Examining the Impact of Credit Risk Management Challenges on Bank Performance: The Mediating Role of Best Practices

Nicholas Dacre[1], Odai AlJaloudi[2], M.K.S. Al-Mhdawi[3], Mouhamed Thiam[4], Muath Abdel Qader[5], and Abroon Qazi[6]

[1]University of Southampton, UK; [2]University of Gloucestershire, UK; [3]Teesside University, UK; [4]Nottingham Trent University, UK; [5]Australian University, Kuwait; [6]American University of Sharjah, UAE

Abstract

In the evolving landscape of banking, effective credit risk management (CRM) is crucial for maintaining financial stability and optimising performance. Commercial banks face numerous challenges in managing credit risk, which can significantly impact their overall performance and resilience. Understanding the relationship between CRM challenges and bank performance, along with the mediating role of best practices, is essential for navigating the complexities of modern banking systems, an area often overlooked in previous financial risk management literature. This study, therefore, investigates the impact of CRM challenges on bank performance, with a particular focus on the mediating role of CRM best practices. Employing a mixed-method research approach, the study integrates qualitative insights from credit risk experts with quantitative analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess the effects of operational, regulatory, and technological challenges on bank performance. Initial findings highlight specific best practices that can mitigate these challenges and enhance banks' capacity to manage credit risk despite resource constraints. This research thus contributes to the existing literature by advancing the understanding of CRM dynamics in emerging markets and offering insights for banking practitioners and policymakers. The study also supports the development of adaptable CRM practices that strengthen stability and resilience within Jordan’s banking sector, with broader implications for similar markets.

Keywords: credit risk, bank performance, best practices, SEM analysis, financial stability, Jordan banking sector.

1. Introduction

The dynamics of the global financial landscape have undergone substantial transformations in recent years, marked by heightened volatility, intricate regulatory frameworks, and rapid technological developments. Within this environment, the banking sector assumes a pivotal role in maintaining economic stability and promoting growth, particularly in developing and emerging markets (Adel & Naili, 2024; Mateev et al., 2021; Sonjit et al., 2021c). At the centre of this complex financial ecosystem lies the critical function of credit risk management, which has become increasingly challenging yet indispensable for ensuring the stability, profitability, and overall performance of banking institutions (Jungo et al., 2022). Credit risk, defined as the potential for a borrower to default on their financial obligations, represents one of the most significant vulnerabilities to bank performance and financial system stability (Jiménez & Saurina, 2004). The 2008 global financial crisis and subsequent economic turbulence have had a profound impact on our understanding of the importance of effective credit risk management practices (Reddy et al., 2014). These events have underscored the need for a deeper understanding of the complexities of challenges banks face in managing credit risk, as well as the strategies they can employ to mitigate these challenges effectively (Dacre, Eggleton, Gkogkidis, et al., 2021; Eggleton et al., 2023).

Thus far extant research has examined various facets of credit risk management and its impact on bank performance. For example, studies have investigated the direct relationships between credit risk factors and key performance metrics, such as asset quality ratios (Akhanolu et al., 2020) and net interest margins (Oke & Wale-Awe, 2018). Furthermore, researchers have explored the influence of macroeconomic factors on bank performance, including the impact of GDP growth rates, inflation rates, and exchange rate fluctuations (Nguyen & Nguyen, 2018). Despite these significant contributions, there remains a notable lacuna in our understanding of how banks effectively navigate the complex interplay between credit risk challenges and best practices. This knowledge gap is particularly pronounced in emerging markets, where banks often operate under unique economic pressures, evolving regulatory frameworks, and operational constraints that may differ substantially from those in more developed economies. Insights from risk management practices in other sectors, such as critical infrastructure projects (Dacre, Yan, Dong, et al., 2024; Manh et al., 2024), also highlight the broader applicability of systematic approaches to risk, which can be adapted to bolster credit risk management in banking (Al-Mhdawi et al., 2024).

The banking sector of Jordan presents an exemplary case study for investigating the complexities of credit risk management in emerging markets (Alalwan et al., 2015; Alalwan et al., 2016; Dacre, AlJaloudi, et al., 2024). As a pivotal institution in the Middle East and North Africa (MENA) region, Jordan's financial system has demonstrated remarkable resilience in the face of regional instability and global economic instability (Adel & Naili, 2024). However, it also confronts unique challenges in credit risk management, which are shaped by factors such as macroeconomic volatility, regulatory regime shifts, and the imperative for technological integration (Mateev et al., 2021). A critical examination of how Jordanian banks navigate these complexities and implement best practices in credit risk management can provide valuable insights that transcend the MENA region to other emerging markets and the broader banking sector. This study therefore seeks to address a significant knowledge gap in the existing literature by adopting a mixed-methods approach, which integrates qualitative insights from industry experts with quantitative analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM). The application of advanced methodologies, including artificial intelligence (Corbin et al., 2024; Dacre & Kockum, 2022a; Mohamed et al., 2024) and systemic modelling and data analytic techniques (Brookes et al., 2020; Dacre & Kockum, 2022a; Dacre et al., 2020), has become increasingly significant in credit risk management, affording banks enhanced predictive capabilities and effective risk mitigation strategies (Al-Mhdawi, Dacre, et al., 2023). Thus, leveraging this combined interdisciplinary methodology (Reynolds & Dacre, 2019), this research aims to contribute meaningfully to our understanding of credit risk management in emerging markets and inform the development of effective strategies for banking institutions worldwide (Jungo et al., 2022).

2. Literature Review

2.1 Credit Risk Management and its Influence on Bank Performance

Credit risk management (CRM) stands as a fundamental concern for banks, directly influencing their stability and profitability (Saleh & Abu Afifa, 2020). Defined as the risk that borrowers will fail to meet their financial obligations, credit risk has been the focus of considerable research aiming to reduce vulnerabilities within financial systems (Barboza et al., 2017). Early work in CRM laid the foundation for modern practices, emphasising the importance of managing credit exposure to protect bank performance and foster financial stability (Altman & Saunders, 1997; Cebenoyan & Strahan, 2004). This perspective has evolved significantly with studies indicating that CRM frameworks should adapt to an increasingly complex financial landscape characterised by new regulatory demands, economic uncertainty, and technological advancements (Saunders & Allen, 2010; Van Gestel & Baesens, 2009).

In response to these regulatory pressures, the influence of frameworks such as the Basel Accords has been significant in shaping CRM practices across the banking sector (Altman & Saunders, 1997). These regulatory requirements mandate the maintenance of sufficient capital reserves, which in turn underpins systemic stability and mitigates risk exposure (Kashyap & Stein, 2004). However, the strictness of these regulations may, in contrast, constrain the operational flexibility of banks, potentially limiting their adaptability and competitiveness within evolving markets (Bessis, 2011; Van Gestel & Baesens, 2009). In emerging markets, where regulatory frameworks can be fluid or less established, CRM practices are likely to evolve in response to both shifting regulatory demands and unique local market dynamics (Dong & Dacre, 2024), fostering a continuous interplay that invites further exploration (Harb et al., 2023; Ismail & Ahmed, 2023). Thus, regulation emerges as both a stabilising force and a source of challenge, influencing CRM's development in varied market contexts.

Amid these regulatory priorities, the task of accurately assessing credit risk has spurred the evolution of CRM methodologies, particularly with the advent of machine learning (Bussmann et al., 2021). Traditionally, CRM relied on established risk assessment models, but recent innovations in data science now allow banks to process larger datasets and achieve greater predictive precision (Babenko et al., 2021; Montevechi et al., 2024). This shift towards data-centric approaches underscores machine learning's transformative potential within CRM, while simultaneously introducing critical considerations regarding model interpretability (Bao et al., 2020).

Advanced techniques such as decision trees, random forests, and neural networks, have shown an ability to outperform traditional models when applied to complex datasets, including customer behavioural data and macroeconomic indicators (Breiman, 2001; Hsu et al., 2021a; Hsu et al., 2021b). However, the opacity of these "black-box" models has prompted calls for frameworks that reconcile predictive performance with transparency to engender decision-makers' trust (Alvi et al., 2024; Chang et al., 2024; Giudici et al., 2019). Thus, current CRM practices represent a synthesis of traditional methodologies with sophisticated, data-driven techniques designed to meet market demands, while adhering to ethical and transparent standards in credit risk management (Doumpos et al., 2019; Kumari et al., 2024).

Further deepening the scope of CRM, researchers have explored its broader impact on bank performance beyond risk reduction alone (Temba et al., 2024). Strategic CRM has been associated with not only a reduction in default rates but also enhanced profitability and asset quality, underscoring CRM's potential as a driver of financial success (Duho et al., 2023; Eggleton et al., 2021; Zhang et al., 2016). In emerging markets such as Jordan, CRM is particularly challenging due to economic volatility and the subjective nature of some credit approval processes. Here, studies suggest that banks which adapt CRM strategies to fit local conditions are better able to manage risk and enhance their performance, though subjective decision-making still plays a role, especially in smaller institutions where CRM practices may not be as formalised (Bekhet & Eletter, 2012; Harb et al., 2023). These findings suggest that CRM, when effectively adapted to local and regulatory contexts, can serve as a competitive advantage in navigating the evolving landscape of modern banking.

2.2 Operational, Regulatory, and Technological Challenges in Credit Risk Management

Operational challenges within CRM stem from internal limitations, such as constrained resources, outdated infrastructure, and reliance on subjective decision-making (Fadun & Silwimba, 2023). In Jordan, many banks, especially smaller institutions, may struggle with these issues, as limited technological capacity and expertise hinder the implementation of advanced, data-driven risk assessment models (Cipovová & Dlasková, 2016; Elsilä, 2015). In such environments, CRM processes often rely on basic methodologies or human judgement, which can introduce bias and reduce the accuracy and consistency of risk assessments (Bastos & Matos, 2022; Becha et al., 2020). Limited resources also inhibit banks' ability to develop or attract staff with specialised CRM expertise, creating operational bottlenecks that restrict the adoption of systematic, data-oriented risk assessment tools (Al-Mhdawi, O'Connor, et al., 2023; Al-Mhdawi, Qazi, et al., 2023; Koopman & Lucas, 2005). This lack of operational flexibility prevents banks from evolving CRM practices in response to market demands, resulting in a cycle where limited capacity exacerbates exposure to external economic pressures (Hong et al., 2014).

Regulatory requirements add another layer of complexity, with frameworks such as the Basel Accords imposing strict capital and risk-weighted asset guidelines intended to promote systemic stability (Thakor, 2014). While these standards are crucial for reducing overall financial risk, they can restrict a bank's operational flexibility, particularly during economic downturns when maintaining capital reserves becomes more challenging (Drumond, 2009; Van Gestel & Baesens, 2009). For example, the procyclical effects of Basel II have been shown to tighten credit conditions during recessions, potentially undermining the stability that these frameworks are designed to support (Fraisse & Laporte, 2022). In emerging markets, regulatory compliance can impose a financial strain that reduces profitability and affects banks' competitive standing, requiring careful balancing between regulatory adherence and sustainable growth (Cipovová & Dlasková, 2016; Koulafetis, 2017).

Technological innovations, while offering significant benefits in terms of predictive power, also present banks with substantial integration and compliance challenges (Frame & White, 2014; Gong et al., 2022). Adopting advanced models such as machine learning requires substantial upfront investments in infrastructure, data management, and model validation processes (Barboza et al., 2017; Hsu et al., 2021a; Hsu et al., 2021b). The importance of adhering to established standards, as observed in other sectors such as satellite systems, where compliance improves reliability and mitigates critical failures, is similarly relevant for financial institutions managing CRM technologies (Xu et al., 2023). For Jordanian banks, integrating such technologies can be prohibitive where limited technical expertise and financial resources may exist between the potential of advanced CRM models and their practical application. Smaller institutions face barriers in acquiring the technical expertise and resources necessary to implement these technologies effectively, creating a gap between technological potential and practical application (Yan et al., 2015). Additionally, models such as deep learning algorithms often lack interpretability, which is a significant barrier to compliance, as regulatory bodies increasingly require transparency in CRM practices to avoid unethical or biased decision-making (Bussmann et al., 2021; Luo et al., 2017). This opacity is a substantial compliance issue, as regulatory bodies increasingly mandate transparency in AI-driven CRM processes to prevent unethical or biased outcomes (Dwivedi et al., 2021). Bussmann et al. (2021) suggest that explainable AI (XAI) models, such as those utilising Shapley value decomposition, can address this by providing variable-level contributions to model predictions, thereby enhancing transparency and accountability.

The use of Shapley values, derived from cooperative game theory, allows banks to break down each prediction by attributing portions of the outcome to specific variables (Černevičienė & Kabašinskas, 2024). This approach provides both a personalised and comprehensive explanation for each decision, addressing regulatory expectations for interpretability (Bussmann et al., 2021). However, implementing Shapley-based models also requires significant resources, from data preparation to post-processing analysis, further straining smaller institutions that may lack the technical or financial means to deploy these complex models effectively (Kockum & Dacre, 2021; Yan et al., 2015). Additionally, even though Shapley values improve model transparency, they increase computational demands, as calculating these values across extensive datasets is resource-intensive (Milojević & Redzepagic, 2021; Zhang, 2024). In the following table we summarise key CRM challenges supported by existing literature.

Table 1: CRM Challenges

Challenge Type	Description	Associated Best Practices	Impact on Performance
Operational	Resource constraints, outdated infrastructure, and reliance on subjective decision-making hinder credit risk assessments, particularly in smaller banks (Becha et al., 2020; Fadun & Silwimba, 2023).	Standardisation of training and processes, and data governance to reduce bias and improve consistency (Chen et al., 2024; Saltz et al., 2018).	Reduces risk through improved consistency, though it may limit adaptability for institutions with fewer resources (Cipovová & Dlasková, 2016).
Regulatory	Strict regulatory frameworks, such as Basel Accords, require capital reserves and risk-weighted assets, reducing operational flexibility (Bessis, 2011;	Compliance with Basel III guidelines, flexible capital allocation models to adapt to regulatory shifts (Drumond, 2009; Thakor, 2014).	Promotes stability but may constrain flexibility and profitability, especially during downturns (Fraisse & Laporte, 2022).

	Van Gestel & Baesens, 2009).		
Technological	Advanced models like machine learning are needed for predictive accuracy, but integration and compliance present challenges, especially in smaller banks (Bussmann et al., 2021; Luo et al., 2017).	Implementation of XAI models for transparency, alongside investments in data management and model validation (Bussmann et al., 2021; Černevičienė & Kabašinskas, 2024).	Enhances predictive accuracy and compliance but is resource-intensive, often inaccessible for smaller institutions (Yan et al., 2015).

In summary, our review of the literature suggests that CRM is essential for bank stability and profitability, especially amid economic volatility, regulatory demands, and rapid technological change (Bussmann et al., 2021; Saleh & Abu Afifa, 2020). While advanced CRM techniques such as machine learning enhance predictive accuracy, they also create operational and compliance challenges, particularly for smaller institutions in emerging markets (Černevičienė & Kabašinskas, 2024; Yan et al., 2015).

3. Methodology

This study employs a mixed-method research design to examine the mediating role of CRM best practices in mitigating the effects of credit risk challenges on bank performance (Greene et al., 1989; Reynolds & Dacre, 2019; Tashakkori, 2010). In the qualitative phase, we are conducting semi-structured interviews with a number of credit risk experts in Jordan to capture preliminary insights into prominent CRM challenges and effective practices specific to the region. Purposeful sampling guides the participant selection, focusing on individuals with extensive CRM experience to provide contextually relevant insights (Palinkas et al., 2015). Interview data are being analysed using thematic analysis, a technique that enables us to identify key themes related to economic, operational, regulatory, and technological challenges, along with foundational CRM best practices addressing these areas (Clarke & Braun, 2017).

In the subsequent quantitative phase, Partial Least Squares Structural Equation Modelling (PLS-SEM) will be employed to statistically validate the relationships identified during the qualitative phase. This model will allow us to assess both the direct and indirect effects of CRM challenges on bank performance, specifically focusing on the mediating role of CRM best practices (Sarstedt et al., 2021). PLS-SEM is well-suited to our exploratory goals due to its effectiveness in handling complex, multi-variable relationships and its suitability for smaller sample sizes (Chin, 1998). Through this mixed-method approach, we aim to provide a deeper understanding of the impact of CRM challenges on bank performance, alongside insights into the extent to which best practices can mediate these effects, offering valuable direction for practitioners and policymakers in the banking sector.

4. Results and Discussion

Our initial insights suggest that "best practices" in CRM represent a set of widely endorsed, systematic approaches developed to strengthen banks' abilities to identify, evaluate, and mitigate risks effectively, thus contributing to overall financial stability (Gavalas & Syriopoulos, 2014). However, through preliminary analysis, we observe that these best practices, while theoretically universal, face practical challenges when applied across institutions with varying sizes, resources, and operational constraints (Cheng et al., 2024). This observation is consistent with literature indicating that CRM frameworks must be tailored to the complex and dynamic financial environment, particularly as banks in emerging markets encounter distinct pressures and operational constraints (Harb et al., 2023; Mateev et al., 2021). This early finding underscores the need to critically examine how CRM best practices function in real-world settings, as their impact may vary significantly depending on the specific context of each bank. In order to clarify the practical impact of each best practice, we summarise the key CRM best practices in Table 2.

Table 2: CRM Best Practice

CRM Best Practice	Description	Impact on Performance
Data Governance Policies	Structured policies ensuring data accuracy, consistency, and compliance within CRM models (Alnor et al., 2024; Boot & Thakor, 2012).	Ensures reliable data for CRM, contributing to informed decision-making and regulatory compliance (Winkler, 2013).
Adaptive Capital Allocation	Flexible capital models that adjust reserves based on economic conditions to improve adaptability (Drumond, 2009; Thakor, 2014).	Enhances financial stability and resilience to market shifts, particularly in volatile environments (Fraisse & Laporte, 2022).
XAI Models	AI models with transparent, interpretable results that comply with regulatory standards (Bussmann et al., 2021; Černevičienė & Kabašinskas, 2024).	Improves predictive accuracy while meeting regulatory transparency requirements, supporting compliance (Dwivedi et al., 2021).
Standardised Training & Processes	Uniform training programs and process standardisation to reduce human bias in credit assessments (Chen et al., 2024; Saltz et al., 2018).	Increases assessment consistency, reduces bias, and strengthens risk management efficiency (Pokrovskaya, 2019).

At the core of CRM best practice lies data governance, a foundational approach to managing data integrity and compliance within CRM models (Alnor et al., 2024). Effective data governance is intended to ensure that the data underpinning risk models are accurate, consistent, and compliant with regulatory standards, thereby enabling more precise risk assessments and informed decision-making (Boot & Thakor, 2012). In practice, however, implementing data governance requires significant investment in infrastructure, analytics, and personnel, resources that smaller institutions may lack (Winkler, 2013). Consequently, smaller bank, lacking the resources to maintain high data governance standards, face increased vulnerability to data inconsistencies and regulatory pressures, challenging the feasibility of data governance as a universal best practice (Chen et al., 2024; Saltz et al., 2018), further emphasising the operational challenges highlighted in previous research (Cipovová & Dlasková, 2016).

From a regulatory perspective, best practices frequently emphasise flexible capital allocation models that align with Basel III guidelines, allowing banks to adapt their capital reserves in response to economic and regulatory shifts (Wen et al., 2013). As summarised in Table 1, regulatory frameworks like Basel III provide stability but can constrain operational flexibility, a challenge particularly noted in our findings. This flexibility benefits larger institutions operating in diverse markets by supporting competitive positioning within regulatory standards, whereas smaller banks find adaptive capital allocation models costly and complex, especially in liquidity-constrained downturns (Pantielieieva et al., 2020; Silva Buston, 2016). The regulatory best practice of adaptive capital reserves, while beneficial for systemic stability, thus becomes a liability for less-resourced institutions, which struggle to balance compliance costs with financial sustainability (Alsaleh et al., 2017). This issue resonates with the broader literature, which identifies Basel Accords as both a stabilising factor and a challenge to operational flexibility in CRM (Bessis, 2011; Van Gestel & Baesens, 2009).

The technological dimension of CRM best practice introduces additional challenges (Misheva et al., 2021). XAI models in particular, promise transparency in risk assessment by clarifying variable contributions to predictions, which is crucial for regulatory compliance, however, their implementation impose significant infrastructure, computational power, and expertise, making them inaccessible for many smaller institutions and highlighting a gap between innovation and practical application (Malik & Singh, 2020; Manukyan & Parsyan, 2024). Furthermore, the interpretability of XAI models introduces significant operational and financial burdens, as these methods require continuous auditing and recalibration to maintain compliance, thus intensifying the resource demands (Jiang et al., 2023). As a result, while XAI has emerged as a best practice in credit risk management for large banking institutions, its practical application remains constrained for smaller institutions that lack the capacity to meet the extensive resource commitments associated with these advanced technologies (Zhong et al., 2024).

Operational best practices in CRM also illustrate this imbalance. Standardising training, allocating resources, and minimising reliance on subjective judgement are recommended practices meant to enhance CRM efficacy across institutions (Dillnut, 2006). These practices, though designed to reduce bias and improve consistency, often impose procedural rigidity that can conflict with the need for flexibility in institutions operating in volatile or emerging markets, where strict adherence to uniform standards may hinder the agility required to respond to rapid market changes (Huysentruyt et al., 2021). Agile project management offers a practical framework to address this challenge, enabling institutions to adopt iterative and adaptive approaches that foster responsiveness to evolving CRM demands (Al-Mhdawi, Dacre, et al., 2023; Baxter et al., 2023; Dong et al., 2024; Zhang et al., 2023). Agile methodologies, which emphasise collaboration, flexibility, and incremental improvements, can equip banks to tackle operational and regulatory challenges effectively while maintaining efficiency in dynamic environments (Dong et al., 2021a, 2021b; Dong et al., 2022; Sonjit et al., 2021b).

Smaller institutions, however, may lack dedicated CRM personnel or automated risk management tools, requiring them to rely on more flexible but less standardised approaches that reflect the realities of their operating environments (Dacre, 2024; Dacre & Kockum, 2022b; Pokrovskaya, 2019; Sonjit et al., 2021a). In order to address these gaps, project management education for future professionals plays a critical role, equipping them with essential skills in resource management, risk mitigation, and strategic decision-making (Barber et al., 2021; Dacre, Eggleton, Cantone, et al., 2021; Gkogkidis & Dacre, 2023; Pontin & Dacre, 2024; Tite et al., 2021b). Such education strengthens the ability of banking professionals to implement CRM best practices while remaining responsive to dynamic and constrained environments (Dacre et al., 2014; Dacre et al., 2019). Thus, while operational best practices foster standardisation, they may inadvertently constrain the adaptability that certain institutions need to navigate diverse regulatory and economic landscapes effectively.

In sum, our preliminary insights suggest that while CRM best practices in data governance, regulatory compliance, technology, and operations provide a foundation for risk management, they may disproportionately benefit larger institutions with greater resources. Smaller institutions, meanwhile, face significant constraints in adopting these practices fully, highlighting a need for flexible best practices that can accommodate varying levels of institutional capacity. This conclusion reinforces the argument that CRM frameworks must be adaptable, particularly in the context of emerging markets where institutional constraints demand customised solutions (Harb et al., 2023; Nguyen et al., 2023). Moving forward, our study aims to investigate these insights further to support the development of adaptable best practices in CRM that foster resilience and stability across the banking sector, promoting a financial system where institutions of all sizes can effectively manage credit risk.

5. Conclusion

In this paper we set out to examine the impact of CRM challenges on bank performance, with particular focus on the mediating role of best practices within Jordan's banking sector. The primary contributions to knowledge lie in advancing the understanding of CRM dynamics in emerging markets, where economic pressures, regulatory shifts, and resource limitations create distinct challenges for banks (Harb et al., 2023; Saleh & Abu Afifa, 2020). The study extends existing literature by underscoring the importance of adaptive CRM frameworks that are tailored to local market conditions (Mateev et al., 2021). Additionally, it highlights the complexities associated with implementing data-driven CRM practices, especially the constraints faced by smaller institutions in adopting advanced technologies and meeting regulatory standards (Bussmann et al., 2021; Černevičienė & Kabašinskas, 2024). Innovative engagement methods in education, such as gamification, can enhance the learning experience for future professionals by making CRM concepts more accessible and practical (Antonopoulou & Dacre, 2021; Dacre et al., 2015; Dacre et al., 2022; Dacre et al., 2018; Gkogkidis & Dacre, 2020a, 2020b). Ensuring the sustainability of such educational initiatives is crucial to building long-term institutional capacity in emerging markets (Dacre, Yan, Frei, et al., 2024; Gkogkidis & Dacre, 2021; Tite et al., 2021a).

In terms of practical contributions, this research identifies specific best practices that strengthen risk management amidst diverse challenges, offering a framework that banks in emerging markets can employ to enhance stability and performance (Dillnut, 2006). Tables 1 and 2 consolidate these insights, presenting a structured summary of CRM challenges and the impact of best practices, which provide banks with a practical reference for implementing effective risk management strategies. Furthermore, the study emphasises the requirement of flexible CRM strategies that accommodate institutional resource disparities, thereby supporting smaller banks in effectively managing credit risk within constrained operational settings (Pokrovskaya, 2019).

However, as an ongoing study, the findings presented here are preliminary and subject to further refinement. The study's limitations include its focus on Jordan's banking sector, which may impact the generalisability of the findings to other emerging markets. Additionally, the sample size in the qualitative phase, while adequate for exploratory insights, restricts the depth of perspectives obtained from industry experts. As such several promising avenues exist for future research. Studies could examine CRM practices across various emerging markets, comparing how local economic and regulatory conditions shape CRM challenges and best practices (Babenko et al., 2021). Longitudinal studies would also be valuable for observing how CRM practices adapt over time in response to shifting regulatory frameworks, particularly as advancements in technology reshape CRM processes and data governance. Further research might also investigate the impact of CRM best practices on specific performance metrics, such as profitability and asset quality, or explore the potential of alternative CRM frameworks that incorporate emerging technologies such as XAI (Bussmann et al., 2021). Finally, sectoral studies within diverse banking environments could provide insights into how different types of financial institutions, ranging from small community banks to large multinational corporations, are affected by and respond to CRM challenges.

In conclusion, as the banking sector continues to evolve, the strategies and frameworks that underpin effective credit risk management must also advance. Embracing innovation and adaptability enables banks to mitigate risk while fostering sustainable growth and resilience in complex financial landscapes.

References

Adel, N., & Naili, M. (2024). Geopolitical risk and banking performance: evidence from emerging economies. *Journal of Risk Finance*, *25*(4), 646-663. https://doi.org/10.1108/JRF-10-2023-0243

Akhanolu, I. A., Ehimare, O. A., Mathias, C. M., Deborah, K. T., & Yvonne, O. K. (2020). The impact of credit risk management and macroeconomic variables on bank performance in Nigeria. *WSEAS Transactions on Business and Economics*, *17*, 947-955, Article 94. https://doi.org/10.37394/23207.2020.17.94

Al-Mhdawi, M. K. S., Dacre, N., Brito, M., Baxter, D., Xu, K., & Young, C. (2023). An Agile compliance framework for the European Cooperation for Space Standardization. *IEEE Aerospace*, 12. https://doi.org/10.1109/AERO55745.2023.10115917

Al-Mhdawi, M. K. S., O'Connor, A., Qazi, A., Dacre, N., & Al-Saedi, M. W. (2023). A Proposed Fuzzy-based Optimisation Model for Evaluating Construction Projects' Risk Response Strategies. *Applications of Statistics and Probability in Civil Engineering*, 9. https://www.tara.tcd.ie/handle/2262/103651

Al-Mhdawi, M. K. S., O'connor, A., Qazi, A., Rahimian, F., & Dacre, N. (2024). Review of studies on risk factors in critical infrastructure projects from 2011 to 2023. *Smart and Sustainable Built Environment*, 35. https://doi.org/10.1108/SASBE-09-2023-0285

Al-Mhdawi, M. K. S., Qazi, A., Alzarrad, A., Dacre, N., Rahimian, F., Buniya, M. K., & Zhang, H. (2023). Expert Evaluation of ChatGPT Performance for Risk Management Process Based on ISO 31000 Standard. *SSRN Electronic Journal*, 6. https://doi.org/10.2139/ssrn.4504409

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., Lal, B., & Williams, M. D. (2015). Consumer adoption of Internet banking in Jordan: Examining the role of hedonic motivation, habit, self-efficacy and trust. Journal of Financial Services Marketing,

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P. P., & Williams, M. D. (2016). Consumer adoption of mobile banking in Jordan: Examining the role of usefulness, ease of use, perceived risk and self-efficacy. *Journal of Enterprise Information Management*, *29*(1), 118-139. https://doi.org/10.1108/JEIM-04-2015-0035

Alnor, N. H. A., Mohammed, O. A. A., Al-Matari, E. M., Ahmed, A., Benlaria, H., Elhefni, A. H. M., Kouki, F., & Elshaabany, M. M. (2024). The role of bank governance in managing the risks associated with banking institutions.

International Journal of Advanced and Applied Sciences, *11*(4), 194-206. https://doi.org/10.21833/ijaas.2024.04.021
Alsaleh, M. N., Al-Shaer, E., & Husari, G. (2017). ROI-Driven Cyber Risk Mitigation Using Host Compliance and Network Configuration. *Journal of Network and Systems Management*, *25*(4), 759-783. https://doi.org/10.1007/s10922-017-9428-x
Altman, E. I., & Saunders, A. (1997). Credit risk measurement: Developments over the last 20 years. *Journal of banking & finance*, *21*(11-12), 1721-1742.
Alvi, J., Arif, I., & Nizam, K. (2024). Advancing financial resilience: A systematic review of default prediction models and future directions in credit risk management. *Heliyon*, *10*(21), Article e39770. https://doi.org/10.1016/j.heliyon.2024.e39770
Antonopoulou, K., & Dacre, N. (2021). Exploring Diffusion Characteristics that Influence Serious Games Adoption Decisions. *Innovation in Information Infrastructures*, 10. https://doi.org/10.48550/arXiv.2105.01745
Babenko, V., Panchyshyn, A., Zomchak, L., Nehrey, M., Artym-Drohomyretska, Z., & Lahotskyi, T. (2021). Classical machine learning methods in economics research: Macro and micro level examples. *WSEAS Transactions on Business and Economics*, *18*, 209-217. https://doi.org/10.37394/23207.2021.18.22
Bao, Y., Ke, B., Li, B., Yu, Y. J., & Zhang, J. (2020). Detecting accounting fraud in publicly traded US firms using a machine learning approach. *Journal of Accounting Research*, *58*(1), 199-235.
Barber, C., Dacre, N., & Dong, H. (2021). Reframing Project Management Process Paralysis: An Autoethnographic Study of the UK Fire Service. *Advanced Project Management*, *21*(6), 4. https://doi.org/10.31235/osf.io/hxm68
Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications*, *83*, 405-417. https://doi.org/10.1016/j.eswa.2017.04.006
Bastos, J. A., & Matos, S. M. (2022). Explainable models of credit losses. *European journal of operational research*, *301*(1), 386-394. https://doi.org/10.1016/j.ejor.2021.11.009
Baxter, D., Dacre, N., Dong, H., & Ceylan, S. (2023). Institutional challenges in agile adoption: Evidence from a public sector IT project. *Government Information Quarterly*, *40*(4), 15. https://doi.org/10.1016/j.giq.2023.101858
Becha, M., Dridi, O., Riabi, O., & Benmessaoud, Y. (2020). Use of machine learning techniques in financial forecasting. Proceedings of 2020 International Multi-Conference on: Organization of Knowledge and Advanced Technologies, OCTA 2020,
Bekhet, H. A., & Eletter, S. F. K. (2012). Credit risk management for the Jordanian commercial banks: A business intelligence approach. *Australian Journal of Basic and Applied Sciences*, *6*(9), 188-195. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84871686790&partnerID=40&md5=8beafff8f21dcacd87ddd7f524c2b596
Bessis, J. (2011). *Risk management in banking*. John Wiley & Sons.

Boot, A. W. A., & Thakor, A. V. (2012). The Accelerating Integration of Banks and Markets and its Implications for Regulation. In *The Oxford Handbook of Banking*. https://doi.org/10.1093/oxfordhb/9780199640935.013.0003

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5-32.

Brookes, N., Lattuf Flores, L., Dyer, R., Stewart, I., Wang, K., & Dacre, N. (2020). *Project Data Analytics: The State of the Art and Science*. Association for Project Management. https://doi.org/10.61175/wgsv1658

Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable Machine Learning in Credit Risk Management. *Computational Economics*, *57*(1), 203-216. https://doi.org/10.1007/s10614-020-10042-0

Cebenoyan, A. S., & Strahan, P. E. (2004). Risk management, capital structure and lending at banks. *Journal of banking & finance*, *28*(1), 19-43.

Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. *Artificial Intelligence Review*, *57*(8), 216.

Chang, V., Xu, Q. A., Akinloye, S. H., Benson, V., & Hall, K. (2024). Prediction of bank credit worthiness through credit risk analysis: an explainable machine learning study. *Annals of Operations Research*. https://doi.org/10.1007/s10479-024-06134-x

Chen, D., Chen, L., Zhang, Y., Lin, S., Ye, M., & Sølvsten, S. (2024). Automated fire risk assessment and mitigation in building blueprints using computer vision and deep generative models. *Advanced Engineering Informatics*, *62*, Article 102614. https://doi.org/10.1016/j.aei.2024.102614

Cheng, Y., Yang, Q., Wang, L., Xiang, A., & Zhang, J. (2024). Research on Credit Risk Early Warning Model of Commercial Banks Based on Neural Network Algorithm. *arXiv preprint arXiv:2405.10762*.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research/Lawrence Erlbaum Associates*.

Cipovová, E., & Dlasková, G. (2016). Comparison of different methods of credit risk management of the commercial bank to accelerate lending activities for SME segment. *European Research Studies Journal*, *19*(4), 17-26. https://doi.org/10.35808/ersj/577

Clarke, V., & Braun, V. (2017). Thematic analysis. *The journal of positive psychology*, *12*(3), 297-298.

Corbin, D., Marqui, A., & Dacre, N. (2024). The Intersection of Artificial Intelligence and Project Management in UK Construction: An Exploration of Emerging Trends, Enablers, and Barriers. *European Operations Management Association*, 16. https://doi.org/10.2139/ssrn.5015982

Dacre, N. (2024). *Diversity in project teams: purpose, progress and delivery*. Association for Project Management. https://www.apm.org.uk/v2/media/yskhsac5/diversity-in-project-teams-purpose-progress-and-delivery.pdf

Dacre, N., AlJaloudi, O., Thiam, M., Abdel Qader, M., Al-Mhdawi, M. K. S., & Qazi, A. (2024). Capturing Fintech's Role in Optimising Financial Risk Management. *Operational Research Society*, 9. https://doi.org/10.2139/ssrn.4985879

Dacre, N., Constantinides, P., & Nandhakumar, J. (2014). Instantiation of Organisational Routines in Cross-Expertise Collaborative Enterprise Systems. *Process Organization Studies*, 5. https://doi.org/10.31235/osf.io/ky8s7

Dacre, N., Constantinides, P., & Nandhakumar, J. (2015). How to Motivate and Engage Generation Clash of Clans at Work? Emergent Properties of Business Gamification Elements in the Digital Economy. *International Gamification for Business*, 11. https://doi.org/10.48550/arXiv.2103.12832

Dacre, N., Dong, H., Gkogkidis, V., & Kockum, F. (2022). Innovative Strategies for Distance Learning: Gamification, Serious Play, and Miro in the Development of Project Management Competencies *Operational Research Society*, 22. https://doi.org/10.2139/ssrn.4997288

Dacre, N., Eggleton, D., Cantone, B., & Gkogkidis, V. (2021). Why People Skills Lead to Project Success: Towards Dynamic Conditions for People Skills and Leadership in Project Management *Project*, *307*, 14. https://doi.org/10.2139/ssrn.4998962

Dacre, N., Eggleton, D., Gkogkidis, V., & Cantone, B. (2021). Expanding the Paradigm of Project Success: A Review of Diversity as a Critical Success Condition in Project Management *SSRN Electronic Journal*, 23. https://doi.org/10.2139/ssrn.5001594

Dacre, N., Gkogkidis, V., & Jenkins, P. (2018). Co-Creation of Innovative Gamification Based Learning: A Case of Synchronous Partnership. *Society for Research into Higher Education*, 6. https://doi.org/10.48550/arXiv.2103.13273

Dacre, N., & Kockum, F. (2022a). *Artificial Intelligence in Project Management: A review of AI's usefulness and future considerations for the project profession*. Association for Project Management. https://doi.org/10.61175/DOGX9829

Dacre, N., & Kockum, F. (2022b). Strategic Project Leadership: The Case for Integrating Systems Thinking and Artificial Intelligence *Operational Research Society*, 20. https://doi.org/10.2139/ssrn.5015629

Dacre, N., Kockum, F., & Senyo, P. (2020). Transient Information Adaptation of Artificial Intelligence: Towards Sustainable Data Processes in Complex Projects. *British Academy of Management*, *2*(63), 9. https://doi.org/10.48550/arXiv.2104.04067

Dacre, N., Senyo, P., & Reynolds, D. (2019). Is an Engineering Project Management Degree Worth it? Developing Agile Digital Skills for Future Practice. *Engineering Education Research Network*, 8. https://doi.org/10.31235/osf.io/4b2gs

Dacre, N., Yan, J., Dong, H., Al-Mhdawi, M. K. S., & Frei, R. (2024). Assessing the Influence of Industry 5.0 on Supply Chain Integration and Performance: An Empirical Analysis within the Manufacturing Sector. *Operational Research Society*, 12. https://doi.org/10.36227/techrxiv.173091022.25517688/v1

Dacre, N., Yan, J., Frei, R., Al-Mhdawi, M. K. S., & Dong, H. (2024). Advancing sustainable manufacturing: a systematic exploration of industry 5.0 supply chains for sustainability, human-centricity, and resilience. *Production Planning & Control*, 31. https://doi.org/10.1080/09537287.2024.2380361

Dillnut, R. (2006). Surviving the information explosion. *Engineering Management*, *16*(1), 39-41. https://doi.org/10.1049/em:20060109
Dong, H., & Dacre, N. (2024). Commutable Strategies and Institutional Dynamics in Agricultural Co-operatives: A Project Management Perspective on Crisis Resilience and Sustainability *Earth and Space Science*, 22. https://doi.org/10.22541/essoar.173134645.56504196/v1
Dong, H., Dacre, N., & Bailey, A. (2021a). Sustainability in Complex Agriculture Projects: A Study of Agile Agricultural Co-operative Institutions. *British Academy of Management*, 10. https://doi.org/10.2139/ssrn.3879454
Dong, H., Dacre, N., & Bailey, A. (2021b). Sustainable Agile Project Management in Complex Agriculture Projects: An Institutional Theory Perspective. *Advanced Project Management*, *21*(3), 7. https://doi.org/10.31235/osf.io/v4je2
Dong, H., Dacre, N., Baxter, D., & Ceylan, S. (2022). *Understanding Agile in Project Management*. Association for Project Management. https://doi.org/10.61175/PUSU1455
Dong, H., Dacre, N., Baxter, D., & Ceylan, S. (2024). What is agile project management? Developing a new definition following a systematic literature review. *Project Management Journal*, 21. https://doi.org/10.1177/87569728241254095
Doumpos, M., Lemonakis, C., Niklis, D., & Zopounidis, C. (2019). Introduction to Credit Risk Modeling and Assessment. In *EURO Advanced Tutorials on Operational Research* (pp. 1-21). https://doi.org/10.1007/978-3-319-99411-6_1
Drumond, I. (2009). Bank capital requirements, business cycle fluctuations and the basel accords: A synthesis. *Journal of Economic Surveys*, *23*(5), 798-830. https://doi.org/10.1111/j.1467-6419.2009.00605.x
Duho, K. C. T., Duho, D. M., & Forson, J. A. (2023). Impact of income diversification strategy on credit risk and market risk among microfinance institutions. *Journal of Economic and Administrative Sciences*, *39*(2), 523-546. https://doi.org/10.1108/JEAS-09-2020-0166
Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., & Eirug, A. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, *57*, 101994.
Eggleton, D., Dacre, N., Cantone, B., & Gkogkidis, V. (2021). *Dynamic conditions for project success*. Association for Project Management. https://doi.org/10.61175/FXCU4654
Eggleton, D., Dacre, N., Cantone, B., & Gkogkidis, V. (2023). From hypothesis to evidence: testing the Ika and Pinto four dimensional model of project success. *British Academy of Management*, 23. https://doi.org/10.2139/ssrn.5003846
Elsilä, A. (2015). Trade Credit Risk Management: The Role of Executive Risk-Taking Incentives. *Journal of Business Finance and Accounting*, *42*(9-10), 1188-1215. https://doi.org/10.1111/jbfa.12130

Fadun, O. S., & Silwimba, P. (2023). Does credit risk management impact the financial performance of commercial banks? *International Journal of Business Ecosystem & Strategy (2687-2293)*, *5*(2), 55-66.

Fraisse, H., & Laporte, M. (2022). Return on investment on artificial intelligence: The case of bank capital requirement. *Journal of Banking and Finance*, *138*, Article 106401. https://doi.org/10.1016/j.jbankfin.2022.106401

Frame, W. S., & White, L. J. (2014). *Technological change, financial innovation, and diffusion in banking*. SSRN.

Gavalas, D., & Syriopoulos, T. (2014). Bank credit risk management and rating migration analysis on the business cycle. *International Journal of Financial Studies*, *2*(1), 122-143.

Giudici, P., Hadji-Misheva, B., & Spelta, A. (2019). Network Based Scoring Models to Improve Credit Risk Management in Peer to Peer Lending Platforms. *Frontiers in Artificial Intelligence*, *2*, Article 3. https://doi.org/10.3389/frai.2019.00003

Gkogkidis, V., & Dacre, N. (2020a). Co-Creating Educational Project Management Board Games to Enhance Student Engagement. *Game Based Learning*, 15. https://doi.org/10.48550/arXiv.2104.04063

Gkogkidis, V., & Dacre, N. (2020b). Exploratory Learning Environments for Responsible Management Education Using Lego Serious Play. *ArXiv Computers and Society* 13. https://doi.org/10.48550/arXiv.2104.12539

Gkogkidis, V., & Dacre, N. (2021). How to use Lego Serious Play as a Gamification Teaching and Learning Framework? A Responsible Management Approach. *SocArxiv*, 13. https://doi.org/10.31235/osf.io/vdzsu

Gkogkidis, V., & Dacre, N. (2023). The educator's LSP journey: creating exploratory learning environments for responsible management education using Lego Serious Play. *Emerald Open Research*, *1*(12), 16. https://doi.org/10.1108/EOR-12-2023-0004

Gong, Z., Dacre, N., & Dong, H. (2022). Fostering digital transformation through project integration management. *British Academy of Management*, 19. https://doi.org/10.2139/ssrn.5003601

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational evaluation and policy analysis*, *11*(3), 255-274.

Harb, E., El Khoury, R., Mansour, N., & Daou, R. (2023). Risk management and bank performance: evidence from the MENA region. *Journal of Financial Reporting and Accounting*, *21*(5), 974-998. https://doi.org/10.1108/JFRA-07-2021-0189

Hong, L. J., Juneja, S., & Luo, J. (2014). Estimating sensitivities of portfolio credit risk using Monte Carlo. *INFORMS Journal on Computing*, *26*(4), 848-865. https://doi.org/10.1287/ijoc.2014.0602

Hsu, M.-w., Dacre, N., & Senyo, P. (2021a). Identifying Inter-Project Relationships with Recurrent Neural Networks: Towards an AI Framework of Project Success Prediction. *British Academy of Management*, 8. https://doi.org/10.2139/ssrn.3880328

Hsu, M.-w., Dacre, N., & Senyo, P. K. (2021b). Applied Algorithmic Machine Learning for Intelligent Project Prediction: Towards an AI Framework of

Project Success. *Advanced Project Management*, *21*, 6. https://doi.org/10.31235/osf.io/6hfje

Huysentruyt, K., Kjoersvik, O., Dobracki, P., Savage, E., Mishalov, E., Cherry, M., Leonard, E., Taylor, R., Patel, B., & Abatemarco, D. (2021). Validating Intelligent Automation Systems in Pharmacovigilance: Insights from Good Manufacturing Practices. *Drug Safety*, *44*(3), 261-272. https://doi.org/10.1007/s40264-020-01030-2

Ismail, S., & Ahmed, E. (2023). The impact of liquidity risk, credit risk, and operational risk on financial stability in conventional banks in Jordan. *Uncertain Supply Chain Management*, *11*(2), 433-442. https://doi.org/10.5267/j.uscm.2023.3.006

Jiang, M., Chen, L., Blome, C., & Jia, F. (2023). Digital technology adoption for modern slavery risk mitigation in supply chains: An institutional perspective. *Technological Forecasting and Social Change*, *192*, Article 122595. https://doi.org/10.1016/j.techfore.2023.122595

Jiménez, G., & Saurina, J. (2004). Collateral, type of lender and relationship banking as determinants of credit risk. *Journal of Banking and Finance*, *28*(9), 2191-2212. https://doi.org/10.1016/j.jbankfin.2003.09.002

Jungo, J., Madaleno, M., & Botelho, A. (2022). The Effect of Financial Inclusion and Competitiveness on Financial Stability: Why Financial Regulation Matters in Developing Countries? *Journal of Risk and Financial Management*, *15*(3), Article 122. https://doi.org/10.3390/jrfm15030122

Kashyap, A. K., & Stein, J. C. (2004). Cyclical implications of the Basel II capital standards. *Economic Perspectives-Federal Reserve Bank Of Chicago*, *28*(1), 18-33.

Kockum, F., & Dacre, N. (2021). Project Management Volume, Velocity, Variety: A Big Data Dynamics Approach. *Advanced Project Management*, *21*, 6. https://doi.org/10.31235/osf.io/k3h9r

Koopman, S. J., & Lucas, A. (2005). Business and default cycles for credit risk. *Journal of Applied Econometrics*, *20*(2), 311-323. https://doi.org/10.1002/jae.833

Koulafetis, P. (2017). *Modern credit risk management: Theory and practice*. https://doi.org/10.1057/978-1-137-52407-2

Kumari, B., Kaur, J., & Swami, S. (2024). Adoption of artificial intelligence in financial services: a policy framework. *Journal of Science and Technology Policy Management*, *15*(2), 396-417. https://doi.org/10.1108/JSTPM-03-2022-0062

Luo, C., Wu, D., & Wu, D. (2017). A deep learning approach for credit scoring using credit default swaps. *Engineering Applications of Artificial Intelligence*, *65*, 465-470. https://doi.org/10.1016/j.engappai.2016.12.002

Malik, V., & Singh, S. (2020). Artificial intelligent environments: Risk management and quality assurance implementation. *Journal of Discrete Mathematical Sciences and Cryptography*, *23*(1), 187-195. https://doi.org/10.1080/09720529.2020.1721883

Manh, P. L., Dabscheck, D., Simpson, A., Temes, P., Shehhi, H. A., Balushi, Z. A., Jindong, Z., Li, Z., Jiang, F., Garro, F., Singh, D., Ojekhekpen, F., Guha, A., Montgomery, O., Metpally, F., Kapoor, V., Griffiths, M., Mathur, M., Aguiñaga, G. A., . . . Dacre, N. (2024). *Pulse of the Profession 2024 The Future of Project Work*. Project Management Institute. https://www.pmi.org/-/media/pmi/documents/public/pdf/learning/thought-leadership/pmi-pulse-of-the-profession-2024-report.pdf

Manukyan, H., & Parsyan, S. (2024). CUSTOMER CREDIT WORTHINESS IN THE DIGITAL AGE: A MANAGEMENT APPROACH TO MACHINE LEARNING APPLICATION IN BANKING. *Proceedings on Engineering Sciences*, *6*(2), 665-672. https://doi.org/10.24874/PES06.02.023

Mateev, M., Tariq, M. U., & Sahyouni, A. (2021). Competition, capital growth and risk-taking in emerging markets: Policy implications for banking sector stability during COVID-19 pandemic. *PLoS ONE*, *16*(6 June), Article e0253803. https://doi.org/10.1371/journal.pone.0253803

Milojević, N., & Redzepagic, S. (2021). Prospects of Artificial Intelligence and Machine Learning Application in Banking Risk Management. *Journal of Central Banking Theory and Practice*, *10*(3), 41-57. https://doi.org/10.2478/jcbtp-2021-0023

Misheva, B. H., Osterrieder, J., Hirsa, A., Kulkarni, O., & Lin, S. F. (2021). Explainable AI in credit risk management. *arXiv preprint arXiv:2103.00949*.

Mohamed, M., Al-Mhdawi, M. K. S., Dacre, N., Ojiako, U., Qazi, A., & Rahimian, F. (2024). Theoretical and Practical Instantiations of Generative AI in Construction Risk Management: An Analytical Exposition of Its Latent Benefits and Inherent Risks. *Sage Advance*, 14. https://doi.org/10.31124/advance.173139703.39850030/v1

Montevechi, A. A., Miranda, R. D. C., Medeiros, A. L., & Montevechi, J. A. B. (2024). Advancing credit risk modelling with Machine Learning: A comprehensive review of the state-of-the-art. *Engineering Applications of Artificial Intelligence*, *137*, Article 109082. https://doi.org/10.1016/j.engappai.2024.109082

Nguyen, H. H., Viviani, J. L., & Ben Jabeur, S. (2023). Bankruptcy prediction using machine learning and Shapley additive explanations. *Review of Quantitative Finance and Accounting*. https://doi.org/10.1007/s11156-023-01192-x

Nguyen, H. T. K., & Nguyen, D. T. (2018). Globalisation and bank performance in Vietnam. *Malaysian Journal of Economic Studies*, *55*(1), 49-70. https://doi.org/10.22452/mjes.vol55no1.3

Oke, M. O., & Wale-Awe, O. I. (2018). Credit risk management and financial performance among deposit money banks in nigeria: A case study of zenith bank PLC. *Forum Scientiae Oeconomia*, *6*(4), 23-36. https://doi.org/10.23762/FSO_VOL6_NO4_2

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and policy in mental health and mental health services research*, *42*, 533-544.

Pantielieieva, N., Khutorna, M., Lytvynenko, O., & Potapenko, L. (2020). FinTech, RegTech and Traditional Financial Intermediation: Trends and Threats for Financial Stability. In *Lecture Notes on Data Engineering and Communications Technologies* (Vol. 42, pp. 1-21). https://doi.org/10.1007/978-3-030-35649-1_1

Pokrovskaya, M. (2019). Risk mitigation based on innovative solutions. Proceedings of the International Astronautical Congress, IAC,

Pontin, D., & Dacre, N. (2024). The future of project management simulation exercises. *Engineering Education Research Network*, 14. https://doi.org/10.2139/ssrn.5003143

Reddy, K. S., Nangia, V. K., & Agrawal, R. (2014). The 2007–2008 Global Financial Crisis, and Cross-border Mergers and Acquisitions: A 26-nation Exploratory Study. *Global Journal of Emerging Market Economies*, *6*(3), 257-281. https://doi.org/10.1177/0974910114540720

Reynolds, D., & Dacre, N. (2019). Interdisciplinary Research Methodologies in Engineering Education Research. *Engineering Education Research Network*, 7. https://doi.org/10.48550/arXiv.2104.04062

Saleh, I., & Abu Afifa, M. (2020). The effect of credit risk, liquidity risk and bank capital on bank profitability: Evidence from an emerging market. *Cogent Economics & Finance*, *8*(1), 1814509.

Saltz, J., Goul, M., Armour, F., & Sharda, R. (2018). Key Management and Governance Challenges when Executing Data Science / Analytics Projects. Americas Conference on Information Systems 2018: Digital Disruption, AMCIS 2018,

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Springer.

Saunders, A., & Allen, L. (2010). *Credit risk management in and out of the financial crisis: new approaches to value at risk and other paradigms*. John Wiley & Sons.

Silva Buston, C. (2016). Active risk management and banking stability. *Journal of Banking and Finance*, *72*, S203-S215. https://doi.org/10.1016/j.jbankfin.2015.02.004

Sonjit, P., Dacre, N., & Baxter, D. (2021a). *Covid-19 & Homeworking Project Management Agility as the New Normal* British Academy of Management, Online, UK.

Sonjit, P., Dacre, N., & Baxter, D. (2021b). Disruption and Agility Dynamics in Project Management Processes: An Institutional Theory Approach. *Advanced Project Management*, *21*(7), 4. https://doi.org/10.2139/ssrn.3830762

Sonjit, P., Dacre, N., & Baxter, D. (2021c). Homeworking Project Management & Agility as the New Normal in a Covid-19 World. *Advanced Project Management*, *21*(5), 5. https://doi.org/10.2139/ssrn.3823901

Tashakkori, A. (2010). *SAGE handbook of mixed methods in social & behavioral research*. Sage.

Temba, G. I., Kasoga, P. S., & Keregero, C. M. (2024). Impact of the quality of credit risk management practices on financial performance of commercial banks in Tanzania. *SN Business & Economics*, *4*(3), 38.

Thakor, A. V. (2014). Bank capital and financial stability: An economic trade-off or a Faustian bargain? *Annu. Rev. Financ. Econ.*, *6*(1), 185-223.

Tite, C. N. J., Pontin, D., & Dacre, N. (2021a). Embedding Sustainability in Complex Projects: A Pedagogic Practice Simulation Approach. *Advanced Project Management*, *21*, 7. https://doi.org/10.48550/arXiv.2104.04068

Tite, C. N. J., Pontin, D., & Dacre, N. (2021b). Inspiring the Next Generation of Project Managers: Embedding Sustainability in Engineering Projects through Project Management Teaching and Learning. *Ingenium*, 9. https://doi.org/10.2139/ssrn.3880499

Van Gestel, T., & Baesens, B. (2009). *Credit Risk Management: Basic Concepts Financial Risk Components, Rating Analysis, Models, Economic and Regulatory Capital* (Vol. 9780199545117). https://doi.org/10.1093/acprof:oso/9780199545117.001.0001

Wen, Z., Peng, X., Liu, X., Sun, X., & Bai, X. (2013). Asset allocation under the basel accord risk measures. *arXiv preprint arXiv:1308.1321*.

Winkler, T. J. (2013). IT governance mechanisms and administration/IT alignment in the public sector: A conceptual model and case validation.

Xu, K., Brito, M., Young, C., Al-Mhdawi, M. K. S., Dacre, N., & Baxter, D. (2023). *Statistical analysis and modelling of small satellite reliability* 33rd European Safety and Reliability Conference, Southampton, UK. https://doi.org/10.3850/978-981-18-8071-1_P627-cd

Yan, J., Yu, W., & Zhao, J. L. (2015). How signaling and search costs affect information asymmetry in P2P lending: the economics of big data. *Financial Innovation*, *1*(1), Article 19. https://doi.org/10.1186/s40854-015-0018-1

Zhang, F., Tadikamalla, P. R., & Shang, J. (2016). Corporate credit-risk evaluation system: Integrating explicit and implicit financial performances. *International Journal of Production Economics*, *177*, 77-100. https://doi.org/10.1016/j.ijpe.2016.04.012

Zhang, S. (2024). Research on Personal Credit Risk Prediction Based on Soft Voting Ensemble Learning. ACM International Conference Proceeding Series,

Zhang, Y., Dong, H., Baxter, D., & Dacre, N. (2023). Agile Meets Digital: A Systematic Literature Review on the Interplay between Agile Project Management and Digital Transformation *British Academy of Management*, 16. https://doi.org/10.2139/ssrn.5007866

Zhong, J., Wang, X., & Zhang, T. (2024). Network Security Governance Policy and Risk Management: Research on Challenges and Coping Strategies. *Journal of Machine and Computing*, *4*(1), 153-169. https://doi.org/10.53759/7669/jmc202404015