophistication and accuracy, processing speed, system stability and ease of integration with existing bank infrastructure – all essential for dependable automated risk assessment (Wong *et al.*, 2022).
- *Information quality:* This pertains to the value, accuracy and utility of the outputs generated by the AI risk management systems. To be effective, AI-driven insights (e.g. risk scores, forecasts, anomaly alerts) must be accurate, timely, relevant, complete and sufficiently interpretable to directly inform and improve risk assessment and decision-making processes (Umutoni and Njenga, 2024).
- *System use and user satisfaction:* These interconnected dimensions underscore that AI's technical potential is only actualized through consistent adoption (Use) and positive end-user experiences (User Satisfaction). Within the specific operational environment of Palestinian banks, factors such as perceived usefulness, ease of use, adequate training and organizational support significantly influence whether AI tools

are effectively integrated into daily risk management workflows and ultimately contribute to achieving desired outcomes (Wong *et al.*, 2022).

Furthermore, the D&M model inherently recognizes IS success as an iterative process, not a static outcome. This aligns well with practical implementation realities, suggesting Palestinian banks can strategically adopt AI capabilities incrementally within existing frameworks, mitigating the risks associated with disruptive wholesale overhauls. Such an adaptive, gradual approach facilitates progressive enhancements in operational efficiency and risk mitigation, critically fostering organizational resilience against evolving challenges and bolstering long-term institutional stability within their unique operating environment (Wong *et al.*, 2022).

Therefore, using the DeLone and McLean IS Success Model provides this research with a robust, theoretically grounded lens for examining AI's multifaceted role in risk management. It facilitates a systematic analysis of how technical dimensions (System Quality), the utility of AI-generated insights (Information Quality) and crucial organizational factors (Service Quality, Use, User Satisfaction) dynamically interact to yield tangible Net Benefits – manifesting as reduced losses, improved efficiency and enhanced resilience – specifically within the context of the Palestinian banking industry (Tanbour and Nour, 2024).

2.6 Artificial intelligence as a catalyst for strengthening risk governance in fragile financial systems

Risk governance frameworks constitute the foundational architecture through which financial institutions systematically identify, assess, manage and monitor risks. Among the most prominent of these is the committee of sponsoring organizations of the treadway commission (COSO) Enterprise Risk Management (ERM) framework, which delineates a comprehensive process encompassing risk identification, assessment, control, continuous monitoring and transparent reporting to all relevant stakeholders (COSO, 2017). The significance of such frameworks lies in their capacity to provide a structured, procedural architecture. This architecture enables institutions to not only identify and analyze potential threats but also to make informed, data-driven decisions based on accurate and timely information.

Within the challenging context of Palestinian banking – characterized by an unstable business environment and infrastructural deficits – Artificial Intelligence (AI) emerges as a pivotal enabler, capable of significantly enhancing the implementation of these governance frameworks. It achieves this by:

- *improving data and information quality* through the analysis of large-scale data sets, which enhances the precision of risk assessment and control;
- *enabling early risk detection* via predictive models that identify anomalies and warning signals in real time, facilitating proactive intervention;
- *strengthening internal control mechanisms* by automating control processes and performance reporting, thereby reducing human error and increasing transparency; and
- *supporting strategic decision-making* with deep, data-driven insights for the formulation of more effective risk management strategies.

Moreover, AI's role transcends mere technical enhancement; it serves as a critical link connecting the technical, managerial and institutional facets of governance. This positions AI not as a standalone technological tool, but as an integral component of a holistic risk management ecosystem.

This integration highlights the imperative for Palestinian banking institutions to develop the requisite organizational and technical infrastructure to fully leverage AI's capabilities. In such politically and economically constrained contexts, effective risk management demands a synergistic integration of technology, policy and human expertise (Tanbour and Nour, 2024).

2.6.1 Integration of the technology acceptance model in artificial intelligence adoption. To comprehensively understand the individual-level factors influencing the adoption of Artificial Intelligence (AI) within Palestinian banks, this study incorporates the Technology Acceptance Model (TAM). A seminal framework in information systems research, TAM posits that an individual's acceptance of a new technology is primarily determined by two core beliefs: *Perceived Usefulness (PU)* and *Perceived Ease of Use (PEOU)* (Davis, 1989). Within the context of AI-driven risk management, PU reflects the degree to which banking professionals believe that using AI will enhance their job performance in identifying, assessing and mitigating risks. PEOU, conversely, pertains to the degree to which an individual believes that using a particular AI system would be free of effort.

Empirical research has consistently validated that these constructs significantly influence technology acceptance within financial institutions, particularly where technological change intersects with complex operational environments (Venkatesh and Bala, 2008). By integrating TAM, this study aims to elucidate how individual attitudes, and cognitive assessments mediate the adoption of AI in risk governance, thereby providing a crucial behavioral foundation that complements the broader structural and institutional perspectives.

2.6.2 Institutional theory and artificial intelligence adoption in constrained environments. Institutional Theory offers a powerful analytical lens for examining the external, macro-level pressures that shape AI adoption in emerging and conflict-affected economies such as Palestine. This theory posits that organizations conform to normative, mimetic and coercive pressures exerted by regulatory bodies, industry standards and peer institutions to gain legitimacy and ensure their survival (DiMaggio and Powell, 1983).

Within the Palestinian banking sector, significant institutional constraints – including regulatory ambiguity, geopolitical instability and profound infrastructural deficits – impose considerable challenges on technology adoption. These pressures shape how banks approach AI adoption, framing it not merely as a technological innovation for efficiency gains but as a strategic response to achieve institutional legitimacy and compliance amid pervasive uncertainty. Integrating Institutional Theory thus enables this study to capture the critical socio-political and regulatory dynamics that are indispensable for understanding the trajectory and outcomes of AI implementation within constrained financial ecosystems (Scott, 2014).

2.7 Previous research

Grounded in contemporary Information Systems (IS) theory, the DeLone and McLean IS Success Model (D&M model, 2003) provides a coherent analytical framework for understanding the relationship between system characteristics and organizational effectiveness. This model posits that the success of an information system – such as artificial intelligence Intelligence (AI) is determined by the interplay of six interrelated dimensions: system quality, information quality, service quality, system use, user satisfaction and net organizational benefits. Within this framework, AI is conceptualized as an advanced information system designed to enhance information flow, analytical quality and decision-making accuracy, particularly within complex operational environments like the banking sector.

Drawing upon this conceptual model, the study's hypotheses were formulated to examine the causal relationships between the implementation of AI technologies and the effectiveness of managing specific financial risk categories – namely, credit risk, market risk and operational risk. It is posited that AI contributes to enhanced predictive accuracy, improved process efficiency and greater responsiveness to risk, thereby elevating the overall quality of risk management practices within Palestinian banking institutions (Al-Hattami, 2021).

2.7.1 Credit risk management practices. Recent scholarship consistently affirms the transformative potential of Artificial Intelligence (AI) in credit risk management. AI applications demonstrably enhance decision-making accuracy and speed in credit evaluations, contributing to more robust scoring models and reduced default rates (Savchenko, 2024). Studies highlight that AI-based models frequently outperform traditional methods in identifying high-risk borrowers (Brown, 2024), with specific implementations showing remarkable quantitative improvements – Xu *et al.* (2024a, 2024b), for instance, quantified a 20% gain in prediction accuracy over conventional techniques. A study by Kapate *et al.* (2025) demonstrated that Artificial Intelligence enhances credit risk management by leveraging machine learning for more accurate scoring, reduced default probabilities and proactive lending, thereby outperforming traditional methods and bolstering financial stability. The study by Heß and Damásio (2025). demonstrated that the application of machine learning techniques in banking risk management is primarily concentrated on credit risk, whereas areas such as liquidity and governance risks remain comparatively underexplored.

Furthermore, AI optimizes associated processes, including data preparation, risk modeling sophistication and stress testing procedures (Bogojevic Arsic, 2021), while also strengthening internal control and risk auditing mechanisms (Rashwan and Alhelou, 2022). The capability of advanced algorithms, such as hybrid graph convolutional neural networks (GCNNs), to effectively process the complex, large-scale data sets typical of financial risk environments further underscores AI's superior predictive power (Sun *et al.*, 2024; Bahoo *et al.*, 2024). A study by Henneberry *et al.* (2025) demonstrated AI's efficacy in aviation risk management, with findings transferable to banking; their analysis underscores AI's capacity to process complex data for proactive decision-making, reinforcing its role as a strategic enabler for anticipatory credit risk management.

Addressing concerns about model opacity, the integration of Explainable AI (XAI) techniques (Brown, 2024) and interpretable models like Random Forest and Gradient Boosting (Chang *et al.*, 2024) is enhancing transparency. This not only aids regulatory compliance but also fosters crucial stakeholder and customer trust (Kalyani and Gupta, 2023). The overall impact points toward AI and Machine Learning (ML) revolutionizing credit risk assessment accuracy and addressing emerging financial challenges (Milojević and Redzepagic, 2021).

While acknowledging necessary caution regarding potential systemic risks and over-reliance effects (Danielsson *et al.*, 2022), the predominant evidence strongly indicates significant positive impacts of AI on operational efficiency and risk mitigation effectiveness in credit management.

Based on the substantial body of empirical evidence demonstrating AI's widespread benefits in improving the accuracy, efficiency and robustness of credit risk management globally, this study posits that similar positive effects will be observed within the Palestinian banking sector. Therefore, the following hypothesis is proposed:

H1. The implementation of artificial intelligence has a signifiant positive impact on credit risk management practices in Palestinian banks.

2.7.2 Market risk management practices. Artificial Intelligence (AI) is increasingly recognized as pivotal for advancing market risk management, enabling financial institutions to move toward more proactive and data-driven strategies. Research highlights AI's capacity to significantly improve the detection of market anomalies and irregularities; for instance, Kamisetty (2024a, 2024b) documented substantial reductions in false positives and response times in detecting unusual activities, crucial for maintaining market integrity. The study by Eskandarany *et al.* (2024) demonstrated that artificial intelligence (AI) and machine learning (ML) technologies provide substantial benefits to Saudi banks by detecting threats, preventing fraud, automating processes and mitigating market risks, thereby enabling banks to comply with regulatory standards and enhance cybersecurity resilience.

Beyond anomaly detection, AI demonstrably enhances core market risk identification and assessment capabilities, facilitating more timely and effective mitigation strategies (Xu *et al.*, 2024a, 2024b). This is often catalyzed by the integration of big data analytics, enabling more dynamic and responsive risk management frameworks (Yazdi *et al.*, 2024). Furthermore, AI strengthens associated governance structures by reinforcing compliance and risk oversight mechanisms (Al-Boridi, 2023). A study by Mubarroq *et al.* (2025) demonstrated that Artificial Intelligence enhances market risk management by using real-time analytics and deep learning to model market fluctuations, forecast price movements and support agile investment strategies, thereby improving portfolio resilience against sudden shifts.

AI's application extends to sophisticated market analysis and prediction. Bahoo *et al.* (2024) illustrated AI's role in refining stock market analysis, developing trading models and improving volatility forecasting, empowering institutions to manage market exposures with greater precision. This aligns with findings on AI's effectiveness in asset pricing and evaluating the efficacy of market regulation, leveraging techniques like deep learning (Xiao and Ke, 2021; Nour *et al.*, 2025). The incorporation of broader risk factors, such as economic and environmental variables as shown by Urbano *et al.* (2023) in related investment contexts, also informs more comprehensive market risk assessment approaches potentially enabled by AI. A study by Khan (2025) demonstrated that the EU AI Act's risk-based framework enhances governance of high-risk AI, a principle applicable to market risk management for improving volatility forecasting and ensuring accountable investment decisions, while alignment with standards like ISO 31000 fortifies transparency and compliance.

The integration of AI and Machine Learning (ML) into algorithmic trading and broader financial market operations is well-documented (El Hajj and Hammoud, 2023; Kharoub and Nour, 2025), signifying a fundamental shift in how market risks are managed. These technologies are critical for strengthening financial risk prevention and control systems overall (Hu and Chen, 2022). However, the transformative effects also bring emerging regulatory and ethical challenges that require careful consideration to ensure market stability (Vuković *et al.*, 2025).

Despite these considerations, the collective evidence points toward AI offering significant advantages in analyzing market dynamics, predicting exposures and enhancing control mechanisms related to market risk.

Based on the compelling evidence illustrating AI's capabilities in enhancing various facets of market risk analysis, prediction and control globally, this study anticipates that similar positive contributions can be realized within the Palestinian banking sector, despite potential contextual challenges. Therefore, the following hypothesis is proposed:

H2. The implementation of artificiel intelligence has a signifiant positive impact on market risk management practices in Palestinian banks.

2.7.3 Operational risk management practices. Artificial Intelligence (AI) is increasingly recognized as a transformative force in operational risk management, offering significant improvements in oversight, efficiency and resilience within financial institutions. A key contribution lies in strengthening governance frameworks; AI promotes greater transparency, embeds ethical considerations (Kalkan, 2024; Rabaia, *et al.*, 2025) and demonstrably enhances internal audit functions to mitigate fraud, thereby reinforcing control environments (Bonrath and Eulerich, 2024). A study by Ajayi (2025) demonstrated that AI significantly mitigates operational risk through advanced analytics, a capability that in banking fortifies internal controls, while also enhancing credit and market risk management by improving data and analytical quality. The study by Dichev *et al.* (2025) demonstrated that advanced machine learning algorithms, such as Classification and Regression Trees, Gradient Boosting and Extreme Gradient Boosting, significantly outperformed traditional methods in detecting banking fraud, thereby providing valuable insights for enhancing the security and resilience of financial systems.

Central to AI's operational risk impact is its advanced analytical capability. By processing vast and complex data sets with high precision, AI significantly improves early risk detection and prevention mechanisms (Sari and Indrabudiman, 2024; Bahoo *et al.*, 2024). This analytical power is crucial for navigating growing operational uncertainties, including technological disruptions and heightened cybersecurity threats (Kaswan *et al.*, 2023). Furthermore, AI integration drives operational efficiency, leading to cost reductions and bolstering institutional competitiveness (Diab, 2022; Abualhassan *et al.*, 2024). It also enhances risk analysis accuracy and regulatory compliance processes (Daiya, 2024). A study by Vyhmeister and Castane (2025) demonstrated that integrating Trustworthy AI principles, grounded in ISO 31000, enhances an organization's capacity to assess ethical and technical risks, enabling proactive identification of failure modes and improved risk control in complex environments.

Beyond core risk functions, AI contributes to broader operational resilience. It aids in strengthening business continuity planning (Sotamaa *et al.*, 2025) and supports Environmental, Social and Governance (ESG) objectives, linking operational performance with wider corporate responsibility initiatives (Płońska and Kądzielawski, 2023; Nguyen *et al.*, 2025; Younis *et al.*, 2025). A study by Sotamaa *et al.* (2025) demonstrated that AI adoption enhances small and medium-sized enterprises risk management by providing data-driven tools that improve risk anticipation and bolster operational resilience, enabling more precise and agile decisions in dynamic digital environments.

However, realizing these benefits requires careful management. Effective AI implementation in operational risk necessitates continuous human oversight to ensure accountability and ethical alignment (Biolcheva, 2021; Al-Fadel and Nour, 2006). Additionally, while enhancing efficiency, AI may introduce new systemic vulnerabilities or tail risks that demand vigilant monitoring and mitigation strategies (Danielsson *et al.*, 2022).

Despite these necessary considerations, the substantial body of evidence highlights AI's capacity to significantly strengthen operational controls, improve risk detection and prevention, increase efficiency and bolster overall operational resilience.

Based on the extensive literature demonstrating AI's positive contributions to various facets of operational risk management globally – including governance, fraud detection, efficiency and resilience – this study expects similar advantages to accrue within the Palestinian banking context. Therefore, the following hypothesis is formulated:

H3. The implementation of artificiel intelligence has a signifiant positive impact on operational risk management practices in Palestinian Banks.

While Artificial Intelligence (AI) has been widely recognized for enhancing risk prediction, credit scoring, market surveillance and operational resilience, most empirical studies focus on developed-country contexts with stable institutions and advanced digital infrastructures (Savchenko, 2024; Xu *et al.*, 2024a, 2024b; Mubarroq *et al.*, 2025). Practically, this leaves a critical gap regarding AI's feasibility and effectiveness in resource-constrained, politically fragile environments, such as Palestine. Theoretically, although Explainable AI (XAI) has gained attention for improving transparency and accountability (Brown, 2024; Chang *et al.*, 2024), questions persist about tradeoffs between interpretability and predictive performance. Moreover, prior research often examines risk domains in isolation, overlooking governance integration and institutional readiness factors. This study addresses these gaps by empirically analyzing AI's differentiated impact across credit, market and operational risks in the Palestinian banking sector, advancing context-sensitive theoretical understanding and providing actionable insights for AI governance in emerging economies.

Palestine represents a distinctive yet underexplored context for investigating the integration of Artificial Intelligence (AI) into banking risk management. This distinctiveness arises from the complex interplay of volatile political factors, persistent economic constraints and uneven technological development. The Palestinian banking sector operates within an environment characterized by enduring instability, significant external fiscal pressures including capital controls and restricted access to high-quality data. These conditions collectively pose substantial challenges to the effective adoption and deployment of AI-driven innovations (Khan and Youssef, 2022; Salem *et al.*, 2025).

Although previous studies have addressed various facets of FinTech adoption in Palestine, such as mobile banking and digital payment systems (Al-Qudah *et al.*, 2023; Hirzallah *et al.*, 2024), empirical research specifically focused on AI applications in financial risk management remains notably scarce. This research lacuna is particularly critical given the strategic imperative of leveraging AI to enhance governance frameworks and risk mitigation strategies within the financial sector. By addressing this gap, the present study contributes nuanced insights to the broader scholarly discourse on FinTech in Palestine and underscores the necessity for technology-specific research agendas meticulously tailored to distinct FinTech domains.

Furthermore, the Palestinian case possesses analytical value that transcends its geographical confines. The confluence of institutional fragility, resource scarcity, and an accelerating digital transformation agenda renders it a salient model for examining AI's operational performance and limitations under severely constrained conditions. Accordingly, this study enriches the extant literature on technology adoption within fragile and transitional economies, offering comparative perspectives pertinent to other developing nations confronting analogous institutional and infrastructural challenges (Ahmed and Ali, 2023; Smith and Lee, 2021; Fares and Nour, 2024; Saleem *et al.*, 2023).

Therefore, this research not only fills a substantive and contextual void in the existing literature but also constructs a conceptual bridge linking local empirical findings with global debates concerning the responsible and effective integration of AI within the financial sector.

2.8 Study model

The research model guiding this study outlines the hypothesized relationships between artificial intelligence (AI) implementation and the effectiveness of key risk management practices within Palestinian banks (see Figure 1). Specifically, it posits that AI adoption positively influences:

- Credit Risk Management (ERM-C);
- Market Risk Management (ERM-M); and
- Operational Risk Management (ERM-OP).

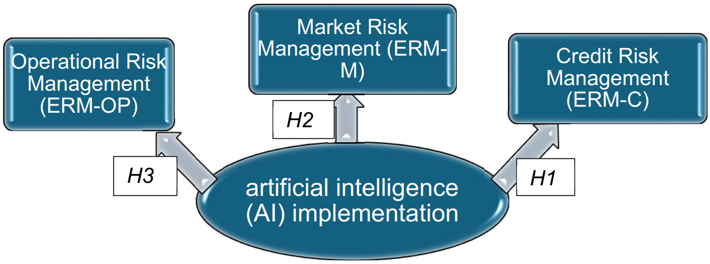

Figure 1. Conceptual framework
Source: Authors' own creation

The model proposes that AI enhances these areas by refining decision processes, improving predictive capabilities and strengthening risk mitigation strategies.

3. Research design

3.1 Population and sampling procedure

To investigate the population of 95 internal auditing professionals ($n = 95$) in Palestinian banks using an explanatory sequential mixed-methods approach, this study applied phase-specific sampling strategies: quantitative sampling aimed for statistical representation, while qualitative sampling targeted data richness.

The explanatory sequential mixed-methods design is a research methodology that commences with the collection and analysis of quantitative data to establish statistical trends and significant relationships. This initial phase is subsequently followed by the collection and analysis of qualitative data, which is strategically used to explain, interpret and elaborate upon the quantitative findings in greater depth and context.

The principal strength of this design lies in its capacity to systematically integrate rich qualitative insights with robust quantitative results. This integration facilitates a more comprehensive and nuanced understanding of the phenomenon under investigation and is particularly effective for elucidating unexpected or anomalous statistical findings (Creswell and Creswell, 2018).

3.1.1 Quantitative phase sampling. For the quantitative phase, simple random sampling (SRS) was applied to select 80 participants ($n = 80$) from the population of 95 internal auditors. This probability method ensures each individual has an equal and independent chance of selection, thereby minimizing selection bias and supporting the statistical generalization of findings (Cochran, 1977), yielding a representative sample for analysis.

The demographic profile of the quantitative sample ($n = 80$), detailed in Table 1 reveals a participant group deeply embedded in risk oversight roles within Palestinian banks. The majority served as internal auditors (57.5%), with significant representation from departmental directors (22.5%) and department heads (20.0%). Educational qualifications were high, with most holding bachelor's degrees (72.5%) and a notable segment possessing master's degrees or higher (25.0%). The sample was highly experienced, with over half (52.5%) reporting more than 15 years and 40.0% having 5–15 years of professional experience. Furthermore, the prevalence of professional auditing certifications (60.0%) underscores the participants' qualifications. Overall, the sample comprises experienced and certified professionals well-suited to comment on AI applications in risk management.

3.1.2 Qualitative phase: design, sampling and trustworthiness. To provide explanatory depth to the quantitative findings and fulfill the tenets of an explanatory sequential mixed-

Table 1. Demographic characteristics of the study sample

Factor	Category	Frequency	%
Job title	Departmental director	18	22.5
	Department head	16	20.0
	Internal auditor	46	57.5
	Total	*80*	*100*
Educational background	Master's degree or higher	20	25.0
	Bachelor's degree	58	72.5
	Intermediate diploma	2	2.5
	Total	*80*	*100*
Years of experience	Less than 5 years	6	7.5
	5–15 years	32	40.0
	More than 15 years	42	52.5
	Total	*80*	*100*
Professional certification in auditing	Yes	48	60.0
	No	32	40.0
	Total	*80*	*100*

Source(s): Authors' own creation

methods design (Creswell and Creswell, 2018), the qualitative phase of this study was executed with methodological rigor. This encompassed a clearly articulated sampling strategy, a semi-structured interview protocol, systematic thematic analysis and adherence to established criteria for ensuring trustworthiness in qualitative research.

3.1.2.1 Participant selection and sampling. Purposive sampling was used to identify and recruit participants possessing extensive professional experience and direct relevance to the study's core objectives. A total of 23 participants ($n = 23$) were selected based on their current employment within Palestinian banking institutions, a minimum of five years of professional experience in internal auditing, risk management, compliance or banking IT, and demonstrated familiarity with AI-based systems or risk governance processes. The selection strategy was intentionally guided by the principle of informational richness rather than statistical representativeness, in alignment with established qualitative inquiry principles (Creswell and Creswell, 2018; Saunders *et al.*, 2019).

Data collection continued until theoretical saturation was achieved, operationally defined as the point at which no new substantive themes, concepts or relationships emerged from subsequent interviews. Saturation was preliminarily observed after the 15th interview; three additional interviews were then conducted to confirm thematic stability and conceptual completeness. This approach adheres to the guidance proposed by Saunders *et al.* (2019), who emphasize saturation as a function of conceptual depth rather than a predetermined sample size.

3.1.2.2 Interview protocol and data collection. A semi-structured interview guide (see Appendix) was developed in alignment with the study's conceptual framework, particularly the DeLone and McLean IS Success Model and key AI risk governance dimensions. The interviews were designed to explore participants' practical experiences with AI deployment in risk management, their perceptions of its effectiveness and the contextual enablers and constraints influencing its application.

Interviews were conducted between May 1 and November 30, 2024. Each session, lasting approximately 45–60 min, was audio-recorded with explicit participant consent and subsequently transcribed verbatim to ensure data fidelity. The interviewer adopted a neutral, open-ended questioning strategy, allowing participants to elaborate freely to ensure both the depth and authenticity of the elicited responses.

3.1.2.3 Thematic analysis and coding procedures. Thematic analysis was systematically conducted following Braun and Clarke's (2006) well-established six-phase approach:

(1) data familiarization;
(2) initial code generation;
(3) theme development;
(4) review and refinement of themes;
(5) defining and naming final themes; and
(6) report generation.

The coding process was primarily deductive, guided by the study's research questions and theoretical constructs (e.g. ERM-C, ERM-M, ERM-OP).

Coding and theme development were performed manually to facilitate direct, immersive engagement with the data and allow for the iterative refinement of analytical categories (Alsaleh, 2017). Initial codes were organized into four core analytical domains corresponding to the primary constructs:

(1) artificial intelligence;
(2) credit risk management;
(3) market risk management; and
(4) operational risk management.

Themes were subsequently refined based on pattern recognition, internal consistency and theoretical alignment.

3.1.2.4 Ensuring trustworthiness. To bolster the credibility, dependability, confirmability and transferability of the qualitative findings, the following validation strategies were systematically used:

- *Credibility:* Ensured through member checking, whereby a subset of participants reviewed and validated key interpretations and the accuracy of emergent themes.
- *Dependability:* Supported by maintaining a clear audit trail, which documented all coding decisions, theme development processes and analytical reflections.
- *Confirmability:* Enhanced through peer debriefing sessions and consistent reflexive journaling to identify and mitigate potential researcher bias.
- *Transferability:* Facilitated by providing rich, thick descriptions of participant roles and institutional settings, thereby enabling readers to assess the potential for analytical generalization to analogous contexts.

3.2 Participant recruitment and ethical considerations

Potential participants for both quantitative and qualitative phases were identified and contacted through official communication channels within the participating Palestinian banking institutions. Prior to enrollment, each individual received a comprehensive information sheet detailing the study's objectives, methodology, data handling procedures and intended use of findings, along with a consent form. Written informed consent was mandatory and obtained from every participant before their involvement in data collection commenced.

This research was conducted in strict adherence to established ethical principles. Participants were explicitly assured of:

- the voluntary nature of their participation;
- complete anonymity and confidentiality of their individual responses; and
- the right to withdraw from the study at any time without consequence.

These safeguards were crucial for protecting participant rights and fostering trust. Formal ethical approval for this study protocol was granted by the Ethics Committee of the Higher Institute of Accounting and Business Administration, University of Manouba, Tunisia.

3.3 Study design and methodological approach

To investigate the impact of artificial intelligence (AI) on risk management effectiveness (specifically concerning credit, market and operational risks) within Palestinian banks, this study used a sequential explanatory mixed-methods design (Creswell and Creswell, 2018). This approach was deliberately chosen for its strength in integrating quantitative and qualitative data. It allows for initial statistical assessment followed by in-depth qualitative exploration, there by providing a comprehensive and nuanced understanding by interpreting numerical.

The selection of an explanatory sequential mixed methods design for this study was deliberate and essential for achieving its research objectives. While a standalone quantitative approach could have provided a broad statistical overview and identified generalizable patterns of AI's impact, it would have been insufficient for explaining the underlying reasons for those patterns, particularly any observed variations or unexpected results.

Conversely, a standalone qualitative approach, while offering rich contextual insights, would have lacked the statistical generalizability needed to assess the broader prevalence and significance of these findings across the sector.

Therefore, the power of the mixed-methods design lies in its synergistic and complementary nature. The initial quantitative phase furnishes a robust, generalizable "what" identifying the statistical significance and magnitude of AI's influence across different risk domains. The subsequent qualitative phase then provides the crucial "why" and "how" delving into the contextual nuances, institutional barriers and practical experiences that explain and elaborate upon the quantitative results. This integration ensures a more holistic, valid, and deeply contextualized understanding of how Artificial Intelligence truly influences risk management effectiveness within Palestinian banking institutions.

The initial quantitative phase of this explanatory sequential mixed-methods study used a structured questionnaire as the primary data collection instrument. Developed specifically for this research and rigorously validated, the questionnaire was designed to reliably measure the study's core constructs. Items were adapted from established measurement scales validated in prior research (Kalkan, 2024; Bogojevic Arsic, 2021; Rashwan and Alhelou, 2022; Diab, 2022; Yazdi *et al.*, 2024; Biolcheva, 2021; Alimoradi and Ahmad, 2019; Berisha *et al.*, 2023).

The instrument comprised two sections. Section A gathered participant demographic information (job title, banking experience, educational attainment, relevant professional certifications) to provide context. Section B consisted of 22 items measuring the study's latent variables using a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Four distinct latent variables were assessed in this study:

(1) the utilization of artificial intelligence (AI), measured by 5 items;

(2) credit risk management practices (ERM-C), comprising 5 items;

(3) market risk management practices (ERM-M), operationalized with 6 items; and
(4) operational risk management practices (ERM-OP), also measured by 6 items.

Table 2 provides a detailed mapping of these constructs to their respective measurement items.

4. Results

4.1 Quantitative data analysis

The following metrics were used to evaluate the measurement model:

4.1.1 Common method bias. To assess the potential impact of common method bias (CMB), a diagnostic test was conducted. CMB can arise when variance is attributable to the measurement method itself (e.g. single survey instrument, respondent tendencies) rather than the constructs being measured. This assessment is crucial for ensuring that the observed relationships between variables are valid and not artificially inflated or deflated due to the data collection method, thereby confirming the integrity of the measurement model (Podsakoff *et al.*, 2003).

Common Method Bias (CMB) presents a significant methodological concern in research that relies on data collected through single-source questionnaires. CMB primarily arises from the respondents' propensity to provide consistent ratings across items, which can artificially inflate or deflate the observed relationships among variables, thereby threatening the validity of the study's conclusions (Jordan and Troth, 2020).

To rigorously assess the potential presence of CMB in this study, the full collinearity Variance Inflation Factor (VIF) was calculated for each item in the measurement instrument. VIF values serve a dual diagnostic purpose, indicating both the severity of multicollinearity and the potential for common method variance (Kock, 2015). According to established methodological criteria, VIF values below the threshold of 5.0 are generally considered indicative that a model is not contaminated by common method bias (Hair *et al.*, 2019).

In the present study, the calculated VIF values ranged from 1.431 to 4.983. As all values were comfortably below the critical threshold of 5.0, this result provides strong evidence for the absence of significant common method bias within the data set. This finding bolsters the validity and accuracy of the inferred relationships among the model's constructs.

Furthermore, the item loadings exhibited high values, ranging from 0.795 to 0.959, all of which substantially exceed the conventional cutoff value of 0.7 (see Table 3). This demonstrates the robustness of the measurement instrument and indicates a strong association between the measurement items and their respective latent constructs. Consequently, these results support the convergent validity and reliability of the data used for subsequent quantitative analyses and hypothesis testing.

4.1.2 Validity and reliability of data. The internal consistency reliability of the measurement scales was rigorously evaluated using both Cronbach's alpha and composite reliability (CR) coefficients. These indices assess the degree to which items intended to measure the same latent construct yield consistent and interrelated results. In accordance with established psychometric guidelines (e.g. Hair *et al.*, 2019), coefficient values exceeding the conventional threshold of 0.70 for both Cronbach's alpha and CR are indicative of acceptable internal consistency.

Following an initial assessment of the measurement model, a purification process was conducted. Items ERM-C4, ERM-C5, ERM-M1 and ERM-M2 were removed due to their outer loadings falling below the requisite threshold (typically 0.70), indicating they did not sufficiently capture their intended latent construct.

Table 2. Constructs and item measurements

Construct	Code	Item measurement
Independent variable: Artificial intelligence implementation	AIU1	The bank has an early warning system for detecting risks using artificial intelligence
	AIU2	Artificial intelligence provides innovative tools for analyzing financial risks
	AIU3	Our bank uses machine learning techniques to analyze big data related to risks
	AIU4	Our bank relies on artificial intelligence technologies to assess the impact of macroeconomic variables on market risks
	AIU5	The risk management department in our bank leverages artificial intelligence technologies to reduce the time required for handling critical events
Dependent Variables: 1. Credit Risk Management practices	ERM-C1	Our bank has clear policies for assessing customers' creditworthiness
	ERM-C2	The tools used by the bank accurately identify default risks
	ERM-C3	Effective strategies are implemented to reduce the ratio of nonperforming loans
	ERM-C4	Credit risk management systems contribute to improving the credit decision-making process
	ERM-C5	The performance of customers with credit facilities is monitored periodically and regularly
2. Market risk management practices	ERM-M1	Our bank has an effective system for continuously monitoring fluctuations in financial markets
	ERM-M2	Advanced analytical models are used to predict market movements and potential changes
	ERM-M3	Market risk management mechanisms help protect the bank from losses caused by price fluctuations
	ERM-M4	Market risk management reports provide accurate and reliable information for investment decision-making
	ERM-M5	Effective strategies are implemented to diversify the investment portfolio and minimize risks
	ERM-M6	Market risk management systems contribute to improving the efficiency of the bank's investments in the long term
3. Operational risk management practices	ERM-OP1	Our bank has a comprehensive system for detecting and addressing operational errors
	ERM-OP2	Operational processes are continuously monitored using modern tools and techniques
	ERM-OP3	Operational risk management policies help minimize human errors in the workplace
	ERM-OP4	Operational risk management mechanisms reduce the negative impact of operational disruptions on institutional performance
	ERM-OP5	Operational incidents are investigated and documented to ensure lessons are learned and performance is improved
	ERM-OP6	Operational risk management contributes to enhancing operational efficiency and reducing risk-related costs

Source(s): Authors' own creation

Table 3. VIF test and item loading results

Item	Item loading	VIF	Item	Item loading	VIF
ERM-C1	0.844	1.844	ERM-OP1	0.912	2.263
ERM-C2	0.795	1.544	ERM-OP2	0.959	2.893
ERM-C3	0.889	1.844	ERM-OP3	0.928	2.330
ERM-M3	0.957	1.431	ERM-OP4	0.928	2.880
ERM-M4	0.943	1.672	ERM-OP5	0.814	2.992
ERM-M5	0.929	2.672	ERM-OP6	0.943	2.262
ERM-M6	0.925	4.792			
AIU1	0.906	3.686			
AIU2	0.932	4.983			
AIU3	0.812	2.685			
AIU4	0.917	2.520			
AIU5	0.841	4.181			

Source(s): Authors' own creation

The psychometric properties of the refined measurement model were then rigorously assessed, with the results detailed in Table 4. The internal consistency reliability of the constructs was strongly supported. Cronbach's alpha coefficients ranged from 0.799 to 0.958, all substantially exceeding the 0.70 benchmark. Similarly, composite reliability estimates (ρA and ρC) for all constructs surpassed the 0.70 threshold. It is noted that one construct yielded a ρC value of 1.049; such values, which can slightly exceed 1.0 in some PLS-SEM algorithms, are interpreted as indicative of exceptionally high internal consistency for the given construct.

Convergent validity was also firmly established. The Average Variance Extracted (AVE) for all constructs ranged from 0.712 to 0.881, comfortably exceeding the recommended 0.50 criterion. This demonstrates that, on average, more than 71% of the variance in the items was explained by their respective latent constructs.

Collectively, these robust psychometric results confirm that the measurement model possesses high levels of internal consistency reliability and convergent validity. This provides a solid foundation for the subsequent structural model analysis and the testing of the study's substantive hypotheses.

4.1.3 Discriminant validity. To ensure that each latent construct measured a concept distinct from the others, *discriminant validity* was rigorously assessed using two complementary approaches: the *Heterotrait-Monotrait Ratio of Correlations (HTMT)* and the *Fornell–Larcker criterion.*

4.1.3.1 HTMT analysis. Following methodological standards recommended by Henseler *et al.* (2015**)** and later refined by Franke and Sarstedt (2019**)**, discriminant validity is considered

Table 4. Reliability and validity results

Construct	Cronbach's alpha	Composite reliability (ρA)	Composite reliability (ρC)	Average variance extracted (AVE)
ERM-C	0.799	0.818	0.881	0.712
ERM-M	0.956	1.049	0.967	0.881
ERM-OP	0.962	0.990	0.969	0.838
AIU	0.958	0.985	0.965	0.797

Source(s): Authors' own creation

adequate when *HTMT values remain below 0.85*, which is a conservative threshold ensuring low conceptual overlap between constructs.

As shown in Table 5, all computed HTMT values in this study ranged from *0.196 to 0.806*, confirming that the constructs are sufficiently distinct:

The *highest HTMT value (0.806)* occurred between *ERM-M* and *ERM-C*, while the *lowest value (0.196)* was observed between *AIU* and *ERM-M*. All values remained well below the 0.85 benchmark, thus indicating robust discriminant validity across all pairs of constructs. These results provide *quantitative evidence* that the latent variables capture *unique conceptual domains*, not measurement redundancies.

4.1.3.2 Fornell–Larcker criterion. To complement the HTMT test, the *Fornell–Larcker criterion* was used. This method compares the *square root of the Average Variance Extracted (√AVE)* for each construct with its *interconstruct correlations*. Discriminant validity is supported when √AVE is higher than the correlations with all other constructs.

As presented in Table 6, the √AVE values for all constructs exceeded their corresponding inter-construct correlations:

For example, √AVE for *ERM-M* was *0.939*, which is significantly greater than its highest correlation (0.700 with *ERM-C*), and the same pattern holds across all constructs. This reinforces the conclusion that the constructs demonstrate *strong discriminant validity* per both HTMT and Fornell–Larcker standards.

4.1.4 Evaluation of model fit. The goodness-of-fit for both the measurement and structural models was rigorously evaluated using a comprehensive set of fit indices, with the results summarized in Table 7. Collectively, these indicators provide robust evidence that the hypothesized model demonstrates a satisfactory and well-supported fit to the empirical data.

Specifically, the Standardized Root Mean Square Residual (SRMR) for both the saturated and estimated models was 0.045. This value is substantially below the recommended maximum threshold of 0.08 (Hu and Bentler, 1998), indicating a very small discrepancy

Table 5. Discriminant validity assessment using Heterotrait-Monotrait ratio (HTMT)

Relationship	HTMT value
ERM-M ↔ ERM-C	0.806
ERM-OP ↔ ERM-C	0.762
ERM-OP ↔ ERM-M	0.658
AIU ↔ ERM-C	0.600
AIU ↔ ERM-M	0.196
AIU ↔ ERM-OP	0.358

Source(s): Authors’ own creation

Table 6. Fornell–Larcker criterion for discriminant validity

Construct	√AVE	ERM-C	ERM-M	ERM-OP	AIU
ERM-C	0.844	–			
ERM-M	0.939	0.700	–		
ERM-OP	0.915	0.677	0.611	–	
AIU	0.893	0.528	0.170	0.284	

Source(s): Authors’ own creation

between the observed and model-implied correlation matrices. As such, the SRMR value confirms a high degree of absolute model fit.

Further assessment of absolute fit was conducted using discrepancy-based indices. The Unweighted Least Squares Discrepancy (d_ULS) was 0.793 for the saturated model and 0.730 for the estimated model, while the Geodesic Discrepancy (d_G) was 2.146 for both. While these indices are primarily descriptive and sensitive to scaling, their values in this context provide additional support, suggesting the model reproduces the empirical covariance structure with minimal distortion.

The model's chi-square (χ^2) statistics were 468.350 (saturated) and 473.968 (estimated). Although these values are statistically significant, it is widely acknowledged in structural equation modeling literature that the chi-square test is highly sensitive to sample size and often rejects well-fitting models in larger samples (Hair *et al.*, 2019). Therefore, in line with modern best practices, this statistic is interpreted with caution and considered supplementary to other, more robust fit indices.

Crucially, the assessment of incremental fit provided strong support for the model. The Normed Fit Index (NFI) achieved a value of 0.944 in both models. This comfortably exceeds the commonly accepted cutoff criterion of 0.90, indicating that the hypothesized model represents a substantial improvement in fit over the baseline null model.

In summary, the collective evidence from the model fit indices confirms that the specified model provides an excellent representation of the empirical data. All indicators fall within their respective acceptable or ideal ranges, demonstrating that the model is both statistically sound and theoretically coherent, thus providing a robust foundation for the subsequent hypothesis testing.

4.1.5 Structural model evaluation. The structural model was evaluated to examine the relationships among the latent variables and to test the study's hypotheses. Several statistical indices were used to determine the validity and strength of the structural model. These indices are discussed in the following sections.

4.1.5.1 Path coefficients. The hypothesized relationships within the structural model were tested using a bootstrapping procedure with 5,000 resamples. This nonparametric method was used to robustly estimate the significance, magnitude and directionality of the path coefficients. The detailed results, including standardized path coefficients (β), standard errors, t-values and p-values, are presented in Table 8. In accordance with conventional criteria, a path was considered statistically significant if its associated p-value was less than 0.05.

The analysis reveals that the utilization of artificial intelligence (AIU) exerts a statistically significant and strong positive influence on credit risk management (ERM-C) ($\beta = 0.558$, $t = 4.531$, $p < 0.001$). This result provides robust empirical support for *H1*. The magnitude of

Table 7. Model fit indices

Fit index	Saturated model	Estimated model
SRMR	0.045	0.045
d_ULS	0.793	0.730
d_G	2.146	2.146
Chi-square (χ^2)	468.350	473.968
NFI	0.944	0.944

Source(s): Authors' own creation

Table 8. Path coefficient results

Hypotheses	Relationship	Original sample (O)	Sample mean (M)	Standard deviation (SD)	T-statistics	*p*-values	Result
H1	AIU → ERM-C	0.558	0.589	0.123	4.531	0.000	Supported
H2	AIU → ERM-M	0.214	0.234	0.207	1.034	0.301	Not supported
H3	AIU → ERM-OP	0.394	0.420	0.136	2.900	0.004	Supported

Source(s): Authors' own creation

the standardized coefficient, which exceeds 0.50, indicates that this effect is not only statistically significant but also practically substantial.

Furthermore, AIU was found to have a moderate yet statistically significant positive effect on operational risk management (ERM-OP) (β = 0.394, t = 2.900, p = 0.004). This finding provides clear empirical support for *H3*.

Conversely, the hypothesized relationship between AIU and market risk management (ERM-M) was not supported by the data. The path coefficient was statistically nonsignificant (β = 0.214, t = 1.034, p = 0.301), leading to the rejection of *H2* within the context of this study.

Collectively, these findings indicate that while AI integration contributes meaningfully to the management of credit and operational risks within Palestinian banking institutions, its direct effect on market risk management appears to be negligible or nonexistent. This suggests the influence of AI on market risk may be more complex, potentially being moderated or mediated by other contextual or organizational factors not explicitly modeled in this research.

4.1.5.2 Coefficient of determination (R^2). The explanatory and predictive power of the structural model was evaluated by examining the coefficient of determination (R^2) and the adjusted R^2 for each endogenous latent variable. The R^2 value quantifies the proportion of variance in a dependent construct that is collectively explained by its predictor variables within the model. The adjusted R^2, which accounts for the number of predictors relative to the sample size, provides a more conservative and arguably more accurate estimate of the model's in-sample explanatory power.

The results, as detailed in Table 9, reveal distinct levels of explanatory power across the different risk domains:

- For *credit risk management (ERM-C)*, the model accounts for 31.2% of the variance (R^2 = 0.312; Adj. R^2 = 0.303). In accordance with established benchmarks (Cochran, 1977; Hair *et al.*, 2019), this is considered a *moderate* level of explanatory power.
- For *operational risk management (ERM-OP)*, the model explains 15.6% of its variance (R^2 = 0.156; Adj. R^2 = 0.145). This value indicates a *small to moderate* effect size, suggesting that AI utilization is a relevant but not exhaustive predictor.

Table 9. R^2 and adjusted R^2 values

Dependent variable	R^2	Adjusted R^2
ERM-C	0.312	0.303
ERM-M	0.046	0.034
ERM-OP	0.156	0.145

Source(s): Authors' own creation

- For *market risk management (ERM-M)*, the model explains a mere 4.6% of the variance (R^2 = 0.046; Adj. R^2 = 0.034). This result signifies *weak* explanatory power, indicating that AI utilization, as operationalized in this study, has very limited influence on this construct.

These findings collectively imply that while Artificial Intelligence utilization (AIU) is a meaningful predictor of variations in credit and, to a lesser extent, operational risk management, its predictive relevance for market risk management is negligible within the current model specification. This pronounced difference in explanatory power strongly suggests the presence of other, more influential determinants of market risk management that are not captured by this model, highlighting the potential need to investigate additional mediating or moderating variables in future research.

When interpreted concurrently, the R^2 values, path coefficients and f^2 effect sizes provide a holistic and nuanced assessment of the structural model. This triangulation of evidence confirms both the model's substantive predictive relevance for specific endogenous constructs and its overall theoretical robustness.

4.1.5.3 Effect size (f^2). The *effect size (f^2)* was computed to quantify the substantive impact of each predictor variable on the respective dependent constructs within the structural model. This measure assesses the change in the coefficient of determination (R^2) when a given predictor is omitted from the model, thereby indicating the relative contribution of each predictor to explaining variance.

The results presented in Table 10 reveal that the *utilization of artificial intelligence (AIU)* exerts a *moderate effect* on *credit risk management (ERM-C)*, with an *f^2 value of 0.422*, which according to Cochran's (1977) conventions corresponds to a moderate to large effect size.

In contrast, AIU exhibits a *very small effect* on *market risk management (ERM-M)*, with an *f^2 value of 0.047*, indicating a negligible influence in this domain.

The impact of AIU on *operational risk management (ERM-OP)* is characterized as *small*, with an *f^2 value of 0.160*, representing a modest but meaningful effect.

These findings suggest that while AI adoption significantly enhances credit risk management practices, its influence on operational and market risk management is comparatively more limited, underscoring potential contextual or operational factors that may moderate these effects (Zainal Abidin, 2021).

4.2 Qualitative data analysis

4.2.1 The role of artificial intelligence in enhancing credit risk management. This section delves into the qualitative findings concerning *H1*, which proposed a significant positive impact of artificial intelligence (AI) on credit risk management (ERM-C) within Palestinian banks. Thematic analysis of interview data from internal auditors provides rich contextual evidence supporting this hypothesis, illuminating how AI enhances ERM-C practices and

Table 10. Effect size (f^2) results

Predictor variable	Effect size (f^2)
AIU → ERM-C	0.422
AIU → ERM-M	0.047
AIU → ERM-OP	0.160

Source(s): Authors' own creation

aligning these mechanisms with key dimensions of the DeLone and McLean (2003) IS Success Model (DeLone and McLean, 2003).

A predominant theme was enhanced credit risk assessment accuracy through advanced analytics. Participants consistently highlighted the superior capabilities of AI systems, particularly those using machine learning, in evaluating creditworthiness more effectively than traditional methods. These systems were valued for their ability to discern subtle, nonlinear patterns within large data sets, enabling proactive identification of potential defaults. As one internal auditor described, “Our AI platform identifies anomalous patterns in real-time, before they escalate into significant financial losses. This allows us to intervene earlier in the credit cycle” (P6). This finding directly reflects the System Quality dimension of the D&M model, where the technical sophistication and analytical power of the AI system enable superior performance.

A closely related theme centered on improved quality, consistency and objectivity in credit evaluations. Interviewees perceived AI applications as significantly mitigating human biases and subjective judgments often present in manual assessments. By anchoring evaluations more firmly in empirical data processed through standardized algorithms, AI fosters greater consistency and objectivity. “Previously, decisions could be partially based on subjective judgment. Now the system provides us with objective indicators guiding our credit risk evaluations” (P12). This directly aligns with the Information Quality dimension of the D&M model, emphasizing AI’s capacity to generate accurate, reliable and unbiased outputs crucial for sound decision-making.

The third key theme identified was AI’s enablement of continuous monitoring and dynamic risk adaptation. Participants described how AI facilitates more frequent and timely updates to credit risk models by processing real-time data on borrower behavior and evolving market conditions. “We now update our risk models more frequently because AI allows us to track clients’ financial behavior almost in real time” (P19). This enhanced responsiveness, representing effective system Use, allows banks to dynamically adjust their risk postures. The resulting improvement in adaptability and potential reduction in credit losses directly contribute to the Net Benefits dimension of the D&M model, manifesting as enhanced organizational resilience.

In synthesis, the qualitative evidence strongly corroborates the quantitative results supporting *H1*. The interviews provide nuanced insights into the mechanisms through which AI positively transforms credit risk management within the Palestinian banking context. By enhancing analytical precision (System Quality), improving the integrity of assessments (Information Quality) and enabling adaptive monitoring leading to tangible improvements (Use and Net Benefits), AI applications clearly demonstrate their value, aligning robustly with the theoretical constructs of the D&M IS Success Model (DeLone and McLean, 2003) and underscoring their beneficial impact on ERM-C practices.

4.2.2 Barriers to artificial intelligence impact on market risk management. This section addresses the qualitative findings related to *H2*, which posited a positive impact of artificial intelligence (AI) on market risk management (ERM-M) within Palestinian banks. Contrary to initial expectations, quantitative analysis did not support this hypothesis. Thematic analysis of interview data provides crucial explanatory insights, revealing significant contextual and institutional barriers that hinder AI’s effective application in the ERM-M domain, thereby accounting for the nonsignificant quantitative results. These barriers are interpreted through the DeLone and McLean (D&M) IS Success Model (DeLone and McLean, 2003), primarily highlighting deficiencies related to Information Quality, System Use and the organizational factors influencing them.

A predominant theme emerging from the interviews was severe infrastructural limitations hindering access to relevant market data. Participants consistently reported that existing AI tools predominantly analyze internal data sources (credit, operational) and lack integration with essential real-time external market data streams. As one auditor articulated, “We don’t have consolidated real-time market data feeds… Our AI tools are trained mainly on internal operational or credit data and not on macroeconomic or financial market trends” (P6). This fundamental gap directly compromises the Information Quality dimension of the D&M model. Without adequate, timely and relevant market data inputs, AI systems cannot generate meaningful insights for ERM-M, severely limiting their utility and potential impact.

A second critical barrier identified was a pronounced skills gap in specialized AI expertise. Respondents emphasized that effectively using AI for the complexities of market risk analysis requires advanced skills – not just to operate tools, but crucially, to interpret sophisticated outputs, validate models against dynamic market conditions and adapt algorithms appropriately. “Our teams currently lack the necessary expertise to effectively construct or train AI models that can model currency fluctuations or geopolitical disruptions” (P14). This deficiency directly impedes effective System Use. As the D&M model suggests, particularly in complex domains like market risk, realizing Net Benefits is highly contingent on user proficiency, which is often fostered by adequate training and support (related to Service Quality). The lack of requisite expertise acts as a major bottleneck.

Furthermore, the qualitative data pointed to competing strategic priorities that currently marginalize AI applications in market risk. Participants indicated that AI implementation efforts in Palestinian banks are predominantly focused on areas like credit scoring, fraud detection and regulatory compliance, often perceived as offering more immediate returns or addressing pressing regulatory mandates. “We’re still at a stage where AI is being applied largely to compliance and credit analysis. Market risk is perceived as less pressing or perhaps harder to model and measure with AI currently” (P20). This strategic allocation limits dedicated investment and resources for ERM-M applications, resulting in under-utilization (System Use) and consequently constraining the potential Net Benefits achievable in this specific risk domain. This highlights how organizational strategy and perceived value directly shape the technology adoption pathways and outcomes anticipated by the D&M model.

In conclusion, the qualitative findings offer a compelling explanation for the statistically nonsignificant results regarding *H2*. The limited impact of AI on market risk management within the Palestinian banking context appears less attributable to inherent technological limitations and more to significant infrastructural, human capital and strategic constraints. Deficiencies in data infrastructure (undermining Information Quality), inadequate specialized expertise (hindering effective System Use) and competing strategic priorities (limiting dedicated Use and investment) collectively curtail AI’s potential in ERM-M. Interpreted through the D&M model, these findings underscore how shortcomings in critical inputs and organizational alignment prevent the realization of Net Benefits. Addressing these multifaceted challenges through targeted investments in data infrastructure, specialized training and strategic prioritization appears prerequisite for AI to meaningfully enhance market risk management practices in this banking environment (DeLone and McLean, 2003).

4.2.3 Artificial intelligence’s enhancement of operational risk management. This section presents the qualitative findings pertaining to *H3*, which posited a significant positive impact of artificial intelligence (AI) on operational risk management (ERM-OP) within Palestinian banks. Thematic analysis of interviews with internal auditors provides compelling evidence that corroborates this hypothesis, illuminating the specific mechanisms through which AI enhances ERM-OP. These mechanisms align strongly with key dimensions of the DeLone and McLean (D&M) IS Success Model (DeLone and McLean, 2003), particularly System Quality, Information Quality, System Use and Net Benefits.

A primary theme identified was enhanced operational efficiency and error reduction via AI-driven automation. Participants consistently emphasized AI's effectiveness in automating routine, high-volume operational tasks, thereby mitigating the inherent risks of manual errors and significantly improving process efficiency. As one internal auditor illustrated, "Since we integrated AI into our operational processes, the rate of manual processing errors has declined considerably. The system detects discrepancies that we used to overlook" (P3). This capability directly reflects the System Quality dimension of the D&M model, where the AI system's reliability, efficiency and performance characteristics bolster operational stability and accuracy.

Another prominent theme was improved risk detection through real-time monitoring and anomaly alerts. Interviewees highlighted AI systems' capacity for continuous, automated oversight of transactions and workflows, enabling the early identification of deviations or potential threats that might otherwise remain undetected. An auditor remarked:

> AI tools notify us instantly when there's an anomalous transaction volume or deviation from typical workflows—something that was practically impossible to achieve manually with the same speed and scope (P9).

This functionality enhances responsiveness to operational risks, embodying the Information Quality dimension (providing timely, relevant alerts) and facilitating more effective System Use for immediate intervention, ultimately contributing to Net Benefits through proactive risk mitigation.

Furthermore, the qualitative data underscored AI's enablement of proactive risk mitigation through predictive analytics. Participants described leveraging AI to analyze historical and real-time operational data, allowing them to forecast potential risks and develop data-driven mitigation strategies. According to one participant, "We now use predictive analytics powered by AI to forecast potential process failures or system downtimes. It's a game-changer in planning our risk responses" (P16). This predictive power represents a superior level of Information Quality (actionable foresight) and directly drives Net Benefits by enhancing strategic risk preparedness and overall organizational resilience.

In synthesis, these qualitative insights strongly reinforce the quantitative findings supporting *H3*, offering rich contextual evidence of AI's positive influence on ERM-OP in Palestinian banks. Through key mechanisms – process automation (reflecting System Quality), real-time anomaly detection (enhancing Information Quality and System Use) and predictive analytics (driving advanced Information Quality and Net Benefits) – AI demonstrably validates the theoretical principles of the D&M IS Success Model in this practical context. These findings confirm that AI integration not only mitigates existing operational risks but also holds the potential to fundamentally strengthen operational risk governance within the Palestinian banking sector (DeLone and McLean, 2003).

5. Discussion

This study investigated the differential impact of Artificial Intelligence (AI) on credit, market and operational risk management within Palestinian banks, using an explanatory sequential mixed-methods design that integrated quantitative survey data with qualitative interview insights. The findings reveal a domain-specific and heterogeneous impact: AI exerts statistically significant positive effects on both credit and operational risk management, while its influence on market risk management is currently not statistically significant, a result attributable to specific, identifiable contextual barriers.

These findings are highly consistent with the theoretical underpinnings of the DeLone and McLean Information Systems (IS) Success Model (2003), which posits a dynamic interplay between system quality, information quality, service quality, system use and net benefits. Regarding credit risk management (*H1*), participants highlighted AI's capacity to enhance credit scoring accuracy, identify complex patterns in large data sets and facilitate more objective, data-driven assessments of creditworthiness. These results align seamlessly with international studies (Brown, 2024; Savchenko, 2024), which affirm AI's potential to reduce default rates and improve risk classification, as well as with Xu *et al.* (2024a, 2024b), who reported a 20% increase in predictive accuracy using AI-based models over traditional approaches.

Similarly, in the domain of operational risk management (*H3*), both empirical and qualitative findings supported the hypothesis of AI's positive impact. Interviewees emphasized AI's role in improving internal controls, enhancing fraud detection capabilities and automating routine tasks. These mechanisms are congruent with studies (Ajayi, 2025; Kaswan *et al.*, 2023; Bonrath and Eulerich, 2024), which underscore AI's contribution to internal governance, real-time monitoring and the mitigation of human error. Such outcomes reflect high system quality and effective system use, contributing directly to the realization of net benefits as delineated in the IS Success Model.

Conversely, the study did not find empirical support for *H2*, which posited a significant AI impact on market risk management. While this result diverges from findings in technologically advanced contexts – such as those by Bahoo *et al.* (2024) and Mubarroq *et al.* (2025), who documented AI's effectiveness in forecasting market volatility and enhancing asset pricing – the qualitative data in this study identified critical, context-specific barriers. Chief among these were the lack of real-time market data integration, deficient technological infrastructure and a pronounced shortage of the specialized expertise required to build, validate and interpret complex AI models for dynamic market environments. These findings resonate powerfully with cautionary research (Khan, 2025; Vuković *et al.*, 2025), who argue that without institutional readiness and robust data infrastructure, AI's application in market risk domains may yield suboptimal outcomes or even introduce new vulnerabilities.

This study thus furnishes compelling evidence for the differentiated nature of AI's effectiveness, which is not merely a function of the technology itself but is profoundly mediated by organizational capacity, strategic alignment and the maturity of the data ecosystem. The stronger results in credit and operational risk management can be interpreted as reflecting domains where internal data availability is higher and where organizational priorities are more acutely focused. In contrast, the limited effectiveness in market risk underscores critical dependencies on external data integration, advanced analytical talent and institutional maturity – factors often less developed in emerging economies.

This study offers significant theoretical contributions by interpreting its empirical findings through a multilayered theoretical framework, primarily drawing upon the DeLone and McLean (D&M) Information Systems (IS) Success Model, the Technology Acceptance Model (TAM) and Institutional Theory. The observed variation in AI's impact across different risk domains provides a fertile ground for demonstrating the complementary power of these perspectives.

The pronounced positive influence of AI on *credit and operational risk management* aligns seamlessly with the core tenets of both the D&M model and TAM. The effectiveness in these domains, as described by participants, points to high *System Quality* (robust algorithms) and *Information Quality* (accurate, timely risk indicators). This, in turn, fosters a high *Perceived Usefulness (PU)* among practitioners, who see these tools as directly enhancing their decision-making accuracy and efficiency. This high PU, combined with the *Perceived Ease of Use (PEOU)* of automated systems, drives user acceptance and meaningful *System Use*, ultimately culminating in tangible *Net Benefits* such as reduced default rates and improved internal controls. This dynamic provides a clear, microlevel validation of the D&M and TAM frameworks in a novel, resource-constrained context.

Concurrently, the adoption of AI for operational risk is also explained at a macrolevel by *Institutional Theory*. Banks in environments like Palestine face coercive and mimetic pressures to modernize their risk and compliance infrastructures, often emulating global best practices to enhance their legitimacy and satisfy regulatory expectations (DiMaggio and Powell, 1983). This institutional pressure acts as a powerful external driver for adopting technologies that signal modernity and robust governance.

Conversely, the statistically nonsignificant relationship between AI and *market risk management* is where the interplay of these theories becomes most illuminating. This null finding can be predominantly attributed to overriding institutional and infrastructural constraints, as highlighted by Institutional Theory. Effective market risk analytics demand sophisticated capabilities – such as real-time, cross-border data integration and advanced modeling expertise – that often exceed the current technical readiness of institutions in emerging economies. Institutional Theory posits that in the absence of robust normative pressures or clear regulatory mandates; organizations are likely to deprioritize investment in such complex technological domains.

This institutional context directly impacts the constructs of the D&M and TAM models. The lack of requisite data infrastructure severely degrades *Information Quality*, while the shortage of specialized skills hinders effective *System Use*. Consequently, both *Perceived Usefulness* and *Perceived Ease of Use* are suppressed, as practitioners cannot effectively leverage the technology nor easily integrate it into their workflows. Therefore, the null finding for market risk is not merely a reflection of technological limitations but is a theoretically consistent outcome. It powerfully demonstrates that without the necessary institutional drivers and infrastructural preconditions (as explained by Institutional Theory) to support the core tenets of IS success (as delineated by D&M and TAM), the adoption and effective utilization of AI in highly demanding domains are significantly inhibited.

In summary, this study reaffirms and extends the explanatory power of these foundational theories in a fragile, emerging market context. It demonstrates that achieving *Net Benefits* from AI systems necessitates far more than mere system deployment; it requires a synergistic alignment of technology (*System/Information Quality*), individual user acceptance (*PU/PEOU*) and enabling institutional conditions. Practically, this implies that for Palestinian banks to fully leverage AI, a multipronged strategy encompassing technological enhancement, specialized skill development and long-term institutional planning is imperative.

6. Conclusion

This study demonstrates that Artificial Intelligence (AI) has a differentiated impact on risk management within Palestinian banks: credit and operational risks benefit significantly from enhanced decision accuracy, process automation and real-time anomaly detection, whereas market risk remains constrained due to infrastructural and skills limitations. These findings underscore that AI's effectiveness depends on contextual factors, organizational readiness and the implementation environment.

From a theoretical standpoint, the research extends the DeLone and McLean IS Success Model by highlighting how system quality, information quality and strategic alignment mediate AI adoption outcomes across diverse risk domains. *Empirically, moreover,* it provides rare evidence from a politically fragile, resource-constrained context, contributing to a nuanced understanding of AI adoption in emerging economies.

Practically, the study offers actionable guidance for banking institutions and regulators, emphasizing investments in human capital, data infrastructure and adaptive governance frameworks. *Correspondingly, policy implications include* supporting national digital transformation strategies, targeted capacity-building and regulatory frameworks aligned with international standards to ensure transparency, accountability and resilience.

In sum, this research synthesizes empirical, theoretical and policy insights to provide a holistic framework for context-sensitive AI adoption, advancing both scholarly discourse and practical applications in emerging financial systems.

Practical Implications for Bank Managers, Policymakers and Technology Developers

The findings of this study offer actionable insights for three key stakeholder groups integral to the financial ecosystem within Palestine and comparable emerging markets:

(1) For Bank Managers and Executives: Strategic Implementation and Risk-Specific Integration:

- *Tailored AI deployment:* Bank executives are advised to adopt a differentiated AI integration strategy, aligning specific technologies with specific risk categories. Given its demonstrable success, AI should be prioritized for optimizing credit and operational risk management through the deployment of advanced predictive models and real-time anomaly detection systems.
- *Robust governance alignment:* Managers must establish robust internal AI governance protocols that ensure transparency, accountability and compliance with local regulations and international best practices. Institutional readiness – encompassing technical, cultural and ethical dimensions – must be continuously assessed to mitigate risks associated with misuse or overreliance on opaque “black-box” models.
- *Phased and context-sensitive implementation:* Rather than pursuing a wholesale digital transformation, a phased and context-sensitive AI integration strategy is recommended. This approach should be meticulously aligned with evolving institutional capacity and dynamic risk profiles to ensure sustainable and effective adoption.

(2) For Policymakers and Regulatory Authorities: Fostering a Resilient AI Ecosystem:

- *Develop adaptive regulatory frameworks:* Regulatory authorities are encouraged to architect adaptive governance models that adeptly balance the promotion of financial innovation with the imperatives of systemic stability, ethical considerations and public trust.
- *Institutionalize and localize standards:* The adoption of international frameworks, such as ISO/IEC 42001:2023, should be strategically localized to accommodate Palestine’s unique legal, infrastructural and political constraints, thereby creating a pragmatic and enforceable standard.
- *Promote national capacity building:* Policymakers should champion public–private partnerships to develop national programs focused on enhancing AI literacy, fostering risk ethics and establishing regulatory sandboxes. Such initiatives are critical for creating an enabling environment for responsible financial innovation.

(3) For Technology Developers and Solution Providers: Context-Aware and Explainable AI:

- *Design for constrained environments:* AI developers are urged to design solutions that are adaptable to and performant within constrained environments characterized by limited data infrastructure, variable bandwidth and finite human capacity – conditions prevalent across many emerging markets.
- *Prioritize explainability (XAI):* Given the regulatory fragility and the high stakes of financial decision-making, an unequivocal emphasis must be placed on developing explainable AI models. These models should provide clear audit trails and transparent logic paths, thereby bolstering institutional and public trust.
- *Foster collaborative innovation:* Developers are encouraged to engage in co-creation processes with banking institutions and regulators. This collaboration will ensure the development of domain-specific, risk-sensitive AI systems that are directly aligned with practical use cases and governance requirements.

By translating these empirical findings into stakeholder-specific actions, this study aims to promote the strategic, ethical and sustainable adoption of AI within fragile financial ecosystems. These recommendations are intended to empower banking leaders, regulators and innovators to maximize AI's benefits while proactively mitigating systemic and organizational vulnerabilities.

6.1 Limitations and future research

The study acknowledges certain limitations. Primary reliance on internal auditors, while offering crucial oversight, may not capture the full experiential range; future work could benefit from including risk managers, IT specialists and senior management. *Furthermore*, the unique Palestinian politico-economic context necessarily limits direct generalizability, though identified themes regarding infrastructure, skills and strategy likely resonate with other emerging economies.

Building on this study, future research should explore the longitudinal evolution of AI's impact as infrastructure and skills develop. Comparative cross-country studies within diverse emerging markets would further elucidate national context influences. *Additionally, integrating* deeper analysis of organizational culture, change management and specific ethical considerations related to AI decision-making in risk management represents another fruitful avenue. Exploring the specific impact of different AI techniques (e.g. machine learning vs deep learning) across risk domains would also yield valuable insights. *Ultimately, such research will deepen* our understanding of how AI can be effectively and responsibly leveraged to foster resilient global financial systems.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author(s) used Grammarly for assistance in proofreading and enhancing the manuscript's readability. Following its use, the author(s) thoroughly reviewed and revised the content as necessary and assumed full responsibility for the published content.

Third-Party Material

No third-party material was used in this manuscript; all material is original work by the authors.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Further reading

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Appendix. Interview protocol

Qualitative phase – semistructured interview guide

Study title: Integrating Artificial Intelligence into Risk Management Frameworks: A Mixed-Methods Analysis of the Palestinian Banking Sector.

Purpose of the interview:

This interview aims to obtain in-depth, explanatory insights from experienced professionals employed in internal audit and risk management functions regarding the quantitative findings of this study. Specifically, it focuses on the practical implementation and contextual nuances of artificial intelligence (AI) adoption within risk management frameworks in Palestinian banking institutions.

Participant selection criteria:

- Currently employed in a Palestinian banking institution.
- Possess a minimum of five years of professional experience in internal auditing, risk management, compliance, or banking information technology (IT).
- Demonstrate familiarity with AI systems, predictive analytics tools, or advanced decision-support technologies.
- Have direct or indirect involvement in institutional risk governance processes.

Introductory script (To be read *verbatim* by the interviewer):

Thank you for agreeing to participate in this interview. The purpose of this session is to gain a deeper understanding of how Artificial Intelligence is being applied in managing various risks within Palestinian banks, particularly in light of the statistical findings obtained during the initial quantitative phase of our study. All information shared will be treated with the strictest confidentiality and will be anonymized in any subsequent reporting. Please be aware that you are free to decline to answer any question or to withdraw from this interview at any point without any repercussions.

Core interview question:

The quantitative results of our study indicated that Artificial Intelligence has a statistically significant positive impact on the management of credit risk and operational risk, but its impact on the management of market risk was not found to be statistically significant.

In your professional opinion and based on your experience, how can this observed variation in AI's impact across these different risk domains be explained?

Closing question:

Do you have any final comments, additional observations, or insights that you believe are important to this topic and were not sufficiently addressed during our discussion?

Interviewer's instructions:

- Allow participants to articulate their views freely and without undue interruption.
- Use neutral probing questions when necessary to elicit further detail or clarification (e.g. “Could you elaborate on that point?”; “Could you provide a specific example from your experience?”; “What factors do you believe contribute to that?”).
- Maintain strict neutrality and avoid any verbal or nonverbal cues that might influence participant responses.
- Ensure all responses are captured accurately and comprehensively.

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