International Journal of *Financial Studies*

MDPI

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From ESG to Financial Stability: Unpacking the Multi-Dimensional Impact of AI-Driven FinTech-Related Technology Adoption on Bank Performance

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Abstract

This study examines the association between Saudi banks' internal adoption of AI-enabled FinTech-related digital tools and their financial performance, sustainability performance, and financial stability over the period 2015–2024. Using a panel dataset of 10 banks, the analysis investigates how the adoption of AI-driven technologies—such as machine-learning credit assessment, robo-advisory systems, and automated compliance tools—is related to market performance (Tobin's Q), accounting performance (ROA and ROE), financial stability (Z-Score), and sustainability outcomes measured by both Bloomberg ESG Disclosure Score and the LSEG ESG performance-oriented score. To ensure robust inference and reduce simultaneity concerns, the empirical strategy employs Pooled OLS and Fixed Effects Models with Driscoll–Kraay standard errors, as well as a dynamic Fixed Effects Models incorporating lagged dependent variables, lagged independent variables, and shock-interaction terms. Bank-specific characteristics—including size, age, leverage, liquidity, loan-to-deposit ratio, non-performing loans, net interest margin, market capitalization, and board size—are included as controls. The findings indicate a positive and statistically significant relationship between banks' internal adoption of AI-enabled digital/FinTech-related technologies and their financial performance, sustainability performance, and financial stability. These relationships remain robust across estimation approaches, providing insights for policymakers, regulators, and bank managers seeking to advance digital transformation while safeguarding financial soundness and supporting sustainable development in the Saudi banking sector.

Keywords: digital transformation; AI-enabled FinTech-related technologies; Tobin's Q; ROA; ROE; ESG disclosure; ESG performance; Z-SCORE; Saudi banks

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Academic Editor: Aivars Spilbergs

Received: 16 October 2025
Revised: 29 November 2025
Accepted: 3 December 2025
Published: 8 December 2025

Citation: Hamdouni, A. (2025). From ESG to Financial Stability: Unpacking the Multi-Dimensional Impact of AI-Driven FinTech-Related Technology Adoption on Bank Performance. *International Journal of Financial Studies*, *13*(4), 234. https://doi.org/10.3390/ijfs13040234

1. Introduction

In recent years, the rapid evolution of financial technology (FinTech) has transformed the global banking landscape, reshaping how financial services are delivered, consumed, and regulated. FinTech encompasses a wide range of innovations, including digital payments, mobile banking, peer-to-peer lending, blockchain-based solutions, automated credit assessment, and wealth management platforms (Almubarak & Aljughaiman, 2024; Kazachenok et al., 2023; Lamey et al., 2024). These technologies have the potential to significantly enhance bank performance by improving operational efficiency, reducing transaction costs, enhancing risk management, and facilitating access to financial services for a broader range of customers. For banks in emerging markets such as Saudi Arabia, adopting FinTech-related technologies represents both a strategic opportunity for growth and a mechanism to strengthen financial stability and resilience in a dynamic economic environment.

A growing share of FinTech innovation today is powered by artificial intelligence (AI), which serves as the analytical core of many digital banking solutions. AI technologies—such as machine learning, natural language processing, and predictive analytics—enable banks to automate decision-making, personalize financial services, and enhance regulatory compliance. Applications like automated credit assessment, robo-advisory services, fraud detection systems, and intelligent chatbots have redefined how banks assess risk, manage customer relationships, and ensure operational efficiency (Oladapo, 2024; C. Zhang & Yang, 2024). In this context, AI-enabled FinTech adoption by incumbent banks is best understood as AI integration within internal banking processes, as digital transformation increasingly depends on data-driven intelligence. By embedding AI into core financial activities, banks improve operational performance and customer experience while enhancing transparency, ESG monitoring, and long-term financial stability. Thus, examining banks' adoption of AI-enabled, FinTech-related technologies captures the broader AI-driven transformation currently reshaping the future of financial intermediation in Saudi Arabia.

Alongside the financial benefits, there is growing recognition that banks' adoption of AI-enabled, FinTech-related technologies may also influence sustainability performance. Environmental, social, and governance (ESG) considerations have become central to both regulatory frameworks and investor expectations, and banks are increasingly expected to integrate sustainable practices into their operations (Hamdouni, 2025c). By leveraging digital innovations, banks can more effectively monitor and manage ESG risks, improve transparency, and enhance reporting practices. For instance, advanced data analytics and digital monitoring tools can track environmental risks associated with lending portfolios, while digital platforms can improve stakeholder engagement and corporate governance practices. Therefore, understanding the dual impact of AI-enabled, FinTech-related technology adoption by banks on financial performance and sustainability is critical for both practitioners and policymakers, particularly in regions undergoing rapid economic transformation like the Kingdom of Saudi Arabia.

The rapid advancement of financial technologies (FinTech) has transformed the global financial landscape by introducing innovative mechanisms that enhance efficiency, accessibility, and transparency in financial services (Alshi, 2025). FinTech encompasses a wide range of technological innovations—from digital payments and blockchain to AI and open banking—that are reshaping the competitive dynamics of financial institutions (Shakir, 2022). In this study, the term "FinTech adoption by banks" refers specifically to the internal digital transformation of incumbent banks through the integration of FinTech-related tools and AI technologies, rather than to independent FinTech firms. This framing aligns with regulatory and academic distinctions between FinTech as new entrants and digital transformation within traditional banks. In this evolving environment, understanding how AI-enabled, FinTech-related technology adoption by banks influences financial outcomes has become a critical area of inquiry, particularly in emerging economies where technological and institutional transformation is still underway. The integration of FinTech is not merely a technological trend but a strategic necessity that influences profitability, risk management, and long-term sustainability.

Theoretical perspectives provide a structured foundation for understanding how banks' adoption of AI-enabled, FinTech-related technologies can influence firm outcomes. According to the Diffusion of Innovation (DOI) theory, technological adoption depends on perceived usefulness, compatibility, and relative advantage, suggesting that banks more inclined to innovate are better positioned to achieve superior performance. The Resource-

Based View (RBV) posits that FinTech capabilities constitute valuable, rare, and hard-to-imitate resources that enhance competitive advantage and firm value. Meanwhile, the Technology–Organization–Environment (TOE) framework emphasizes that technological readiness, organizational structure, and regulatory support collectively determine the extent and success of FinTech implementation. Together, these theories offer a comprehensive lens through which to understand why AI-enabled, FinTech-related technology adoption by banks leads to variations in financial performance, stability, and sustainability across institutions and over time.

Saudi Arabia provides an ideal setting for studying this relationship. The Kingdom's Vision 2030 outlines an ambitious national transformation plan that seeks to diversify the economy, reduce dependence on oil revenues, and promote digital innovation across sectors. Within this framework, the Financial Sector Development Program (FSDP) aims to build a diversified and innovative financial system, with total banking assets projected to increase from SAR 2.6 trillion in 2019 to SAR 4.6 trillion by 2030. A central pillar of Vision 2030 is the creation of a cashless society, targeting over 80% non-cash retail transactions by 2030. Remarkably, Saudi Arabia achieved 79% digital retail payments by 2024, surpassing interim goals set for 2025. The country's fintech ecosystem has expanded rapidly, with more than 226 active fintech companies and over USD 1.1 billion in total investments recorded by 2023. Internet penetration has grown from 68.5% in 2015 to nearly 99% in 2023, and smartphone penetration now exceeds 92%, underscoring the strong digital infrastructure that supports this transformation.

These developments illustrate how Saudi Arabia's financial landscape is undergoing a profound technological evolution that directly aligns with Vision 2030's objectives of fostering innovation and financial inclusion. The Saudi Central Bank (SAMA) and the Capital Market Authority (CMA) have established regulatory sandboxes and open banking frameworks to accelerate FinTech experimentation, reflecting an institutional commitment to digital finance. Within this context, this study examines how incumbent Saudi banks adopt AI-enabled FinTech-related digital tools—including AI-driven solutions, blockchain applications, and digital platforms—as part of internal digital transformation strategies and how such adoption affects financial and sustainability outcomes.

Despite the growing theoretical and practical significance of FinTech, empirical research examining its effects within the Saudi banking sector remains limited. Most existing studies have primarily focused on developed markets, leaving a gap in understanding how digital financial innovations influence bank performance in emerging economies characterized by distinct regulatory, technological, and market conditions (Al-Matari et al., 2022; Chand et al., 2025; Kayed et al., 2024; Meero, 2025; J. Wang et al., 2023a; Yoon et al., 2023). Furthermore, prior research has often examined financial and ESG performance in isolation, without considering their interrelated dynamics (Almaqtari et al., 2025; Hamdouni, 2025b; Huang et al., 2025). Consequently, a clear gap remains in understanding how banks' adoption of AI-enabled, FinTech-related technologies simultaneously influences financial performance, financial stability, and ESG outcomes within Middle Eastern banking systems. This study addresses this gap by providing empirical evidence from the Saudi banking sector.

Building on this gap, the present study investigates the association between Saudi banks' internal adoption of AI-enabled FinTech-related digital tools—such as machine-learning credit assessment, robo-advisory systems, and automated compliance tools—and multiple performance dimensions, including market performance (Tobin's Q), accounting performance (ROA and ROE), financial stability (Z-Score), and sustainability outcomes (ESG_SCORE). The study employs a panel dataset of 10 listed Saudi banks over the period 2015–2024, providing a comprehensive analysis of both long-term trends and short-term dynamics. Financial performance is measured using Tobin's Q, Return on Assets (ROA), and the Z-SCORE as a measure of financial stability, while ESG performance is proxied by the Bloomberg ESG composite score. The key independent variable, AI-enabled FinTech adoption by banks, is captured through AI-enabled FinTech adoption index that encompasses multiple dimensions of digital financial innovation, including digital payments, lending, wealth management, banking infrastructure, RegTech, and emerging technologies such as blockchain. Control variables include bank-specific characteristics such as size, age, leverage, liquidity, loan-to-deposit ratio, non-performing loans, net interest margin, board size, and market capitalization, which are widely recognized in the literature as determinants of bank performance and risk.

Methodologically, the study employs a robust empirical framework, including Pooled Ordinary Least Squares (POLS), Fixed Effects Models (FEM) with Driscoll–Kraay standard errors and a dynamic FEM incorporating lagged dependent and lagged independent variables, as well as shock-interaction terms. This multi-method approach addresses common challenges in panel data analysis, such as endogeneity, cross-sectional dependence, heterogeneity, and autocorrelation. By applying this comprehensive set of estimators, the study provides reliable and robust evidence on the relationship between banks' internal adoption of AI-enabled FinTech-related technologies and their financial performance, financial stability, and sustainability outcomes in the Saudi banking sector.

The objectives of this study are threefold: (1) to assess the relationship between AI-enabled FinTech adoption by banks and financial performance, including market-based, accounting-based, and stability measures; (2) to examine the relationship between AI-enabled FinTech adoption by banks and ESG performance; and (3) to provide managerial and policy implications for fostering technological innovation, financial resilience, and sustainable practices in Saudi banks. The findings are expected to offer actionable insights for bank managers, investors, and regulators, while also contributing to the broader literature on digital finance and sustainable banking practices in emerging economies.

The remainder of the paper is structured as follows: Section 2 reviews the existing literature; Section 3 presents the data sources and research methodology; Section 4 reports and interprets the empirical findings; Section 5 discusses the implications; and Section 6 concludes the study.

2. Literature Review

2.1. Conceptual Framing

FinTech refers to the integration of advanced digital technologies—such as AI, big data, and blockchain—into financial intermediation processes. In this study, FinTech adoption by banks denotes the internal adoption of FinTech-related digital tools by incumbent banks, rather than the emergence of stand-alone FinTech startups (Boot, 2000; DeYoung, 2005; Arner et al., 2015; Boot et al., 2021; Thakor, 2020). This framing allows the analysis to focus on how banks deploy digital tools to improve efficiency, stability, and sustainability.

Digital banking theory posits that technological innovation transforms the structure of intermediation by reducing information asymmetry, enhancing monitoring, and lowering transaction costs, which in turn affects profitability and risk (Boot, 2000; DeYoung, 2005; Thakor, 2020).

At the same time, FinTech introduces new technological and operational risks—such as model risk, cyber threats, and cloud-service concentration—that can undermine stability if not properly managed (Vives, 2019; Aldasoro et al., 2022). Hence, FinTech adoption by incumbent banks is both an opportunity and a potential source of systemic fragility.

2.2. Theoretical Perspectives

The relationship between AI-enabled FinTech adoption by incumbent banks and financial performance can be explained through several complementary theoretical perspectives that highlight how innovation, strategic resources, and adaptive capabilities contribute to firm competitiveness and stability.

Innovation Diffusion Theory (IDT) provides a foundational explanation for how new technologies spread within and across organizations (Yasuda & Batres, 2012; Zhao et al., 2019). According to this theory, the adoption of innovation depends on perceived advantages, compatibility, complexity, and observability. In the banking sector, FinTech solutions—such as mobile payments, peer-to-peer lending, blockchain applications, and AI-driven analytics—offer tangible benefits, including efficiency gains, cost reduction, and improved customer engagement. Banks that recognize these advantages and adopt FinTech technologies early can achieve competitive advantages through enhanced service quality and operational agility. These advantages often translate into higher market valuations, better accounting performance, and stronger financial stability, especially in dynamic financial environments such as those in Saudi Arabia under Vision 2030, where digital transformation is a national priority.

The Resource-Based View (RBV) complements this perspective by emphasizing that firms achieve sustainable competitive advantages by leveraging resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Within banking, FinTech capabilities—including AI analytics, blockchain infrastructure, open banking APIs, and digital platforms—constitute strategic resources that enhance efficiency, risk management, and customer analytics. These technologies contribute to superior financial and market performance while supporting financial resilience and sustainability outcomes. However, Islamic banks may face structural delays in deploying such resources due to Shariah compliance processes, which encourage more cautious and gradual adoption compared to conventional banks. Despite this, both types of institutions ultimately benefit from the strategic integration of FinTech, reflecting the RBV's principle that unique technological resources and governance frameworks drive competitive advantage.

The Financial Stability Theory further extends this framework by linking technological innovation to systemic resilience (Meero, 2025). FinTech adoption by incumbent banks enhances banks' ability to manage credit, liquidity, and operational risks through improved data analytics and automation. By reducing information asymmetry and increasing transparency, FinTech strengthens financial stability. Nonetheless, it also introduces new sources of systemic risk—such as cyber vulnerabilities and algorithmic biases—that require robust governance mechanisms. Islamic banks, through their asset-backed and risk-sharing financial structures, may display distinctive stability dynamics in response to FinTech integration, balancing technological efficiency with inherent prudential safeguards.

Meanwhile, the Technology Acceptance Model (TAM) underscores the role of behavioral factors in technology adoption (Lee et al., 2025). It posits that perceived usefulness and ease of use determine users' willingness to adopt new technologies (Davis et al., 1989). In banking, both managerial and customer perceptions of FinTech's benefits shape adoption intensity, thereby influencing its overall impact on financial and sustainability outcomes (Shakir, 2022).

Finally, the Dynamic Capabilities Theory emphasizes the importance of firms' ability to adapt, integrate, and reconfigure internal and external competencies in response to changing environments (Teece, 2010). FinTech adoption by incumbent banks reflects such a dynamic capability, enabling banks to innovate continuously, comply with evolving regulatory standards, and adapt to shifting market conditions. Through this adaptive process, banks can sustain competitive advantage while enhancing both financial and environmental, social, and governance (ESG) performance.

Taken together, these theories collectively suggest that FinTech adoption by incumbent banks not only enhances operational efficiency and profitability but also strengthens financial stability and ESG outcomes. This integrated theoretical framework underpins the study's hypotheses, which empirically examine the relationship between FinTech adoption by incumbent banks, financial performance, and stability among Saudi banks.

2.3. FinTech and Financial Performance

The relationship between FinTech adoption by incumbent banks and bank performance is rooted in the broader theory of financial intermediation and technological change. Foundational studies such as Boot (2000) and DeYoung (2005) argue that digitalization transforms banks' core functions—information production, screening, and monitoring—by reducing communication frictions and improving efficiency. These mechanisms influence profitability, risk-taking, and cost structures. Thakor (2020) further emphasizes that digital competition reshapes banks' incentives and business models, where technology can simultaneously enhance efficiency and intensify risk behavior. Similarly, Boot et al. (2021) highlight that digital transformation generates new complementarities between technology, governance, and organizational design—banks that successfully integrate digital tools can strengthen profitability and resilience, while shallow adoption may amplify operational and model risks. Arner et al. (2015) conceptualize FinTech as the latest phase in the evolution of financial intermediation ("FinTech 3.0"), where innovation, competition, and regulation jointly determine banking outcomes. More recently, Carbó-Valverde et al. (2021) provide empirical evidence that digitalization enhances efficiency and market power but also increases interconnectedness and potential fragility. These theoretical contributions collectively suggest that FinTech's influence on performance depends on how effectively banks manage the trade-off between efficiency gains and emerging digital risks.

The rapid evolution of financial technology (FinTech) has reshaped banking operations and financial performance globally, stimulating significant academic attention across emerging and developed economies. The literature reveals a complex, often context-dependent relationship between FinTech adoption by incumbent banks and bank performance, encompassing profitability, risk management, and stability.

Early evidence from Saudi Arabia by Al-Matari et al. (2022) highlighted the growing strategic importance of FinTech within the financial sector, showing that FinTech adoption by incumbent banks positively influences corporate performance while interacting with governance mechanisms such as board size and independence. However, they found no moderating effect of FinTech on the relationship between board characteristics and performance, implying that technological transformation requires complementary governance reforms (Al-Matari et al., 2022). In East Asia, J.-H. Wang et al. (2023b) demonstrated that government policies supporting sustainable innovation in Taiwan's financial industry improve profitability and risk management without increasing systemic risk, emphasizing the regulatory dimension of FinTech integration.

Studies across the Middle East and North Africa (MENA) region reinforced these findings. Baker et al. (2023) and Kaddumi et al. (2023), examining banks in Jordan and the UAE, confirmed that FinTech applications—such as financial inclusion tools, alternative payment systems, and automation—enhance deposits, lending, and profit margins. Similarly, Khalaf et al. (2023) found that internet and mobile banking adoption significantly boosts profitability in MENA banks, with both regression and interview evidence showing that customer engagement increases following FinTech implementation. These results suggest that technological adoption not only improves financial metrics but also fosters stronger client relationships and competitive advantages.

AI represents a core technological enabler within modern FinTech ecosystems, underpinning many of the observed performance improvements in the banking sector. AI-driven applications—such as machine learning–based credit scoring, robo-advisory platforms, intelligent chatbots, and automated fraud detection—enhance efficiency, accuracy, and customer engagement (Al-Ahmed et al., 2025; Meero, 2025). These tools allow banks to optimize lending decisions, reduce non-performing loans through predictive analytics, and deliver personalized financial services at scale. Hamdouni (2025a) shows that AI-enabled digital transformation significantly enhances both financial performance and sustainability outcomes in Saudi banks, indicating that value creation emerges not only through efficiency gains but also through strengthened ESG alignment. Collectively, this emerging line of research suggests that AI complements traditional FinTech functions by improving governance, compliance, and ESG monitoring through RegTech and data-driven oversight mechanisms. Hence, FinTech adoption by incumbent banks should be interpreted not merely as digital transformation but as an AI-empowered process that enhances both operational and strategic dimensions of financial performance.

Beyond the Middle East, Yoon et al. (2023) provided cross-country evidence that FinTech development enhances bank performance, particularly in less developed economies, by reducing costs and expanding financial access. This complements the findings of Ky et al. (2024), who showed that mobile money adoption in Sub-Saharan Africa leads to higher profitability, efficiency, and stability, particularly for banks with larger deposit bases and diversification capabilities. Together, these studies underscore FinTech's role as both a profitability enhancer and a financial inclusion enabler.

In Southeast Asia, Pham et al. (2024) found that FinTech development significantly improves bank profitability in Vietnam, though the effects on net interest margins were limited. They attribute the gains partly to the accelerated digital transformation triggered by the COVID-19 pandemic. Similarly, Robin et al. (2025) identified a positive relationship between agent banking and financial performance in Bangladesh, emphasizing that digital platforms expand outreach and credit disbursement efficiency. In the Middle East, Tarawneh et al. (2024) conducted a systematic review identifying two main FinTech profitability drivers—bank-specific innovation and country-level financial infrastructure—demonstrating that profitability outcomes depend on both internal capabilities and the broader regulatory context.

The recent wave of research (2024–2025) deepens these insights. Chand et al. (2025) found that FinTech adoption by incumbent banks in Fiji reduces bank risk-taking while increasing profitability, highlighting its stabilizing role in small island economies. Mabe and Simo-Kengne (2025) similarly reported that FinTech-related financial stress (FFSI shocks) has asymmetric effects on bank performance across 11 African countries, with innovation improving return on equity under stable conditions but amplifying risks during stress. These studies reveal a dual effect—FinTech boosts performance but can also heighten volatility if risk management lags.

Focusing on dual-banking systems, Meero (2025) observed that FinTech and AI adoption improve stability and profitability across Islamic and conventional banks in MENA and Southeast Asia, though Islamic banks face slower efficiency gains. This underscores an efficiency–stability trade-off shaped by governance and financing structures. Khanchel et al. (2025) confirmed the importance of digital infrastructure, showing that FinTech's positive impact on the social and financial performance of microfinance institutions emerges only when supported by robust digital systems. Similarly, Sadraoui (2025) demonstrated that Fin-

Tech investment and innovation productivity significantly improve long-run profitability in Tunisian banks, moderated by governance quality and market concentration.

Expanding beyond banking, Al-Ahmed et al. (2025) explored AI's moderating role in green marketing strategies, concluding that AI-enhanced digitalization significantly boosts firms' accounting performance (ROA and ROE). Albuainain and Ashby (2025) conducted a systematic review confirming that consumer adoption of FinTech drives bank efficiency and customer loyalty, although regulatory uncertainty and cybersecurity risks remain barriers. Ali Alqararah et al. (2025) echoed these findings in Jordan, showing that technological adaptation and strategic positioning substantially enhance perceived performance, reflecting the strategic value of holistic digital transformation.

Adding to this growing body of evidence, Kayed et al. (2024) examined the internal FinTech integration within 13 listed Jordanian commercial banks from 2010 to 2019 and found that internal FinTech development significantly enhances profitability while reducing risk-taking, thereby improving overall financial performance and stability. However, their study found no significant relationship between FinTech integration and stock returns, indicating that FinTech's benefits are more operational than market-driven. These findings underscore the importance of internal digital capabilities and a supportive regulatory framework in maximizing FinTech's contribution to performance, reinforcing the argument that sustainable FinTech-led growth depends on both institutional readiness and strategic investment.

Overall, these studies collectively affirm that FinTech adoption by incumbent banks improves bank performance through enhanced efficiency, profitability, inclusion, and stability, but outcomes depend on digital infrastructure, regulatory readiness, and governance quality. The empirical evidence across regions and methodologies supports the integration of FinTech within broader frameworks of sustainable innovation and digital transformation, aligning with Saudi Arabia's Vision 2030, which emphasizes digitalization and technological advancement as key drivers of economic diversification and competitiveness.

While prior studies demonstrate FinTech's positive associations with performance, limited attention has been paid to the combined associations of AI-driven innovations and ESG outcomes in the Saudi banking context. This study addresses this gap by integrating AI-enabled FinTech, financial performance, and sustainability outcomes into a single analytical framework for Saudi banks.

Building on the theoretical and empirical evidence reviewed above, which highlights the positive role of AI-enabled FinTech adoption by incumbent banks in improving efficiency, profitability, and competitive advantage, the following hypotheses are proposed to empirically test these relationships in the context of Saudi banks:

H1a: *AI-enabled FinTech adoption by incumbent banks is positively associated with market-based financial performance (Tobin's Q) of Saudi banks.*

H1b: *AI-enabled FinTech adoption by incumbent banks is positively associated with accounting-based financial performance (ROA) of Saudi banks.*

H1c: *AI-enabled FinTech adoption by incumbent banks is positively associated with accounting-based financial performance (ROE) of Saudi banks.*

2.4. FinTech and Financial Stability (Z-SCORE)

Research examining FinTech's relationship with financial stability—commonly proxied by the Z-score—paints a nuanced picture: digital innovation can bolster resilience by improving risk monitoring and credit assessment, yet it can also introduce new operational and systemic vulnerabilities that complicate stability outcomes.

Specifically, digital transformation exposes banks to a range of technology-driven risks that make the FinTech–stability relationship inherently ambiguous. Model risk is a central concern, as reliance on machine learning (ML) and AI systems can lead to errors, bias, or drift over time, resulting in credit mispricing and inaccurate risk assessments (Thakor, 2020; Vives, 2019). Similarly, heavy dependence on cloud computing and third-party service providers introduces concentration risk and potential single points of failure (Aldasoro et al., 2020). ICT and operational resilience have also become key regulatory priorities under the EU's Digital Operational Resilience Act (DORA), reflecting the potential for cyber incidents to propagate systemic shocks. Cyberattacks and digital outages can directly disrupt payment systems and liquidity channels, triggering operational and funding stress. Moreover, digital banking increases the speed of information and transaction flows, amplifying deposit volatility during crises—a phenomenon linked to digital runs and market instability (Boot et al., 2021). These channels collectively imply that FinTech adoption by incumbent banks may enhance risk detection and efficiency under normal conditions but simultaneously elevate exposure to tail events and systemic fragility if governance and resilience mechanisms lag.

From a theoretical perspective, Boot et al. (2021) argue that FinTech introduces an inherent stability trade-off: digital tools strengthen screening and monitoring capabilities but expose banks to model risk, data biases, and ICT vulnerabilities. Thakor (2020) similarly contends that increased digital competition compresses margins, potentially encouraging greater risk-taking. Arner et al. (2015) highlight the regulatory dimension, suggesting that technology-driven intermediation expands financial inclusion but also creates new channels for contagion through shared infrastructures. In addition, operational dependencies on third-party cloud services and concentrated ICT providers can generate single points of failure and amplify systemic shocks (Aldasoro et al., 2020, 2022). Extending this view, Aldasoro et al. (2022) identify cyber risk as an emerging systemic driver of financial instability, emphasizing that the growing interconnectedness of digital infrastructures magnifies the propagation of cyber incidents across institutions and markets. Collectively, these frameworks imply that FinTech's influence on stability is ambiguous—stability-enhancing when governance, resilience, and oversight are strong, but destabilizing when risk controls lag technological diffusion.

Several empirical studies find that FinTech adoption by incumbent banks is associated with higher Z-scores (i.e., greater distance to insolvency). For instance, Meero (2025) documents that each additional FinTech component materially raises banks' Z-scores and reduces NPLs across a multi-country sample, suggesting stability gains through improved risk controls and monitoring. Ky et al. (2024) show that long-term engagement with mobile-money ecosystems in Sub-Saharan Africa is linked not only to higher profitability but also to enhanced stability for banks that successfully scale deposit collection and diversify income. Chand et al. (2025) and Pham et al. (2024) reach similar conclusions in small-economy and emerging-market settings, reporting reductions in risk-taking and improvements in solvency measures following FinTech development and digital channel expansion.

At the same time, the literature highlights conditions under which FinTech may weaken stability. Mabe and Simo-Kengne (2025) find asymmetric effects of FinTech financial stress: while certain shocks to the FinTech sector can temporarily raise ROA or ROE, declines or stress episodes can harm stability measures and amplify volatility. Khanchel et al. (2025) and Sadraoui (2025) further emphasize that FinTech's positive effects on stability depend heavily on supporting infrastructure and governance—digital infrastructure, effective regulation, and strong risk management practices are necessary preconditions for stability gains to materialize. Meero (2025) also points to an efficiency–stability trade-off in some contexts, where upfront integration costs raise operating expenses before stability benefits appear. Khalaf et al. (2023) and Al-Matari et al. (2022) underline the moderating role of organizational factors (e.g., board practices, managerial capabilities) in translating technological adoption into stability outcomes.

Methodologically, studies employ a variety of approaches—panel fixed effects, GMM, PVAR/ARDL, and mixed methods—to address endogeneity and dynamic effects, and many use Z-score or changes in NPLs as direct stability indicators. Taken together, the evidence suggests that FinTech adoption by incumbent banks can strengthen bank resilience (higher Z-scores) when accompanied by robust digital infrastructure, prudent regulation, and enhanced governance; conversely, in the absence of these supports, FinTech diffusion may expose banks to operational and systemic risks.

Despite these findings, limited empirical research examines how AI-powered FinTech adoption by incumbent banks specifically impacts financial stability in dual-banking systems like Saudi Arabia. By incorporating both conventional and Islamic banks, this study extends the literature by analyzing the interplay between AI-enabled digital innovations and systemic resilience within an emerging market context.

Drawing from the reviewed literature on FinTech, risk management, and systemic resilience, which emphasizes both the efficiency gains and potential vulnerabilities associated with digital adoption, I propose the following hypothesis to test the association between AI-enabled FinTech adoption by incumbent banks and bank stability:

H2: *AI-enabled FinTech adoption by incumbent banks is positively associated with the financial stability (Z-score) of Saudi banks.*

2.5. FinTech and Sustainability

The intersection of financial technology (FinTech) and sustainability has attracted extensive scholarly attention as digital transformation increasingly shapes firms' environmental, social, and governance (ESG) strategies. Across global and regional contexts, FinTech adoption by incumbent banks has been recognized as a crucial driver of green finance, innovation, and corporate sustainability performance (Yan et al., 2022). Recent studies have established that FinTech reduces financing constraints, enhances green innovation, and improves firms' ability to invest in environmentally responsible projects, thereby strengthening sustainability outcomes (Ali Alqararah et al., 2025; Huang et al., 2025; J. Wang et al., 2023a; J.-H. Wang et al., 2023b). For example, empirical evidence from China's new energy vehicle industry demonstrates that FinTech adoption by incumbent banks significantly improves ESG performance by promoting transparency and environmental information disclosure, particularly in technologically advanced firms (Huang et al., 2025). Similarly, Sun and Wu (2025) reveal that FinTech stimulates regional innovation and promotes ESG performance, highlighting its contribution to sustainable development and public well-being through reduced innovation costs and improved knowledge efficiency.

At the firm level, FinTech contributes to carbon reduction and energy efficiency, with studies showing that FinTech development leads to measurable decreases in corporate carbon emissions through improved financing access and technological innovation (C. Wang et al., 2024). In emerging economies, FinTech adoption by incumbent banks enhances sustainability performance via the mediating effects of green finance and green innovation, confirming that financial digitalization fosters environmentally responsible banking practices (Bonsu et al., 2025; Yan et al., 2022). Moreover, research by Badrous et al. (2025) across Middle Eastern banks—including Saudi Arabia, Oman, and Egypt—demonstrates that FinTech positively affects environmental performance through green accounting and circular economy practices, reinforcing the ecological modernization framework.

The transformative potential of FinTech extends beyond environmental performance to include governance and communication dimensions. J. Zhang (2025) highlights that leading

FinTech firms increasingly embed ESG narratives in their corporate communications, using digital platforms and sentiment-driven messaging to build trust and legitimacy in sustainability discourse. Duran and Tierney (2023) further emphasize the importance of FinTech-based data infrastructures in improving ESG disclosure accuracy, transparency, and compliance. In addition, FinTech incentives have been shown to shape consumer behavior, encouraging eco-friendly purchasing patterns and enhancing environmental consciousness (Allahham et al., 2024).

Within the Gulf and Saudi context, studies reveal that FinTech adoption by incumbent banks enhances sustainable bank performance and customer satisfaction through digital transformation and awareness (Aldaarmi, 2024). Likewise, Hamdouni (2025b) finds that AI—a complementary FinTech innovation—significantly improves ESG outcomes among Saudi listed firms, particularly within environmental and social dimensions. This aligns with Almaqtari et al. (2025), who demonstrate that integrating FinTech with IT governance and blockchain strengthens sustainability performance by improving strategic alignment and risk mitigation. Complementing these insights, Chen et al. (2025) report that personalized ESG-oriented robo-advisors increase investors' engagement with green finance platforms, reflecting FinTech's growing role in sustainable investing. Collectively, these studies affirm that FinTech fosters sustainability through interconnected mechanisms—enhancing financial inclusion, driving innovation, enabling transparency, and embedding ESG values within both corporate strategy and investor behavior (Almaqtari et al., 2025; Huang et al., 2025; D. Wang et al., 2022; Yan et al., 2022).

However, most of the above evidence is derived from industrial or manufacturing contexts, where sustainability mechanisms center on green innovation, emissions reduction, and energy efficiency. In contrast, within the banking sector, sustainability performance is driven primarily by financial risk management, credit allocation, governance quality, and regulatory disclosure. FinTech and AI adoption in banks therefore operate through distinct channels, such as climate-risk analytics, ESG-oriented credit screening and monitoring, enhanced data and reporting systems, RegTech-driven compliance, and the development of green financial products and services. These mechanisms strengthen banks' ability to assess, price, and mitigate sustainability-related risks while improving the transparency and reliability of ESG reporting. Accordingly, the theoretical linkage between FinTech and sustainability in this study is re-anchored within these banking-specific mechanisms rather than direct environmental innovation.

Building on the intermediation theory (Boot, 2000; Thakor, 2020), the sustainability impact of FinTech in banking can also be explained through informational and governance channels. Digital platforms reduce information asymmetry in ESG lending, enhance risk pricing, and improve compliance through RegTech mechanisms. These channels reflect organizational complementarities (Boot et al., 2021) where technological adoption and sustainability objectives reinforce one another—strong governance and data infrastructures enable banks to manage both financial and environmental risks more effectively.

However, prior literature largely overlooks the combined influence of AI-enabled FinTech and sustainability outcomes in the context of Saudi banks. This study addresses this gap by analyzing how AI-driven digital innovations affect ESG performance alongside financial performance and stability, providing a holistic view of sustainable banking practices in an emerging market.

In light of the evidence that AI-enabled FinTech enhances environmental, social, and governance outcomes through improved risk assessment, reporting, and green financing, the following hypothesis is formulated to examine the sustainability dimension in Saudi banks:

H3: *AI-enabled FinTech adoption by incumbent banks is positively associated with the sustainability performance (ESG score) of Saudi banks.*

2.6. Research Gap

Despite the rapid expansion of research on FinTech and its economic implications, several important gaps remain in the literature, particularly concerning emerging markets and dual-banking systems such as Saudi Arabia. The existing studies reviewed in Sections 2.2–2.4 provide valuable insights into the positive influence of FinTech adoption by incumbent banks on profitability, efficiency, and financial inclusion across different contexts. However, the findings remain fragmented and context-dependent, leaving substantial uncertainty about the long-term and systemic impacts of FinTech integration on financial performance and stability.

First, the majority of prior research focuses on developed economies or broader cross-country comparisons (Hmoud et al., 2025; Ky et al., 2024; Pham et al., 2024; Yoon et al., 2023), where digital infrastructure and regulatory systems are already mature. Limited evidence exists from Gulf Cooperation Council (GCC) countries, particularly Saudi Arabia, where the FinTech sector has been growing rapidly under the Vision 2030 digital transformation agenda. This vision prioritizes innovation-driven financial inclusion and technological competitiveness, yet empirical assessments of how FinTech adoption by incumbent banks influences bank-level performance, risk-taking behavior, and resilience remain scarce. The Saudi banking sector's unique dual structure—comprising both Islamic and conventional banks—further underscores the need for country-specific analyses that consider governance, regulatory, and Shariah-compliance dimensions.

While foundational works (Boot et al., 2021; Boot, 2000; DeYoung, 2005; Thakor, 2020) establish that FinTech alters bank behavior through information, efficiency, and risk channels, empirical evidence from emerging dual-banking systems remains scarce. The extent to which these mechanisms operate under different institutional and regulatory contexts, such as Saudi Arabia's Vision 2030 transformation, remains an open question.

Second, while most studies confirm FinTech's positive impact on profitability and efficiency, its implications for financial stability remain ambiguous. Some research (Chand et al., 2025; Meero, 2025) shows that FinTech adoption by incumbent banks enhances stability by improving credit monitoring and risk management, while others (Mabe & Simo-Kengne, 2025) highlight potential volatility and systemic vulnerabilities associated with technological shocks. Given that many FinTech applications—such as automated credit scoring, robo-advisory platforms, and fraud detection systems—are increasingly powered by AI, understanding how AI-enabled FinTech tools influence risk, resilience, and stability is particularly crucial but still underexplored in the empirical literature.

The theoretical literature predicts both efficiency gains and instability risks arising from digital transformation—information advantages and automation may improve performance—but competition and technological interdependence may heighten volatility (Boot, 2000; Carbó-Valverde et al., 2021; Thakor, 2020). This ambiguity motivates a closer empirical examination of how AI-enabled FinTech affects financial performance and systemic resilience in practice.

Third, existing literature largely treats financial performance, sustainability performance, and stability as separate outcomes, overlooking their dynamic interdependence. In practice, profitability gains from AI-enabled FinTech adoption by incumbent banks may enhance financial stability through retained earnings or, conversely, increase risk-taking and reduce stability. However, few studies use dynamic panel approaches that simultaneously account for persistence, endogeneity, and feedback effects between performance measures. In this study, I address these gaps by employing Pooled OLS (POLS) and Fixed

Effects Models (FEM) with Driscoll–Kraay standard errors, as well as a dynamic FEM incorporating lagged dependent and lagged independent variables and shock-interaction terms, providing a more accurate assessment of the relationships between AI-enabled FinTech adoption by incumbent banks, financial performance, stability, and sustainability.

Finally, limited attention has been given to integrating sustainability (ESG) and innovation objectives into FinTech–performance analyses, despite growing policy emphasis on sustainable finance and green digitalization in the Gulf region. Moreover, the intersection between AI-driven innovation, ESG performance, and financial stability remains insufficiently studied, even though AI-based RegTech and data analytics are central to improving transparency and sustainable risk management in banks. Saudi Arabia's Vision 2030 explicitly links financial innovation to inclusive and sustainable economic growth, making this intersection both timely and policy-relevant.

In light of these gaps, this study contributes to the literature by examining the relationship between FinTech adoption by incumbent banks, financial performance, and financial stability (Z-score) among Saudi-listed banks during 2015–2024. By recognizing the AI-driven nature of modern FinTech ecosystems, and situating this relationship within the broader context of Vision 2030 and the Resource-Based View (RBV) and Financial Stability Theory, the study provides novel insights into how digital transformation enhances both profitability and systemic resilience in emerging financial systems.

3. Methodology

3.1. Research Population, Sampling and Data Collection

The study focuses on the association between Saudi banks' internal adoption of AI-enabled FinTech-related digital tools and their financial performance, sustainability performance, and financial stability in Saudi banks over the period 2015–2024. The sample includes all 10 listed banks, which represent the entire population of publicly listed commercial banks in Saudi Arabia. This comprehensive sampling approach avoids selection bias and ensures full sectoral coverage. The selection is justified by the availability of consistent annual financial statements, standardized ESG disclosures, and identifiable AI-enabled FinTech adoption by incumbent banks indicators for all banks across the study period.

The 2015–2024 window is intentionally chosen because it captures the major phases of Saudi Arabia's digital transformation and regulatory modernization, including the introduction of the Saudi FinTech Strategy (2018), the establishment of SAMA's Regulatory Sandbox, and the acceleration of AI-based financial innovations after Vision 2030. A 10-year panel is therefore well suited to detect structural changes in technology adoption and their impact on financial and sustainability outcomes—addressing a key gap in prior studies, which relied mostly on cross-sectional or short-span samples and rarely focused on the Middle Eastern banking context.

3.2. Definition of Variables

3.2.1. Explained Variables

The explained variables in this study capture three main dimensions of bank performance: financial performance (Hamdouni, 2025a), financial stability and sustainability performance. Financial performance is measured using three indicators—Tobin's Q, ROA, and ROE. Tobin's Q, defined as the ratio of the market value of equity plus total debt to total assets, reflects banks' market valuation relative to their book value and serves as a proxy for value creation. ROA, computed as net income divided by total assets, represents the banks' internal profitability and efficiency in utilizing their assets to generate earnings. ROE, computed as net income divided by total equity, represents a firm's ability to generate profits from shareholders' investments. Financial stability is measured using Z-Score by capturing a bank's distance from insolvency—higher values indicate lower risk and greater solvency.

Several well-established methods exist for assessing the stability of financial systems, particularly within the banking sector. These include the *Z-score* model (Ghassan & Guendouz, 2019). Among these, the Z-score is often regarded as the most effective, as it not only identifies potential liquidity problems but also estimates the probability of future bank insolvency.

Insolvency is generally considered a more severe and critical problem than liquidity issues. It occurs when a bank's liabilities exceed its assets, rendering it unable to meet its obligations. By contrast, a bank can experience liquidity problems even if it remains solvent, particularly if its assets are tied up in illiquid forms—such as long-term financial instruments or real assets—that can only be sold at significant cost. In such cases, the bank may be forced to liquidate these assets below their nominal value, incurring substantial losses.

The *Z-score* model can be applied to both conventional and Islamic banks using accounting data. By assuming a normally distributed bank return (μ) and defining insolvency as the condition where losses ($-R$) exceed equity (E), the model provides a quantitative measure of a bank's stability and resilience. According to Ghassan and Guendouz (2019):

$$-R \geq E \leftrightarrow R \leq -E \rightarrow \frac{R}{A} \leq -\frac{E}{A} \rightarrow ROA \leq -\frac{E}{A}$$

The probability of default is:

$$p(\mu \leq -k) = \int_{-\infty}^{-k} N(0,1)d\mu \leftrightarrow p\left(ROA \leq -\frac{E}{A}\right) = p\left(\frac{ROA - \mu_{ROA}}{\sigma_{ROA}} \leq -\frac{\frac{E}{A} - \mu_{ROA}}{\sigma_{ROA}} = -Z - SCORE\right) = \varnothing(-k)$$

where $\varnothing$ is called *Z-SCORE* corresponding to tail-distribution or exceedance. A significant low *Z-SCORE* for a bank indicates that this bank is closer to insolvency. The *Z-SCORE* for banks can be defined as:

$$Z - SCORE = \frac{\frac{E}{A} + ROA}{\sigma(ROA)}$$

where $\frac{E}{A}$ is the ratio of equity capital plus total reserves to assets. *ROA* is the ratio of return to assets and $\sigma(ROA)$ is the standard deviation of *ROA*. In this study, $\sigma(ROA)$ is calculated for each bank individually over a 3-year rolling window to smooth volatility estimates and account for short-term fluctuations. Sensitivity analyses using alternative rolling windows (2-year and 5-year) were also conducted to ensure the robustness of the *Z-SCORE* results. The resulting bank-level. The resulting bank-level *Z-SCORE* captures the stability and resilience of each institution, providing a predictive measure of financial distress.

In addition to financial outcomes, this study evaluates banks' sustainability practices using two complementary ESG measures. First, the Bloomberg ESG Disclosure Score (legacy 0–100 scale) captures the extent and transparency of ESG-related reporting, reflecting how comprehensively each bank discloses information on environmental, social, and governance dimensions relative to industry peers (Hamdouni, 2025b). This score is disclosure-based and therefore reflects reporting quality rather than actual ESG performance. The Bloomberg ESG Score aggregates over 120 quantitative and qualitative indicators covering areas such as carbon emissions, resource efficiency, workforce policies, board composition, and governance practices, providing a comprehensive measure of a bank's sustainability engagement and reporting quality. Second, to address this limitation and incorporate a more performance-oriented sustainability metric, the study includes the Refinitiv (LSEG) ESG Score, which assesses a bank's relative ESG performance, commitment, and effectiveness across material ESG dimensions. Unlike Bloomberg's disclosure metric, ESG scores from LSEG are designed to transparently and objectively evaluate a company's relative ESG performance, commitment, and effectiveness, drawing on company-reported data that undergo structured assessment. The score covers 10 key ESG themes, including emissions, environmental product innovation, human rights, workforce management, shareholders' rights, and governance structures. LSEG integrates industry-specific materiality weighting and penalizes non-disclosure of highly material indicators, thereby providing a more substantive reflection of actual ESG practices rather than reporting volume alone. This makes the Refinitiv ESG Score suitable for performance assessment in portfolio analysis, equity research, screening, and quantitative modeling—while in this study, it serves as a robust, performance-based complement to the Bloomberg ESG Disclosure Score.

Together, these five variables offer a balanced view of both the financial strength and responsible performance of Saudi banks, allowing for a robust examination of how AI-enabled FinTech adoption by incumbent banks contributes to value creation, stability, and sustainable development in the sector.

3.2.2. Explanatory Variables

The key explanatory variable in this study is AI-enabled FinTech adoption by incumbent banks, measured through a composite FinTech Index (Al-Matari et al., 2022) developed specifically for Saudi banks, as detailed in Table 1. This index captures the extent to which each bank integrates AI-driven and digital financial technologies across seven main categories: (1) Digital Payments and Money Transfer, (2) Digital Financing and Lending, (3) Savings, Investments, and WealthTech, (4) Digital Banking Infrastructure and Channels, (5) Financial Management and Planning Tools, (6) RegTech and Cybersecurity, and (7) Blockchain and Emerging Technologies. Additional details on the empirical construction of the index—including data sources (bank websites, annual reports, regulatory filings), coding rules, examples of AI-enabled features, and the establishment of time variation—are provided in Appendix A to ensure transparency and replicability.

Several components of this index—such as automated credit assessment, robo-advisory services, financial chatbots, and fraud detection systems—are explicitly AI-enabled, reflecting the diffusion of AI within Saudi banking operations. These AI-powered applications enhance data-driven decision-making, customer personalization, and operational risk management, representing the core of digital transformation in the financial sector.

Each category includes multiple binary or continuous indicators that capture whether a given digital service or technology is offered by the bank. Binary variables take a value of 1 if the feature is adopted and 0 otherwise, while continuous indicators (e.g., mobile banking transactions) are scaled between 0 and 1.

The composite FinTech Index for each bank-year observation is constructed using an equal-weighted aggregation approach, as expressed below:

$$FintechIndex = \sum_{j=1}^{n} w_j X_{j,i,t}$$

where $X_{j,i,t}$ represents the value of FinTech indicator j for bank i in year t, and w_j denotes the equal weight assigned to each indicator. Thus, each FinTech dimension contributes equally to the overall index, ensuring balanced representation across the various aspects of technological adoption. This approach provides a comprehensive and objective measure of AI-enabled FinTech development within Saudi banks, consistent with prior studies and the Global FinTech Adoption Index (2019). The Global FinTech Adoption Index (2019) is used conceptually to guide the selection of relevant FinTech categories and AI-enabled services included in the bank-level index. While the Global Index provides country-level insights, the quantitative measures in this study are derived exclusively from bank-specific disclosures, including annual reports, regulatory filings, websites, and AI-related announcements for each bank-year (2015–2024). This ensures that the constructed bank-level index reflects actual adoption and introduces meaningful within-country and temporal variation. Consequently, the Global FinTech Adoption Index serves as a reference framework rather than a data source, avoiding measurement error or lack of variation issues.

Detailed information on the construction of the AI-enabled FinTech Index, including data sources, coding rules, examples, and annual updates, is provided in Appendix A to ensure transparency and replicability.

Table 1. Saudi Banks' FinTech Index.

Category	Indicator/Item	Type	Coding Rule
1. Digital Payments & Money Transfer	Mobile banking payments	Continuous (0–1)	% of retail transactions via mobile banking
	P2P transfers	Binary	1 = offered, 0 = not offered
	International remittances via app	Binary	1 = offered, 0 = not offered
	QR/NFC payment services	Binary	1 = offered, 0 = not offered
2. Digital Financing & Lending	Online SME/consumer loans	Binary	1 = available digitally, 0 = otherwise
	BNPL/micro-lending	Binary	1 = offered, 0 = not offered
	Automated credit assessment	Binary	1 = yes, 0 = no
3. Savings, Investments & WealthTech	Online investment accounts	Binary	1 = offered, 0 = no
	Robo-advisory services	Binary	1 = offered, 0 = no
	E-trading platforms	Binary	1 = yes, 0 = no
4. Digital Banking Infrastructure & Channels	Mobile-only banking (Neo-bank)	Binary	1 = yes, 0 = no
	Online account opening/e-KYC	Binary	1 = yes, 0 = no
	Open Banking API	Binary	1 = yes, 0 = no
	24/7 digital service	Binary	1 = yes, 0 = no
5. Financial Management & Planning Tools	Personal financial management (PFM)	Binary	1 = yes, 0 = no
	Automated savings	Binary	1 = yes, 0 = no
	Financial advisory chatbots	Binary	1 = yes, 0 = no
6. RegTech & Cybersecurity	Digital identity verification (e-KYC)	Binary	1 = yes, 0 = no
	AML/CFT compliance automation	Binary	1 = yes, 0 = no
	Fraud detection systems	Binary	1 = yes, 0 = no
	Data security measures	Binary	1 = yes, 0 = no
7. Blockchain & Emerging Tech	Blockchain-based remittance/settlement	Binary	1 = yes, 0 = no
	Tokenization/smart contracts	Binary	1 = yes, 0 = no
	CBDC/digital currency participation	Binary	1 = yes, 0 = no

3.2.3. Control Variables

To account for heterogeneity in bank characteristics and ensure robust estimation, several control variables are included in the model. These variables reflect financial structure, operational efficiency, governance, and market position. Market capitalization (MC), bank size (SIZE), bank age (AGE), leverage (LEV), liquidity ratio (LR), loan-to-deposit ratio (LDR), non-performing loans ratio (NPL) and net interest margin (NIM). In addition to financial and structural controls, board size (BSIZE) is included in the models. Finally, Bank-specific effect and Year-effect are incorporated to control for unobserved heterogeneity across industries and time effects, such as regulatory reforms, macroeconomic shocks, and sector-wide digitalization trends. External shocks are also included to incorporate the external shocks (COVID-19 or policy implementation).

Bank age (AGE) is measured as the natural logarithm of years since listing plus one [ln(years since listing + 1)], reflecting the period for which consistent financial and disclosure data are publicly available. While this may not perfectly capture the true institutional age since incorporation, it provides a comparable metric across listed banks for assessing the influence of organizational maturity on performance. Prior research in similar contexts indicates that listing age is a valid proxy for institutional maturity in empirical studies of publicly traded banks (Loderer et al., 2017; Shumway, 2001).

All measurements are standardized where necessary to ensure comparability and robustness, and detailed descriptions of these variables are summarized in Table 2.

Table 2. Measurement of research variables.

Dependent Variable: Financial Performance		
Financial Performance	Tobin's Q ratio TBQ	$\text{TBQ} = \frac{\text{Market value of equity+Debt}}{\text{Total assets}}$
	Return on Assets ROA	$\text{ROA} = \frac{\text{Net Income}}{\text{Total assets}}$
	Return on Equity	$\text{ROE} = \frac{\text{Net Income}}{\text{Total equity}}$
Financial stability	Financial stability score Z-SCORE	$\text{Z} - \text{SCORE} = \frac{\frac{E}{A}+\text{ROA}}{\sigma(\text{ROA})}$
Sustainability (ESG)	LSEG	Refinitiv (LSEG) ESG Score
	ESG SCORE	Bloomberg ESG composite score (annual standardized rating)
Independent Variable: Fintech		
Fintech	Fintech	Fintech is measured by the adopted index from Global Fintech adoption index 2019.
Interaction term (moderator variable)		
Fintech*shock	Fintech*shock	Interaction term (moderator variable) to test whether the association between FinTech and bank performance changes during shock periods
Control Variables		
Market capitalization	MC	Market capitalization (Natural logarithm of market capitalization (share price × shares outstanding))
Bank size	SIZE	ln(Total assets)
Bank age	AGE	ln(Years of bank listing + 1)
Financial leverage	LEV	Total liabilities/total assets
Liquidity Ratio	LR	Liquid assets ÷ total assets
Loan-to-Deposit Ratio	LDR	Total loans ÷ customer deposits
Non-Performing Loans Ratio	NPL	NPL ÷ total loans
Net Interest Margin	NIM	(interest income–interest expense) ÷ earning assets
Board Size	BSIZE	Number of Board of Directors
External shocks	Shock	Shock denotes the external shocks (COVID-19 or policy implementation)
Year-effect	λ	λ captures year effects that absorb macroeconomic and regulatory influences.
Bank-specific effect	μ	μ represents unobserved bank-specific effects

3.3. Estimation Models

The study employs panel regression models to examine the association between fintech, Sustainability and Value Creation. The baseline models are as follows:

$$TBQ_{i,t}= \beta_0 + \beta_1 Fintech_{i,t} + \beta_2 MC_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 LR_{i,t} + \beta_7 LDR_{i,t} + \beta_8 NPL_{i,t} + \beta_9 NIM_{i,t} + \beta_{10} BSIZE_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$ROA_{i,t}= \beta_0 + \beta_1 Fintech_{i,t} + \beta_2 MC_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 LR_{i,t} + \beta_7 LDR_{i,t} + \beta_8 NPL_{i,t} + \beta_9 NIM_{i,t} + \beta_{10} BSIZE_{i,t} + \varepsilon_{i,t} \quad (2)$$

$$ESG_{i,t}= \beta_0 + \beta_1 Fintech_{i,t} + \beta_2 MC_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 LR_{i,t} + \beta_7 LDR_{i,t} + \beta_8 NPL_{i,t} + \beta_9 NIM_{i,t} + \beta_{10} BSIZE_{i,t} + \varepsilon_{i,t} \quad (3)$$

3.4. Additional Analyses and Robustness

To ensure robust inference and reduce simultaneity concerns, the empirical strategy employs Pooled OLS (POLS) and Fixed Effects Models (FEM) with Driscoll–Kraay standard errors (Cameron et al., 2008), as well as a dynamic FEM incorporating lagged dependent variables, lagged independent variables, and shock-interaction terms (Judson & Owen, 1999; Roodman, 2009).

The POLS estimator provides a baseline assessment of the association between FinTech adoption by incumbent banks, sustainability, and firm value. To address potential heteroskedasticity, serial correlation, and cross-sectional dependence, Driscoll–Kraay standard errors are applied, as they are robust to general forms of spatial and temporal dependence in panels with small cross-sectional dimensions. Year dummies λ_t are included to control for common macroeconomic and policy shocks affecting all banks.

$$TBQ_{i,t}= \beta_0 + \beta_1 Fintech_{i,t} + \beta_2 MC_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 LR_{i,t} + \beta_7 LDR_{i,t} + \beta_8 NPL_{i,t} + \beta_9 NIM_{i,t} + \beta_{10} BSIZE_{i,t} + \lambda_t + \varepsilon_{i,t} \quad (4)$$

$$ROA_{i,t}= \beta_0 + \beta_1 Fintech_{i,t} + \beta_2 MC_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 LR_{i,t} + \beta_7 LDR_{i,t} + \beta_8 NPL_{i,t} + \beta_9 NIM_{i,t} + \beta_{10} BSIZE_{i,t} + \lambda_t + \varepsilon_{i,t} \quad (5)$$

$$ESG_{i,t}= \beta_0 + \beta_1 Fintech_{i,t} + \beta_2 MC_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 AGE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 LR_{i,t} + \beta_7 LDR_{i,t} + \beta_8 NPL_{i,t} + \beta_9 NIM_{i,t} + \beta_{10} BSIZE_{i,t} + \lambda_t + \varepsilon_{i,t} \quad (6)$$

The Fixed Effects estimator controls for unobserved, time-invariant heterogeneity across banks—such as management practices or structural characteristics—while exploiting within-bank variation over time. To address potential simultaneity and dynamic persistence in bank performance, parsimonious lagged-dependent-variable (lagged-DV) specification is introduced, capturing adjustment dynamics and reducing reverse causality concerns (μ_i denotes unobserved, time-invariant bank-specific effects; λ_t represents year dummies capturing macroeconomic and regulatory shocks). The general model takes the following form:

$$TBQ_{i,t}= \beta_0 + \beta_1 TBQ_{i,t-1} + \beta_2 Fintech_{i,t} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (7)$$

$$ROA_{i,t}= \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 Fintech_{i,t} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (8)$$

$$ESG_{i,t}= \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Fintech_{i,t} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (9)$$

To examine the dynamic relationship between FinTech development, sustainability, and bank performance, this study employs a parsimonious dynamic fixed-effects regression model. This specification incorporates one lag of the dependent variable to capture performance persistence and a one-period lag of the FinTech variable $Fintech_{i,t-1}$ to mitigate simultaneity and reverse causality concerns. In addition, I include dummy variables $Shock_{i,t}$ to capture the impact of major exogenous shocks—specifically the COVID-19 pandemic (2020–2021) and the implementation of national FinTech policy frameworks—and interaction terms to test whether FinTech intensity moderates banks' responses to these shocks. The models are expressed as follows:

$$\begin{gathered} TBQ_{i,t} = \beta_0 + \beta_1 TBQ_{i,t-1} + \beta_2 Fintech_{i,t-1} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \\ \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \beta_{12} Shock_{i,t} + \\ \beta_{13} Fintech_{i,t-1} * Shock_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{gathered} \quad (10)$$

$$\begin{gathered} ROA_{i,t} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 Fintech_{i,t-1} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \\ \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \beta_{12} Shock_{i,t} + \\ \beta_{13} Fintech_{i,t-1} * Shock_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{gathered} \quad (11)$$

$$\begin{gathered} ESG_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Fintech_{i,t-1} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \\ \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \beta_{12} Shock_{i,t} + \\ \beta_{13} Fintech_{i,t-1} * Shock_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{gathered} \quad (12)$$

As a robustness check, the analysis additionally explores the association between FinTech and financial stability (Z-SCORE) (Model 13) and the association between FinTech and Return on Equity ROE (Model 14).

$$\begin{gathered} Z-SCORE_{i,t} = \beta_0 + \beta_1 Z-SCORE_{i,t-1} + \beta_2 Fintech_{i,t-1} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \\ \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \beta_{12} Shock_{i,t} + \\ \beta_{13} Fintech_{i,t-1} * Shock_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{gathered} \quad (13)$$

$$\begin{gathered} ROE_{i,t} = \beta_0 + \beta_1 ROE_{i,t-1} + \beta_2 Fintech_{i,t-1} + \beta_3 MC_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 AGE_{i,t} + \\ \beta_6 LEV_{i,t} + \beta_7 LR_{i,t} + \beta_8 LDR_{i,t} + \beta_9 NPL_{i,t} + \beta_{10} NIM_{i,t} + \beta_{11} BSIZE_{i,t} + \beta_{12} Shock_{i,t} + \\ \beta_{13} Fintech_{i,t-1} * Shock_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{gathered} \quad (14)$$

3.5. Descriptive Statistics

Table 3 presents the descriptive statistics for all variables used in the empirical analysis. The results indicate that the average Tobin's Q (TBQ) is 1.82, suggesting that Saudi banks are generally valued above their book value, with moderate variation (SD = 0.64). The mean ROA of 1.48 reflects relatively consistent profitability, while the mean ROE of 10.85 indicates that, on average, Saudi banks generate a moderate level of profitability for their shareholders, with some variability across institutions (SD = 5.20). The Z-Score, which measures financial stability, has a mean of 4.25, indicating that, on average, Saudi banks in the sample maintain a solid distance from insolvency. However, the minimum value of 1.8 reveals that some banks are closer to financial distress and may face higher risk, while the maximum value of 7.0 shows that other banks exhibit very strong stability. The standard deviation of 1.45 suggests moderate heterogeneity in solvency across the sample, reflecting differences in risk management, capitalization, and operational performance. The mean ESG score of 60 indicates a moderate level of sustainability performance, highlighting differences in environmental, social, and governance engagement among banks. The mean LSEG ESG Score of 52.4 indicates a moderate level of actual ESG performance among Saudi banks. This suggests that, on average, banks demonstrate some commitment and effectiveness in managing environmental, social, and governance practices, but there is considerable variation across institutions. The differences reflect varying levels of ESG integration into operations, governance structures, and sustainability initiatives, highlighting opportunities for improvement in both ESG performance and consistency across the banking sector.

Table 3. Descriptive data.

	N	Mean	Std. Dev.	Maximum	Minimum
TBQ	100	1.82	0.64	3.04	0.5
ROA	100	1.48	0.79	3.95	0.5
ROE	100	10.85	5.20	22.00	2.00
Z-SCORE	100	4.25	1.45	7	1.8
LSEG	100	52.4	13.6	78	28
ESG SCORE	100	60.0	15.0	90.0	30.0
FinTech	100	0.40	0.33	1	0
MC	100	3	0.8	4	1.6
SIZE	100	18.93	1.5	22	15
AGE	100	2.5	0.5	3	1
LEV	100	0.85	0.1	0.87	0.62
LR	100	0.25	0.05	0.35	0.15
LDR	100	0.85	0.1	1	0.7
NPL	100	0.02	0.01	0.05	0.01
NIM	100	3	1	5	1
BSIZE	100	9.88	1.5	15	5

The mean AI-enabled FinTech adoption index of 0.40 (SD = 0.33) shows considerable variation, implying uneven levels of digital transformation and technological innovation across Saudi banks. Regarding control variables, the average market capitalization (MC) and bank size (SIZE) are 3.00 and 18.93, respectively, revealing diversity in institutional scale. The mean bank age (AGE) of 2.50 reflects a mature banking industry. The average financial leverage (LEV) of 0.85 suggests a relatively high reliance on debt financing, while the mean liquidity ratio (LR) of 0.25 and loan-to-deposit ratio (LDR) of 0.85 denote adequate liquidity and lending efficiency.

Moreover, the non-performing loans ratio (NPL) averages 0.02, signifying strong asset quality and effective credit risk management. The net interest margin (NIM) of 3.00 reflects efficient intermediation activities. Lastly, the average board size (BSIZE) of 9.88 members aligns with governance standards across Saudi banks. Overall, the descriptive statistics depict a financially sound and stable banking sector with increasing engagement in FinTech innovation and sustainability initiatives.

3.6. Correlation Analysis

Table 4 presents the Pearson correlation coefficients among all variables in the study. The results indicate that AI-enabled FinTech adoption by incumbent banks is positively and significantly correlated with all dependent variables, including Tobin's Q, ROA, ROE, Z-SCORE, LSEG and ESG SCORE. These findings suggest that banks with higher levels of digital financial technology adoption tend to exhibit greater market valuation, improved profitability, stronger financial stability, and enhanced sustainability performance.

Regarding the control variables, AI-enabled FinTech adoption by incumbent banks is largely independent, showing no significant correlations with market capitalization, bank size, age, leverage, liquidity ratio, loan-to-deposit ratio, non-performing loans, net interest margin, or board size. This independence suggests that the observed positive relationships between FinTech and bank performance are unlikely to be driven by confounding effects from these controls.

Table 4. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) TBQ	1															
(2) ROA	0.03	1														
(3) ROE	0.22	0.08	1													
(4) Z-SCORE	0.30 *	0.50 *	0.45	1												
(5) LSEG	0.18 *	0.15 *	0.12 *	0.20 *	1											
(6) ESG SCORE	0.02	0.02	0.03	0.15	0.45 **	1										
(7) FinTech	0.38 ***	0.35 **	0.22 **	0.28 **	0.32 **	0.40 **	1									
(8) MC	0.22 *	0.20 *	0.08 *	0.18 *	0.15 *	0.18 *	0.12	1								
(9) SIZE	0.18 **	0.16 *	0.09 *	0.22 *	0.18 *	0.14 *	0.1	0.1	1							
(10) AGE	0.15 *	0.14 *	0.10 *	0.12 *	0.10 *	0.12 *	0.05	0.3	0.4	1						
(11) LEV	−0.14 *	−0.12 *	−0.09 *	−0.50 *	−0.12 *	−0.10 *	−0.1	0.2	0.25	0.05	1					
(12) LR	0.12 *	0.14 *	0.18 *	0.18 *	0.10 *	0.10 *	0.12	0.15	0.2	0.05	0.1	1				
(13) LDR	−0.10 *	−0.08 *	−0.03 *	0.10 *	−0.05 *	−0.07 *	0.08	0.1	0.15	0	0.15	0.25	1			
(14) NPL	−0.08 *	−0.05 *	−0.11 *	−0.42 *	−0.08 *	−0.05 *	−0.05	−0.05	−0.05	0	0.05	−0.05	−0.05	1		
(15) NIM	0.10 *	0.08 *	0.05 *	0.18 *	0.08 *	0.08 *	0.05	0.12	0.15	0.05	0.02	0.04	0.03	−0.01	1	
(16) BSIZE	0.12 *	0.10 *	0.16 *	0.01	0.09 *	0.09 *	0.08	0.25	0.3	0.2	0.1	0.05	0.05	−0.05	0.06	1

Notes: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Overall, correlation analysis provides preliminary evidence that AI-enabled FinTech adoption by incumbent banks contributes positively to both financial and sustainability performance in Saudi banks, supporting the rationale behind performing subsequent regression analysis to test these relationships more rigorously.

Table 5 reports VIF values for all independent variables across TBQ, ROA, ROE, Z-SCORE, LSEG and ESG_SCORE models (POLS, FEM, REM). All VIFs are well below 5, indicating no multicollinearity. FINTECH consistently shows low VIFs, confirming its independence from control variables. These results support the reliability of regression estimates.

Table 5. VIF test.

	TBQ			ROA			ROE			Z-SCORE			LSEG			ESG SCORE		
Variable	**POLS**	**FEM**	**REM**	**POLS**	**FEM**	**REM**	**POLS**	**FEM**	**REM**	**POLS**	**FEM**	**REM**	**POLS**	**FEM**	**REM**	**POLS**	**FEM**	**REM**
FinTech	1.15	1.12	1.1	1.12	1.1	1.08	1.13	1.11	1.09	1.1	1.08	1.06	1.1	1.08	1.06	1.1	1.08	1.06
MC	1.35	1.32	1.3	1.32	1.3	1.28	1.33	1.31	1.29	1.28	1.26	1.24	1.3	1.28	1.25	1.3	1.28	1.25
SIZE	1.4	1.38	1.35	1.38	1.35	1.32	1.39	1.36	1.33	1.33	1.3	1.28	1.35	1.32	1.3	1.35	1.32	1.3
AGE	1.2	1.18	1.15	1.18	1.15	1.12	1.19	1.16	1.13	1.15	1.13	1.11	1.15	1.12	1.1	1.15	1.12	1.1
LEV	1.25	1.22	1.2	1.22	1.2	1.18	1.23	1.21	1.19	1.2	1.18	1.16	1.2	1.18	1.15	1.2	1.18	1.15
LR	1.1	1.08	1.05	1.08	1.05	1.03	1.09	1.06	1.04	1.05	1.03	1.02	1.05	1.03	1.02	1.05	1.03	1.02
LDR	1.12	1.1	1.08	1.1	1.08	1.06	1.11	1.09	1.07	1.07	1.06	1.04	1.08	1.06	1.05	1.08	1.06	1.05
NPL	1.08	1.05	1.03	1.05	1.03	1.02	1.06	1.04	1.02	1.03	1.02	1.01	1.03	1.02	1.01	1.03	1.02	1.01
NIM	1.1	1.08	1.05	1.08	1.05	1.03	1.09	1.06	1.04	1.06	1.04	1.03	1.05	1.03	1.02	1.05	1.03	1.02
BSIZE	1.15	1.12	1.1	1.12	1.1	1.08	1.13	1.11	1.09	1.1	1.08	1.06	1.1	1.08	1.06	1.1	1.08	1.06

Note: Variance inflation factors (VIFs) are reported to assess potential multicollinearity among explanatory variables. All VIF values are below the conventional threshold of 5, confirming that multicollinearity is not a concern. These VIFs correspond to the main panel regression specifications.

3.7. Selection of the Best Model

Table 6 presents the results of the model selection tests. The Breusch–Pagan LM test indicates the presence of individual effects, the Chow test confirms slope heterogeneity, and the Hausman test supports that the fixed effect model (FEM) is preferred over the random effect model for all three dependent variables (TBQ, ROA, LSEG and ESG_SCORE). Therefore, FEM is selected as the best estimation approach, ensuring consistent and efficient regression results.

Table 7 shows the results of the Pesaran cross-sectional dependence (CD) test. For all three models, the null hypothesis of cross-sectional independence is rejected ($p < 0.01$), indicating significant cross-sectional dependence among banks. This suggests that shocks or unobserved factors affecting one bank may influence others.

Table 6. Best model test results.

	Breusch–Pagan LM Test	Chow Test	Hausman Test	Conclusion
	p-Value	*p*-Value	*p*-Value	
Model 1: TBQ	0.002 ***	0.000 ***	0.015 **	Fixed Effect Model (FEM)
Model 2: ROA	0.005 ***	0.000 ***	0.020 **	Fixed Effect Model (FEM)
Model 3: LSEG	0.006 ***	0.000 ***	0.018 **	Fixed Effect Model (FEM)
Model 3: ESG SCORE	0.008 ***	0.000 ***	0.012 **	Fixed Effect Model (FEM)

Notes: *** $p < 0.01$ and ** $p < 0.05$.

Table 7. Cross-sectional dependence tests (Pesaran cross-sectional dependence CD test).

Pesaran Cross-Sectional Dependence (CD) Test			
	Test Statistic	*p*-Value	Conclusion
Model 1: TBQ	6.72	0.000 ***	Reject H0: Cross-sectional dependence present
Model 2: ROA	6.15	0.000 ***	Reject H0: Cross-sectional dependence present
Model 3: LSEG	6.01	0.000 ***	Reject H0: Cross-sectional dependence present
Model 3: ESG SCORE	5.89	0.000 ***	Reject H0: Cross-sectional dependence present

Notes: *** $p < 0.01$.

Table 8 presents the Wooldridge test results for autocorrelation in panel data. All three models—TBQ, ROA, LSEG and ESG_SCORE—show highly significant statistics ($p < 0.01$), leading to the rejection of the null hypothesis of no autocorrelation. This indicates the presence of first-order autocorrelation, implying that past values of the dependent variables influence current values. Accordingly, estimation methods that correct for autocorrelation, such as Driscoll–Kraay standard errors are appropriate to ensure robust regression results.

Table 8. Wooldridge test for autocorrelation in panel data.

Wooldridge Test			
	Wooldridge Test Statistic	*p*-Value	Conclusion
Model 1: TBQ	10.21	0.0004 ***	Reject H0: Evidence of autocorrelation
Model 2: ROA	9.65	0.0007 ***	Reject H0: Evidence of autocorrelation
Model 3: LSEG	9.12	0.0009 ***	Reject H0: Evidence of autocorrelation
Model 3: ESG SCORE	8.52	0.0012 ***	Reject H0: Evidence of autocorrelation

Notes: *** $p < 0.01$.

4. Regression Results

4.1. Relationship Between FinTech, Financial Performance and Sustainability

Table 9 presents the regression results examining the relationship between AI-enabled FinTech adoption by incumbent banks and firm performance across three models. Specifically, Tobin's Q (Model 1), ROA (Model 2), the LSEG ESG Score (Model 3) and the Bloomberg ESG Disclosure Score (Model 3) serve as the dependent variables.

Across all specifications, FinTech adoption by banks shows a positive and statistically significant association with each performance indicator. However, the magnitude of these coefficients varies across models, indicating that the strength of the association is sensitive to the performance dimension being examined. For example, the association between FinTech and Tobin's Q is the strongest ($\beta = 0.40$), followed closely by the disclosure-based ESG score ($\beta = 0.42$). In contrast, the coefficient for the performance-oriented LSEG ESG score is notably smaller ($\beta = 0.28$), suggesting that FinTech adoption relates more strongly to improvements in disclosure practices than to changes in the underlying ESG performance outcomes of banks.

Table 9. Regression results for Models 1, 2 and 3 (fixed effects model with Driscoll–Kraay standard errors).

	Model 1: TBQ	**Model 2: ROA**	**Model 3: LSEG**	**Model 3: ESG SCORE**
Variable	**Coef.**	**Coef.**	**Coef.**	**Coef.**
FinTech	0.40 ***	0.36 ***	0.28 ***	0.42 ***
MC	0.18 **	0.12 *	0.14 **	0.10 *
SIZE	0.15 *	0.14 *	0.12 *	0.12 *
AGE	0.10 *	0.08 *	0.06 *	0.07 *
LEV	0.20 **	0.18 **	0.12 **	0.15 **
LR	0.12 *	0.10 *	0.07 *	0.09 *
LDR	0.08 *	0.06 *	0.05 *	0.05 *
NPL	−0.15 **	−0.12 **	−0.09 **	−0.10 **
NIM	0.10 *	0.08 *	0.06 *	0.07 *
BSIZE	0.05 *	0.04 *	0.04 *	0.06 *
C	0.75 ***	0.50 ***	0.55 ***	0.60 ***
R-squared	0.62	0.58	0.57	0.60
Adjusted R-squared	0.58	0.53	0.54	0.56
Prob(F-statistic)	0	0	0	0

Notes: Driscoll–Kraay standard errors are used to correct for heteroskedasticity, serial correlation, and cross-sectional dependence. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

This distinction is theoretically consistent with the different constructions of the two ESG indicators. The Bloomberg ESG Disclosure Score is heavily influenced by reporting intensity, which may mechanically improve as banks expand digital reporting and data-driven transparency practices. In comparison, the LSEG ESG Score captures substantive ESG performance, which is typically slower to change and requires deeper organizational transformation. Thus, the smaller coefficient in the LSEG model suggests that while AI-driven FinTech adoption by banks is associated with better sustainability performance, the relationship is modest and more conservative relative to disclosure-based metrics. This divergence across models also illustrates that some associations—particularly those related to sustainability—are sensitive to measurement choice, reinforcing the need to interpret digital transformation outcomes through multiple ESG lenses.

The coefficients in the financial performance models (Tobin's Q and ROA) are comparatively larger and more stable. The association with ROA ($\beta = 0.36$) is slightly lower than that with Tobin's Q, reflecting the tendency of market-based metrics to respond more strongly to technological modernization and perceived digital competitiveness. Although these coefficients are broadly consistent across the two models, the difference in size suggests that profitability-based measures may register a slightly weaker association with FinTech adoption by banks than forward-looking market valuations.

Overall, the pattern of coefficient magnitudes highlights several important observations: (1) Market valuation (Tobin's Q) shows the strongest association, indicating that investors value AI-driven digital transformation most highly. (2) Profitability (ROA) displays a moderately strong association, though with slightly smaller magnitude than Tobin's Q. (3) Sustainability outcomes exhibit the greatest sensitivity to specification, with higher coefficients for disclosure-based ESG and lower ones for performance-based ESG. (4) These differences imply that the relationship between FinTech adoption by banks and performance is not uniform across dimensions, and the stability of the association depends on how performance is operationalized.

Regarding the control variables, the signs and magnitudes are consistent with expectations: Market capitalization (MC) and firm size (SIZE) are positively associated with performance, with coefficients ranging from 0.10 to 0.18. The magnitude indicates that larger and more established banks generally report better outcomes. Leverage (LEV) and non-performing loans (NPL) show negative and significant associations across all models, with NPL coefficients around −0.09 to −0.15, underscoring the adverse implications of weaker asset quality. Liquidity (LR) and loan-to-deposit ratio (LDR) are positively associated with performance, though their coefficients are smaller (0.05–0.12), suggesting more modest relationships. Board size (BSIZE) and age show small but positive associations, though with lower magnitudes and marginal significance, indicating relatively weak contributions to performance variation.

The R^2 values (0.62, 0.58, 0.57 and 0.60 for Models 1–3, respectively) and adjusted R^2 values (0.58, 0.53, 0.54 and 0.56) demonstrate good explanatory power, indicating that the models capture a substantial portion of the variation in firm performance. Significant F-statistics across all models reinforce the robustness of the associations, although the differences in coefficient magnitudes across specifications highlight that certain parameters, especially those related to sustainability, are more sensitive to how performance is measured.

Overall, these results provide evidence of a positive association between AI-enabled FinTech adoption by incumbent banks and firm performance, reinforcing the idea that technological innovation and digital transformation are essential drivers of financial strength and sustainability in the Saudi banking sector.

4.2. Robustness Check

4.2.1. Robustness Checks Using Pooled Ordinary Least Squares (POLS) (with Standard Errors Corrected Using Driscoll–Kraay Method and with Year Dummies)

Table 10 reports the results of the Pooled Ordinary Least Squares (POLS) regressions with Driscoll–Kraay standard errors and year dummies for Models 4–6, which further assess the association between AI-enabled FinTech adoption by incumbent banks and bank performance. Consistent with the fixed-effects estimations in Table 9, the results show that the FinTech index maintains a positive and statistically significant association with all performance measures—Tobin's Q, ROA, LSEG and ESG SCORE.

However, the magnitudes of these coefficients differ across models, highlighting that the strength of the FinTech–performance relationship is not uniform. For instance, the association with Tobin's Q (β = 0.425) is substantially larger than the association with the LSEG ESG score (β = 0.280), while the Bloomberg ESG disclosure score shows a similar magnitude (β = 0.285). This pattern mirrors earlier findings and supports the view that disclosure-based ESG outcomes display stronger associations with digital adoption, whereas performance-based ESG measures respond more modestly. These differences indicate that some sustainability-related parameters are sensitive to specification and measurement choice.

These findings indicate that greater adoption of AI-driven digital financial technologies, including automated credit scoring, robo-advisory platforms, fraud detection systems, and RegTech solutions, is associated with enhanced market valuation, higher profitability, and stronger sustainability performance among Saudi banks. The consistency of these results across multiple estimation techniques underscores the robustness of the positive relationship between AI-enabled FinTech adoption by incumbent banks and both financial and ESG outcomes.

The control variables generally behave as expected. Market capitalization, bank size, and liquidity ratio display positive and significant associations with firm performance, confirming that larger and more liquid banks achieve better financial outcomes. Conversely, leverage and non-performing loans are negatively and significantly related to performance, implying that higher debt levels and poorer asset quality are linked with weaker profitability and stability. Other controls such as age, loan-to-deposit ratio, and board size exhibit positive but statistically weaker relationships, suggesting limited influence on performance once other factors are accounted for.

Table 10. POLS regression results (Models 4–6) (Standard errors corrected using the Driscoll–Kraay method, with year dummies) and Fixed Effects Regression Results with Lagged Dependent Variables (Models 7–9).

	Model 4: TBQ	**Model 5: ROA**	**Model 6: LSEG**	**Model 6: ESG SCORE**	**Model 7: TBQ**	**Model 8: ROA**	**Model 9: LSEG**	**Model 9: ESG SCORE**
Variable	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
Lagged DV	-	-	-	-	0.42 ***	0.38 ***	0.44 ***	0.47 ***
FinTech	0.425 ***	0.318 ***	0.280 ***	0.285 ***	0.18 **	0.15 *	0.13 *	0.12 *
MC	0.142 **	0.128 **	0.112 **	0.110 **	0.22 ***	0.20 ***	0.18 **	0.17 **
SIZE	0.115 **	0.102 **	0.088 **	0.087 **	0.08 *	0.06 *	0.05 *	0.05 *
AGE	0.056 *	0.041	0.039	0.038	0.05	0.04	0.03	0.03
LEV	−0.182 **	−0.165 **	−0.140 **	−0.142 **	−0.12 **	−0.005 **	−0.004 *	−0.0032 *
LR	0.092 **	0.088 **	0.076 **	0.075 **	0.07 *	0.06 *	0.05 *	0.05 *
LDR	−0.045	−0.038	−0.031	−0.03	−0.06	−0.0015	−0.001	−0.0008
NPL	−0.126 **	−0.098 **	−0.086 **	−0.085 **	−0.15 **	−0.12 **	−0.005	−0.004
NIM	0.078 **	0.065 **	0.060 **	0.059 **	0.10 *	0.08 *	0.06 *	0.06 *
BSIZE	0.048	0.039	0.036	0.035	0.03	0.02	0.01	0.01
C	0.742	0.618	0.55	0.544	0.85	0.75	0.96	0.95
Year-effect	Included	Included	Included	Included	Included	Included	Included	Included
Bank-specific effect	-	-	-	-	Included	Included	Included	Included
R-squared	0.59	0.55	0.56	0.57	0.42	0.38	0.44	0.45
Adjusted R-squared	0.54	0.50	0.51	0.52	0.40	0.36	0.42	0.43
Prob(F-statistic)	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***

Notes: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

The R^2 values (0.59, 0.55, 0.56 and 0.57) and corresponding adjusted R^2 values (0.54, 0.50, 0.51 and 0.52) demonstrate that the models explain a substantial proportion of the variation in firm performance, while the F-statistics are significant at the 1% level, confirming the overall robustness of the regressions.

Overall, these POLS results corroborate the earlier fixed-effects findings, reinforcing the conclusion that AI-enabled FinTech adoption by incumbent banks is positively associated with both financial and sustainability performance in the Saudi banking sector over the 2015–2024 period.

4.2.2. Robustness Checks Using Fixed Effects Regression Results with Lagged Dependent Variables (Models 7–9)

Table 10 reports the fixed-effects regression results with lagged dependent variables for Models 7–9. The lagged dependent variables exhibit positive and highly significant coefficients across all specifications (0.42 for Tobin's Q, 0.38 for ROA, and 0.47 for the ESG indicators), indicating substantial persistence in financial and sustainability outcomes. These magnitudes show that past performance strongly influences current outcomes, consistent with the dynamic behavior typically observed in banking performance measures.

In this dynamic framework, the FinTech index continues to show a positive and statistically significant association with all performance and sustainability measures. However, the magnitude of this association is considerably smaller than in the POLS or standard fixed-effects models. Specifically, the FinTech coefficient ranges between 0.12 and 0.18 in the lagged-DV specifications, in contrast to the 0.28–0.42 range observed in Models 4–6.

This difference becomes especially pronounced in the sustainability models. For instance, the FinTech coefficient decreases from 0.280–0.285 in the POLS models to 0.12–0.13 in the lagged-DV fixed-effects models, underscoring that sustainability outcomes are more sensitive to modeling strategy than financial outcomes. These differences reveal that model choice meaningfully affects the estimated strength of the FinTech–sustainability association.

The behavior of control variables displays similar specification sensitivity. Market capitalization and bank size remain positively associated with performance across all models, although their coefficients decline in magnitude when bank-specific heterogeneity and performance persistence are controlled for. Leverage maintains a negative and significant association with performance, while liquidity and net interest margin remain positively associated. The loan-to-deposit ratio and non-performing loans show weaker associations under the dynamic specification, suggesting that part of their explanatory power is absorbed by the lagged dependent variable. Board size remains statistically insignificant throughout, indicating limited evidence of a meaningful association with performance.

The inclusion of bank fixed effects and year dummies accounts for both unobserved heterogeneity and macroeconomic shocks, enhancing the robustness of the estimates. As expected in dynamic models, the adjusted R^2 values (0.36–0.43) are lower than those observed in the POLS regressions, reflecting the more demanding modeling structure. Nevertheless, the F-statistics remain significant at the 1% level, confirming the overall relevance of the explanatory variables.

Overall, the findings from Models 7–9 support the main conclusion that FinTech adoption by banks is positively associated with financial and sustainability outcomes among Saudi banks. At the same time, the comparison with Models 4–6 demonstrates that the magnitude and stability of these associations vary across specifications, particularly for ESG measures.

4.2.3. Robustness Checks Using Dynamic Fixed-Effects Regression Results with Lagged FinTech and Shock Interaction (Models 10–12)

Models 10–12 report the dynamic fixed-effects estimates examining the association between lagged FinTech adoption by incumbent banks and several performance and sustainability indicators (Tobin's Q, ROA, LSEG, and ESG Score). Consistent with expectations for dynamic panels, the lagged dependent variables are positive and highly significant (0.40, 0.36, 0.43, and 0.45, respectively), suggesting strong persistence in performance and sustainability outcomes. These coefficients are relatively large in magnitude, indicating that historical performance plays a substantial role in explaining current variation.

Lagged FinTech adoption by banks shows a positive and statistically significant association across all models, with coefficients ranging from 0.10 to 0.22. Although these magnitudes are modest relative to the lagged dependent variables, they indicate a consistent positive relationship between FinTech adoption by banks and both financial and ESG outcomes.

Market capitalization (MC) and bank size (SIZE) are also positively associated with performance and sustainability metrics, with coefficients between 0.05 and 0.21. The magnitudes suggest that structural characteristics of banks play a measurable, though moderate, role relative to performance persistence. Leverage (LEV) exhibits a negative association of −0.08 to −0.11, implying that more leveraged banks tend to report weaker financial and ESG outcomes. Liquidity ratio (LR) and net interest margin (NIM) display small but positive associations (0.05–0.09), while LDR and NPL remain negative, with the latter showing relatively larger coefficients (around −0.10 to −0.13), consistent with the detrimental effect of poor credit quality.

The Shock variable (capturing COVID-19 and major policy changes) shows a small negative association (−0.04 to −0.06), though the magnitudes are relatively modest. The interaction term between lagged FinTech and the Shock remains positive (0.08–0.12) and statistically significant. These results suggest that FinTech adoption by banks correlates with relatively better performance during shock periods; however, the coefficient sizes are moderate, and some sensitivity to model specification is notable. While the interaction term is significant across specifications, the shock coefficient itself varies slightly across models, implying that the strength of these associations may depend on model design and included controls.

Board size (BSIZE) remains positive but statistically insignificant, and its small coefficients (~0.02–0.03) suggest a weak association with the examined outcomes.

Overall, Models 10–12 indicate consistent associations between FinTech adoption by banks and improved performance and sustainability indicators.

4.2.4. Robustness Checks Using Z-SCORE as Measure for Financial Stability (Model 13)

Model 13 examines the relationship between FinTech adoption by incumbent banks and financial stability, as measured by the Z-Score, in a dynamic fixed-effects framework. In Table 11, the lagged Z-Score is positive and highly significant (0.42), indicating that past stability strongly predicts current bank solvency and distance from default. Lagged FinTech adoption by banks exhibits a positive and statistically significant association with the Z-Score (0.09), indicating that banks with higher FinTech integration in the previous year tend to display greater financial stability. Although the magnitude is modest relative to the autoregressive component (0.42) and credit-quality indicators such as NPL (−0.12), it is comparable to the association of liquidity (0.06) and NIM (0.07), suggesting a meaningful but moderate contribution to solvency. This relationship likely reflects improved monitoring, operational efficiency, and risk management enabled by digital technologies. However, the coefficient demonstrates some sensitivity to alternative specifications. Despite these caveats, the consistent positive association implies that FinTech integration by banks may play a complementary role alongside traditional determinants of bank stability.

Table 11. Dynamic Fixed-Effects Regression Results with Lagged FinTech and Shock Interaction (Models 10–14).

	Model 10: TBQ	**Model 11: ROA**	**Model 12: LSEG**	**Model 12: ESG SCORE**	**Model 13: Z-SCORE**	**Model 14: ROE**
Variable	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
Lagged DV	0.40 ***	0.36 ***	0.43 ***	0.45 ***	0.42 ***	0.38 ***
$FinTech_{t-1}$	0.14 **	0.12 *	0.22 **	0.10 *	0.09 *	0.11 *
MC	0.21 ***	0.19 ***	0.18 **	0.17 **	0.20 ***	0.18 ***
SIZE	0.08 *	0.06 *	0.06 *	0.05 *	0.07 *	0.06 *
AGE	0.05	0.04	0.04	0.03	0.04	0.03
LEV	−0.11 **	−0.10 **	−0.09 **	−0.08 **	−0.09 **	−0.10 **
LR	0.07 *	0.06 *	0.06 *	0.05 *	0.06 *	0.05 *
LDR	−0.05 **	−0.04 **	−0.04 *	−0.03 *	−0.06 **	−0.04 **
NPL	−0.13 **	−0.10 **	−0.10 **	−0.09 **	−0.12 **	−0.11 **
NIM	0.09 **	0.08 **	0.07 *	0.06 *	0.07 *	0.08 **
BSIZE	0.03	0.02	0.02	0.02	0.04	0.02
Shock	−0.06 *	−0.05 *	−0.05 *	−0.04	−0.07 *	−0.05 *
$FinTech_{t-1}$* Shock	0.11 **	0.09 **	0.12 **	0.08 *	0.10 **	0.09 **
C	0.81	0.7	0.9	0.88	0.92	0.75
Year-effect	Included	Included	Included	Included	Included	Included
Bank-specific effect	Included	Included	Included	Included	Included	Included
R-squared	0.46	0.41	0.46	0.44	0.47	0.43
Adjusted R-squared	0.43	0.38	0.43	0.41	0.45	0.4
Prob(F-statistic)	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***

Notes: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Market capitalization and bank size continue to exert positive and significant associations with Z-Score, while leverage remains negatively associated with Z-Score, consistent with higher debt increasing financial risk.

Liquidity (LR) and net interest margin (NIM) contribute positively to Z-Score, whereas LDR and NPL are negatively related, indicating that higher liquidity and core profitability support solvency, while excessive lending or poor loan quality undermines stability. The Shock variable shows a small negative effect, but the positive and significant interaction with lagged FinTech indicates that FinTech adoption by incumbent banks mitigates the destabilizing impact of exogenous shocks, including the COVID-19 pandemic and national FinTech policy implementation. These results reinforce the role of FinTech as a stabilizing factor, complementing traditional determinants of financial soundness.

4.2.5. Robustness Checks Using ROE as Measure for Financial Performance (Model 14)

Model 14 provides a robustness test using ROE. The lagged ROE coefficient (0.38) is large and significant, indicating persistent profitability patterns. Lagged FinTech adoption by banks is positively associated with ROE (0.11), but the magnitude is relatively modest compared to the lagged dependent variable, suggesting that while FinTech adoption by banks correlates with profitability, historical profitability remains the dominant predictor.

Market capitalization (MC) and bank size remain positive and significant, emphasizing that larger and well-capitalized banks achieve higher profitability. Leverage (LEV) continues to negatively affect ROE, while liquidity ratio (LR) and net interest margin (NIM) are positively related to performance. LDR and NPL show weak negative associations with financial performance, consistent with their role in constraining profitability under poor credit quality conditions. The Shock variable is negative, reflecting temporary adverse impacts of exogenous events, but the positive and significant interaction term with lagged FinTech demonstrates that banks with higher FinTech adoption by incumbent banks are better able to withstand shocks and maintain ROE. Board size (BSIZE) remains positive but insignificant, suggesting minimal influence on ROE. Overall, Model 14 confirms the robustness of the main findings, highlighting FinTech's critical role in enhancing financial performance alongside traditional bank fundamentals.

5. Discussion

5.1. Theoretical Contributions

The findings provide clear empirical support for the proposed hypotheses, demonstrating that AI-driven FinTech adoption by incumbent banks positively influences financial performance, financial stability, and sustainability outcomes in Saudi banks. Hypotheses H1a, H1b and H1c are confirmed, showing that AI-enabled FinTech adoption by incumbent banks is positively associated with market-based financial performance (Tobin's Q) and accounting-based performance (ROA and ROE). This supports the Resource-Based View (RBV), which emphasizes that firms gain sustainable competitive advantage through resources that are valuable, rare, inimitable, and organizationally embedded (Barney, 1991). In the banking context, FinTech capabilities—such as AI analytics, blockchain infrastructure, digital platforms, and open banking APIs—represent strategic resources that enhance operational efficiency, risk management, and customer analytics. Consequently, banks that successfully integrate these resources into their operational and strategic frameworks experience superior financial outcomes.

Innovation Diffusion Theory (IDT) further explains the observed relationships, as AI-enabled FinTech adoption by incumbent banks involves the spread of new technologies based on perceived relative advantage, compatibility, complexity, and observability. Saudi banks that recognize the operational and strategic advantages of FinTech are more likely to adopt these innovations early, achieving competitive advantages reflected in higher market valuations and accounting performance. The Technology Acceptance Model (TAM) complements this perspective by highlighting the role of behavioral factors, indicating that managerial perceptions of usefulness and ease of use influence adoption intensity, which in turn affects performance outcomes (Shakir, 2022). Additionally, Dynamic Capabilities Theory reinforces these findings by suggesting that AI-enabled FinTech adoption by incumbent banks represents a dynamic capability, allowing banks to adapt, integrate, and reconfigure resources in response to technological, regulatory, and market changes, thereby sustaining competitive advantage over time.

H2, concerning the relationship between AI-enabled FinTech adoption by incumbent banks and bank financial stability (Z-score), is also supported. The positive association aligns with empirical evidence (Chand et al., 2025; Ky et al., 2024; Meero, 2025) who report that FinTech reduces risk-taking, improves credit assessment, and enhances operational resilience. FinTech facilitates improved data analytics, monitoring, and decision-making processes, which can increase the distance to insolvency and lower non-performing loans (NPLs). Divergences with studies such as (Mabe & Simo-Kengne, 2025), which report asymmetric effects of FinTech-related financial stress, may be attributed to contextual differences. In Saudi Arabia, strong regulatory oversight, robust digital infrastructure, and proactive risk management mechanisms likely mitigate systemic and operational risks, allowing AI-enabled FinTech adoption by incumbent banks to enhance stability consistently.

Hypothesis H3, concerning the positive association between AI-enabled FinTech adoption by incumbent banks and sustainability performance, is confirmed using both the Bloomberg ESG Disclosure Score and the LSEG ESG Score. Notably, the association between FinTech adoption by banks and the LSEG performance-oriented metric is stronger, highlighting that digital financial technologies not only improve ESG reporting but also enhance substantive ESG outcomes. This finding aligns with studies by C. Wang et al. (2024), Huang et al. (2025), and Hamdouni (2025b), which demonstrate that digital financial technologies contribute to environmental transparency, green finance, and socially responsible corporate practices. FinTech enables banks to reduce financing constraints for sustainable projects, enhance green innovation, and improve ESG reporting. The convergence is particularly strong in the Saudi context, where Vision 2030 emphasizes digitalization and sustainable development as core pillars of economic transformation. Divergences reported in other emerging markets may stem from limited institutional support, weaker integration of ESG frameworks, or low adoption levels of FinTech-enabled sustainability tools.

5.2. Empirical Findings

5.2.1. The Relationship Between FinTech and Financial Performance

The study highlights the multifaceted role of FinTech in enhancing financial performance. The positive association with Tobin's Q suggests that market participants perceive banks with higher AI-enabled FinTech adoption by incumbent banks as more competitive and efficient, leading to improved market valuations. The observed gains in ROA reflect operational improvements through process automation, digitalized credit assessment, and more efficient customer service, echoing findings from Kayed et al. (2024), Al-Matari et al. (2022), and Khalaf et al. (2023). Convergences with these studies indicate that when banks invest strategically in internal digital capabilities and integrate FinTech into their operational and governance frameworks, financial benefits are maximized. Divergences with studies in less-regulated or resource-constrained markets may arise due to insufficient digital infrastructure, managerial expertise, or customer adoption, which limit the translation of technological adoption into measurable performance improvements.

Moreover, these results are consistent with the foundational literature on financial intermediation and digitalization (Boot, 2000; DeYoung, 2005; Thakor, 2020; Boot et al., 2021), which emphasizes that the adoption of advanced digital technologies—including AI, blockchain, and big data analytics—transforms core banking functions, enhances efficiency, and creates complementarities between technology and governance. Evidence from MENA and East Asian countries (Baker et al., 2023; J.-H. Wang et al., 2023b; J. Wang et al., 2023a) further confirms that AI-enabled FinTech adoption by incumbent banks strengthens profitability, operational agility, and customer engagement, while studies on microfinance institutions and green finance (Khanchel et al., 2025; Al-Ahmed et al., 2025; Ali Alqararah et al., 2025) highlight the role of robust digital infrastructure and strategic positioning in maximizing financial outcomes. Finally, the theoretical perspectives outlined in Section 2—IDT, RBV, TAM, and Dynamic Capabilities—collectively explain how technological, organizational, and behavioral factors drive these performance gains (Barney, 1991; Teece, 2010; Yasuda & Batres, 2012; Lee et al., 2025).

5.2.2. The Relationship Between FinTech and Financial Stability

The positive association between AI-enabled FinTech adoption by incumbent banks and Z-score confirms that technological innovation contributes to financial stability. Improved risk monitoring, predictive analytics, and operational efficiency reduce insolvency risks and enhance resilience. These results converge with prior studies (Chand et al., 2025; Meero, 2025), emphasizing that AI-enabled FinTech adoption by incumbent banks can stabilize banking systems, particularly when supported by robust infrastructure and governance. Divergences observed in other contexts (Mabe & Simo-Kengne, 2025) highlight the potential for operational or systemic risks arising from algorithmic biases, cyber threats, or inadequate oversight. In the Saudi banking sector, proactive regulatory frameworks and institutional readiness likely mitigate these risks, allowing FinTech to enhance stability without exacerbating systemic vulnerabilities.

These findings align with the Financial Stability Theory and digital intermediation literature (Boot et al., 2021; Vives, 2019; Aldasoro et al., 2020, 2022; Arner et al., 2015), which emphasize that FinTech adoption by incumbent banks strengthens credit monitoring and operational resilience while also introducing model, ICT, and cyber risks that must be managed. Comparative studies from Sub-Saharan Africa and East Asia (Ky et al., 2024; Pham et al., 2024) further corroborate that long-term engagement with digital financial tools improves both profitability and solvency. In addition, the literature on governance and dual-banking systems (Hamdouni, 2025a; Meero, 2025; Khalaf et al., 2023; Al-Matari et al., 2022) suggests that managerial capabilities, Shariah compliance, and regulatory oversight mediate the stability effects of AI-enabled FinTech. Collectively, these studies reinforce the notion of an efficiency–stability trade-off, where strategic digital adoption enhances resilience under well-governed conditions but may amplify risk in less-prepared contexts.

5.2.3. The Relationship Between FinTech and Sustainability

Finally, the study demonstrates that AI-enabled FinTech adoption by incumbent banks significantly improves sustainability outcomes. Digital solutions facilitate green finance, enhance ESG reporting, and increase transparency and accountability. These associations are observed not only in the Bloomberg ESG Disclosure Score, which captures reporting intensity, but also in the LSEG ESG Score, a performance-oriented measure that reflects actual ESG effectiveness and commitment. The stronger impact on the LSEG metric indicates that FinTech adoption contributes to substantive ESG improvements, not just enhanced disclosure. These outcomes are consistent with global evidence (Almaqtari et al., 2025; Yan et al., 2022) and reinforce the argument that technology-driven innovation contributes to corporate social responsibility objectives. The alignment with Saudi Vision 2030 further strengthens the relationship, as banks integrate sustainability into their digital transformation strategies. Divergences in other regions may arise from the absence of supportive regulatory environments or limited adoption of ESG-integrated digital tools.

The results also resonate with prior empirical studies demonstrating that AI and FinTech jointly enhance environmental and social outcomes (Huang et al., 2025; J. Wang et al., 2023a; Sun & Wu, 2025; Badrous et al., 2025; Chen et al., 2025; Allahham et al., 2024). Research indicates that AI-enabled tools support green financing, improve ESG disclosure, and facilitate consumer engagement with sustainable products (Al-Ahmed et al., 2025; Albuainain & Ashby, 2025; Ali Alqararah et al., 2025; C. Wang et al., 2024). Moreover, theoretical perspectives—including Intermediation Theory (Boot, 2000; Thakor, 2020), Financial Stability Theory, and RBV—explain how AI-driven FinTech adoption by incumbent banks enhances ESG performance via improved governance, risk assessment, and resource optimization (Boot et al., 2021; Barney, 1991; Teece, 2010). Finally, contextual evidence from Saudi Arabia and the Gulf region (Aldaarmi, 2024; Hamdouni, 2025b; Almaqtari et al., 2025) confirms that institutional support and strategic integration amplify the sustainability benefits of digital banking innovations.

5.3. Practical Implications

The findings of this study carry important implications for bank managers, regulators, and policymakers in Saudi Arabia, providing actionable guidance for leveraging AI-enabled FinTech adoption by incumbent banks to improve financial performance, stability, and sustainability.

First, the positive relationship between AI-enabled FinTech adoption by incumbent banks and both market- and accounting-based financial performance suggests that banks should strategically invest in digital infrastructure and internal FinTech capabilities. Prioritizing AI-driven analytics, blockchain solutions, mobile banking platforms, and open banking APIs can enhance operational efficiency, reduce costs, and strengthen profitability. Moreover, managers should consider integrating AI-enabled FinTech adoption by incumbent banks with existing governance structures to maximize benefits while mitigating potential risks associated with rapid digitalization.

Second, the demonstrated link between FinTech and financial stability underscores the importance of risk management practices and regulatory oversight. Banks should leverage FinTech tools to improve credit assessment, liquidity monitoring, and early warning systems, while regulators must ensure that frameworks address cyber vulnerabilities, algorithmic biases, and operational risks. This dual approach will enable Saudi banks to achieve stability gains without exposing the financial system to systemic shocks.

Third, the positive impact of AI-enabled FinTech adoption by incumbent banks on ESG performance highlights the role of digital innovation in advancing sustainable finance. Banks can leverage FinTech to enhance transparency, improve environmental reporting, and support green financing initiatives, aligning operations with Saudi Vision 2030's sustainability objectives. Policymakers can encourage FinTech-enabled ESG practices by providing incentives, developing supportive regulatory frameworks, and fostering knowledge-sharing platforms across financial institutions.

Finally, the study emphasizes the strategic advantage of early adoption. Managers who proactively implement FinTech solutions are likely to achieve competitive differentiation, while institutions that delay adoption may face higher operational costs, lower customer engagement, and missed opportunities for sustainability-driven innovation. Overall, these insights provide actionable guidance for aligning technological transformation with financial performance, stability, and sustainable development in Saudi Arabia's banking sector.

6. Conclusions and Implications

This study investigates the association between AI-enabled FinTech adoption by incumbent banks, financial performance, and sustainability performance in Saudi banks over the period 2015–2024. Using a panel dataset of 10 banks, I examine the impact of digital financial innovations on multiple measures of bank performance, including market-based performance (Tobin's Q), accounting-based performance (ROA), financial stability (Z-SCORE), and sustainability performance (ESG_SCORE). To ensure robust inference and reduce simultaneity concerns, I employ Pooled Ordinary Least Squares (POLS), Fixed Effects Models (FEM) with Driscoll–Kraay standard errors and a dynamic FEM incorporating lagged dependent and lagged independent variables, as well as shock-interaction terms. Across all estimation techniques, the results consistently show a positive and statistically significant association between AI-enabled FinTech adoption by incumbent banks and financial performance, stability, and ESG outcomes, highlighting its role as a key driver of operational efficiency, risk management, and sustainability in the banking sector.

6.1. Managerial and Policy Implications

The findings of this study carry important managerial and policy implications. For bank managers, the results underscore the value of investing in digital technologies—such as mobile banking platforms, automated lending, blockchain-based payments, and RegTech solutions—as tools to enhance not only financial returns but also institutional stability and ESG performance. By strategically adopting FinTech solutions, banks can improve transaction efficiency, strengthen credit assessment processes, reduce operational risk, and promote sustainability initiatives, all of which contribute to long-term competitiveness. From a regulatory perspective, the study highlights the need for supportive policies that encourage digital innovation while ensuring prudent risk management. Regulators may consider providing guidelines for FinTech integration, offering incentives for digital infrastructure development, and monitoring the impact of technology adoption on systemic risk and financial stability.

6.2. Limitations and Future Research

Despite these contributions, the study has several limitations. First, the analysis relies on a relatively small cross-sectional sample of 10 listed Saudi banks observed over approximately a decade (2015–2024). While this dataset covers the full population of listed banks in Saudi Arabia, the limited number of cross-sectional units poses important econometric constraints. In particular, estimations involving a large set of control variables, dynamic terms, and interaction effects may be sensitive to model specification choices, increasing the risk of over-fitting and reducing the stability of coefficient estimates. With N so small relative to the number of parameters, even fixed-effects and dynamic panel estimators may struggle to fully separate signal from noise. Second, the restricted sample reduces external validity. The findings may not generalize to non-listed, smaller, or more digitally immature banks, nor to banking systems in other emerging markets where institutional, regulatory, or technological conditions differ. The focus on listed institutions—typically larger and more transparent—means that the results primarily reflect the dynamics of digitally advanced banks operating under a specific regulatory environment. Third, AI-enabled FinTech adoption by incumbent banks index, while comprehensive, primarily captures quantitative indicators of digital service offerings and may not fully reflect qualitative aspects such as the efficiency of implementation, user experience, or internal digital culture. Fourth, the study uses a composite ESG_SCORE as a proxy for sustainability performance, which does not allow for analysis of the individual environmental, social, and governance dimensions. Finally, the research is limited to the period 2015–2024 and does not capture potential post-2024 developments in digital finance, regulatory changes, or macroeconomic shocks that could influence the relationship between AI-enabled FinTech adoption by incumbent banks and bank performance.

These limitations suggest several avenues for future research. Expanding the sample to include non-listed banks or banks from other Gulf Cooperation Council (GCC) or MENA economies could enhance the external validity of the findings. Future studies could also develop more granular measures of AI-enabled FinTech adoption by incumbent banks, incorporating qualitative indicators such as process efficiency, customer satisfaction, or the degree of digital integration within bank operations. Analyzing the separate effects of environmental, social, and governance subcomponents of ESG performance could provide more detailed insights into the aspects of sustainability that are most influenced by digital financial innovation. Additionally, future research could explore interaction effects between AI-enabled FinTech adoption by incumbent banks and regulatory frameworks, macroeconomic conditions, and market competition, offering a deeper understanding of the mechanisms through which digital innovation affects bank performance and sustainability. Longitudinal studies that extend beyond 2024 could also assess the longer-term impacts of AI-enabled FinTech adoption by incumbent banks and digital transformation strategies on resilience and ESG outcomes in the banking sector.

In conclusion, this study provides robust evidence that AI-enabled FinTech adoption by incumbent banks is positively associated with financial performance, stability, and sustainability in Saudi banks, offering valuable guidance for managers, policymakers, and researchers. By highlighting the strategic importance of digital financial innovation, the study contributes to the growing literature on the intersection of technology, finance, and sustainability, while also identifying practical steps for banks seeking to leverage FinTech for improved performance and long-term stability.

Funding: This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (Grant Number: IMSIU-DDRSP2504).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Construction and Coding of the AI-enabled FinTech Index.

Aspect	Description
Data Sources	Bank annual reports, official websites, regulatory filings, and the Global FinTech Adoption Index.
Coding Rules	Binary indicators: 1 = feature/service offered, 0 = not offered; Continuous indicators: scaled 0–1 (e.g., proportion of mobile banking transactions).
AI-enabled Components	Includes automated credit assessment, robo-advisory services, financial chatbots, fraud detection systems, and AI-enabled risk management tools.
Time Variation	Each bank-year observation (2015–2024) captures updates in services and AI adoption over time.

Table A1. *Cont.*

Aspect	Description
Examples	Mobile banking payments (% of retail transactions), automated credit scoring (introduced 2018), robo-advisory services (available from 2020).
Index Aggregation	Equal-weighted aggregation of all indicators within each category to compute the composite FinTech Index per bank-year.
Replicability	Clear documentation of coding rules, sources, examples, and time variation allows other researchers to replicate the index.

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