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Strategic Adaptation of Traditional Banks to FinTech Disruption in Saudi Arabia: A Comprehensive Model for Navigating Digital Transformation and Future Challenges

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Abstract

This Feature Paper presents a groundbreaking analysis of how traditional banks in an emerging market navigate FinTech disruption, offering a novel framework that integrates multi-dimensional drivers and their interplay. It investigates the strategic adaptation of traditional Saudi banks to the disruptive pressures of FinTech, set against the backdrop of the Kingdom's ambitious Vision 2030 digital transformation goals. While FinTech presents significant challenges to conventional banking models, it simultaneously offers pathways for innovation and enhanced competitiveness. Our research develops and empirically tests a comprehensive conceptual framework that goes beyond simple technology adoption to examine the interplay of internal organizational capabilities and external environmental factors. Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) on data collected from 420 participants (bank employees and customers), we analyze the direct and indirect impacts of Technological Adoption (TA) and Customer Satisfaction (CS) on Bank Performance (BP), considering the mediating role of Innovation Capacity (IC) and the moderating influences of Digital Readiness (DR), Digital Leadership (DL), Digital Culture (DC), Cybersecurity Infrastructure (CI), and Regulatory Support (RS). Findings confirm TA as a key driver of BP, with IC partially mediating this relationship, highlighting the critical importance of innovation capability. Furthermore, the effectiveness of TA in building IC and impacting BP is significantly enhanced by strong DR, DL, DC, CI, and RS. This underscores that successful strategic adaptation is contingent not only on adopting technology but also on cultivating a supportive internal digital ecosystem and operating within a conducive regulatory environment. These results offer valuable insights for bank strategists, policymakers, and researchers navigating the complexities of digital transformation in emerging market financial sectors. This study transcends conventional analyses by offering a multi-faceted, empirically validated framework that is specifically calibrated to the unique socio-economic, regulatory, and strategic landscape of Saudi Arabia under Vision 2030, providing a nuanced roadmap for strategic adaptation with significant potential for high impact.

Keywords: FinTech; Digital Transformation; Strategic Adaptation; Traditional Banks; Structural Equation Modeling (SEM); Bank Performance; Innovation Capacity; Digital Readiness; Saudi Arabia; Vision 2030

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1. Introduction

1.1. Background and Context of FinTech Disruption

The global financial services landscape is undergoing a profound and accelerating transformation, primarily driven by the rapid proliferation and adoption of Financial Technology (FinTech). This phenomenon encompasses the innovative application of advanced technologies such as artificial intelligence (AI), blockchain, distributed ledger technology (DLT), Application

Programming Interfaces (APIs), big data analytics, and cloud computing (Gomber et al., 2018; Arner et al., 2015). FinTech companies leverage these technologies to offer faster, cheaper, more accessible, and often more personalized financial services, fundamentally challenging the traditional dominance and operational models of established banks (Alt & Zimmermann, 2019; Buchak et al., 2018; Hornuf & Schwienbacher, 2017). This disruption forces traditional financial institutions to critically reassess their core operations, value propositions, competitive strategies, and overall business models to remain relevant, viable, and competitive in an increasingly digital marketplace (Belleflamme et al., 2020; Gai et al., 2018; Matt et al., 2015).

In Saudi Arabia, this global FinTech revolution converges with the ambitious national transformation agenda outlined in Vision 2030. Vision 2030 explicitly identifies digital transformation as a cornerstone for achieving economic diversification away from oil dependence, enhancing government efficiency, fostering innovation, and significantly improving the quality of life for citizens (Al-Fayomi, 2021; Alqahtani & Drew, 2021; Saudi Vision 2030, 2016). The financial sector is pivotal to realizing this vision, tasked with facilitating broader economic growth, supporting the emergence of new industries, and driving financial inclusion for a young and increasingly tech-savvy population (Saudi Central Bank (SAMA), 2023; Al-Malki, 2020). Consequently, traditional Saudi banks face unprecedented and multifaceted challenges and opportunities. They must not only strategically adapt to the disruptive pressures exerted by agile and innovative FinTech startups but also rigorously align their operational and strategic initiatives with the Kingdom's overarching digital goals and regulatory frameworks. This dual imperative necessitates a fundamental strategic reorientation, moving well beyond the mere digitization of existing services towards a comprehensive and holistic digital transformation that redefines core business models, operational processes, and customer engagement strategies (Tripsas, 2019; Hess et al., 2016; Vial, 2019). The interplay between global technological trends and the Kingdom's specific strategic objectives creates a unique and dynamic context for studying strategic organizational adaptation and resilience.

1.2. Research Objectives

This study aims to comprehensively investigate and analyze the strategic adaptation of traditional banks in Saudi Arabia to the multifaceted challenges and opportunities presented by FinTech disruption, explicitly situated within the broader context and ambitious goals of Vision 2030's digital transformation agenda. Specifically, the research seeks to:

1. To examine the direct impact of technological adoption (TA) on bank performance (BP), while considering the potential mediating role of innovation capacity (IC).
2. To assess the influence of customer satisfaction (CS) on digital banking outcomes and its subsequent direct and indirect effects on overall bank performance (BP).
3. To evaluate how key internal organizational capabilities—specifically digital readiness (DR), digital culture (DC), cybersecurity infrastructure (CI), and digital leadership (DL)—moderate and influence the complex relationships between technological adoption (TA), innovation capacity (IC), and bank performance (BP).
4. To analyze the crucial role of external environmental support, particularly regulatory support (RS) from bodies like SAMA, in either facilitating or constraining the strategic adaptation process and its ultimate impact on bank performance (BP).
5. To provide robust, evidence-based, and actionable recommendations for banks, regulators, and other relevant stakeholders to enhance strategic resilience, foster innovation, and ensure sustained competitiveness for the evolving Saudi banking sector in the digital age.

1.3. Research Questions

This research is guided by the following central and subsidiary questions:

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- What are the key internal organizational capabilities and external environmental factors that most significantly influence the strategic adaptation of traditional Saudi banks to FinTech disruption?
- How does the adoption of FinTech technologies directly and indirectly (through the mediation of innovation capacity) affect the overall financial and operational performance of traditional Saudi banks?
- What role do critical internal organizational capabilities—such as digital readiness, digital culture, cybersecurity infrastructure, and digital leadership—play in moderating or mediating the relationships between technological adoption, innovation capacity, and bank performance?
- How does the regulatory environment in Saudi Arabia, particularly the support and initiatives from SAMA, facilitate or impede the successful strategic adaptation and performance of traditional banks in response to FinTech challenges?
- What are the broader theoretical, practical, and policy implications of these findings for bank strategy, regulatory policy, and future research directions, specifically within the context of Saudi Arabia's digital transformation and Vision 2030?

2. Literature Review

FinTech, defined as technologically enabled financial innovation that makes new business models, processes, and products, marks a paradigm transfer from traditional financial services by leveraging core digital technologies such as AI, blockchain, APIs, big data, cloud computing, and mobile platforms (Gomber et al., 2018; Arner et al., 2015). Contrasting simple digitization, digital transformation in banking encompasses the strategic integration of these technologies across all processes, requiring cultural change, agility, and leadership commitment (Vial, 2019; Westerman et al., 2014). FinTech aids both as a catalyst and a disruptor, accelerating the essential for transformation while challenging incumbents to approve proactive, tech-driven strategies, with platform-based models like Banking-as-a-Platform (Thakor, 2020). This dynamic is particularly relevant in contexts like Saudi Arabia, where Vision 2030 positions the financial sector at the core of a broader digital economic overhaul (Al-Fayomi, 2021).

FinTech interrupts traditional banking through disintermediation—bypassing banks to offer faster, economical, and more accessible services in areas like digital payments, P2P lending, robo-advisory, and neo banking (Alt & Zimmermann, 2019; Buchak et al., 2018). In response, incumbent banks accept three key strategies: compete by developing in-house solutions, collaborate via partnerships or investments, or acquire FinTech's absolute (Belleflamme et al., 2020; Thakor, 2020). Strategic collaboration, exclusively through Banking-as-a-Platform models, has emerged as the most viable path, permitting banks to leverage FinTech innovation while retaining regulatory expertise, capital strength, and customer trust (Gai et al., 2018). FinTech's lean structures, agile innovation, and customer-centric representations challenge traditional banks' legacy systems, prompting the creation of innovation labs, digital units, and venture arms to adapt rapidly (Cumming et al., 2019). This disruption compels banks to line up customer experience and personalization to defend against disintermediation.

Customer satisfaction and trust are perilous in digital banking, influenced by factors such as perceived usefulness, ease of use, system and service quality, security, and privacy—core constructs in TAM, UTAUT, and SERVQUAL models (Davis, 1989; Venkatesh et al., 2003; Parasuraman et al., 1988). In the FinTech context, trust extends to third-party providers, shaped by brand name, brand reputation, transparency, regulatory compliance, and secure user interfaces (Gefen et al., 2003; Kim et al., 2019). The growing use of AI tools like chatbots and robo-advisors affects customer perceptions, requiring a balance between automation and human communication (Huang et al., 2021). In the GCC, particularly Saudi Arabia, while younger generations embrace FinTech, grown-up users prefer traditional channels, highlighting the need for hybrid service models to meet various preferences (Alshammari, 2021; Tarhini et al., 2021). Understanding these behavioral nuances is essential for Saudi banks aiming to boost digital adoption, satisfaction, and loyalty.

The regulatory environment plays a key dual role in the FinTech sector—driving innovation, competition, and financial inclusion, while safeguarding stability, consumer protection, and systemic integrity (Arner et al., 2015; Zetzsche et al., 2017). Regulatory sandboxes, such as those introduced by Saudi Arabia's SAMA in alignment with Vision 2030, allow FinTechs to test innovations in controlled settings, promoting safe experimentation (Buckley et al., 2019; SAMA, 2023; Alqahtani & Drew, 2021). However, the rapid pace of technological change often outpaces regulation, making dynamic, balanced oversight essential to avoid both overregulation—which can stifle growth—and under-regulation, which risks instability (Zmudzinski, 2022; Al-Fayomi, 2021). Complementing this, **Digital Readiness (DR)** refers to a bank's ability to strategically deploy digital tools—ranging from infrastructure and analytics to agile operations and skilled talent—to adapt to technological changes (Nambisan et al., 2017; Chen & Zhang, 2019). **Digital Culture (DC)**, comprising shared values and openness to experimentation, underpins successful transformation by encouraging innovation and customer-centricity (Vial, 2019; Weill & Woerner, 2021). Effective **Digital Leadership (DL)** is essential to steer change, overcome resistance, and align initiatives with strategic goals (Matt et al., 2015; Singh & Hess, 2017). Lastly, **Cybersecurity Infrastructure (CI)** is vital for trust, resilience, and regulatory compliance, especially as digital interconnectivity with FinTech partners growths (Kshetri, 2017; Xu et al., 2020).

Innovation capacity (IC) refers to an organization's inherent ability and capability to systematically generate, rigorously develop, and successfully implement new ideas, products, services, processes, or business models that create demonstrable value for customers, stakeholders, and the organization itself (Teece, 2018; Chesbrough, 2003). In the specific context of FinTech disruption, innovation capacity is not merely about developing new technologies internally but also critically encompasses the absorptive capacity to identify, evaluate, adapt, and seamlessly integrate external innovations, such as those offered by FinTech partners, into the existing business model (Teece et al., 1997; Nambisan & Nambisan, 2008; Teece, 2018).

Banks with high innovation capacity are demonstrably better positioned to respond swiftly and effectively to dynamic market changes, identify and capitalize on emerging opportunities, develop new and diversified revenue streams, significantly improve operational efficiency and cost-effectiveness, and substantially enhance the overall customer experience through novel solutions (Omar et al., 2021; Brem et al., 2021; Teece, 2018). This strategic capability is influenced by a complex interplay of factors, including sustained investment in research and development (R&D), the cultivation of extensive and strategic collaboration networks (open innovation), robust organizational learning mechanisms, and the presence of a deeply supportive and innovation-driven organizational culture (Teece, 2018; Dodgson et al., 2006; Chesbrough, 2003). It acts as a crucial strategic mediator and enabler, translating technological investments and market insights into tangible and sustainable performance outcomes and competitive advantages.

Saudi Arabia's Vision 2030 outlines a bold national strategy to diversify the economy beyond oil, enhance private sector participation, and improve citizens' quality of life through digital transformation, with the financial sector playing a pivotal enabling role (Saudi Vision 2030, 2016; Alqahtani & Drew, 2021). As part of this, the Kingdom prioritizes financial inclusion, SME support, and the development of a robust FinTech ecosystem through initiatives like regulatory sandboxes, national digital payment infrastructure (e.g., mada), open banking, and digital literacy programs (SAMA, 2023; Al-Malki, 2020). This state-led digital push compels traditional banks to align not only with global FinTech trends but also with national policy mandates, requiring accelerated strategic adaptation, technological investment, and cultural transformation to remain competitive and compliant (Al-Fayomi, 2021; McKinsey & Company, 2023)

This study directly addresses these critical gaps by developing and empirically testing a comprehensive and theoretically grounded conceptual model that incorporates these multifaceted

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and interrelated drivers within the specific and dynamic context of Saudi Arabia's ambitious digital transformation agenda outlined in Vision 2030. It aims to provide a nuanced, empirically validated, and actionable understanding of the strategic adaptation process and offer robust, evidence-based insights for banks, regulators, and policymakers.

3. Methodology

3.1. The Model Specification

Understanding the strategic adaptation of traditional Saudi banks to FinTech disruption requires a robust and theoretically grounded model specification that accurately captures the complex interrelationships among the identified constructs. The conceptual model presented in the literature review forms the foundation for the empirical analysis. This model proposes that bank performance (BP) is influenced by technological adoption (TA) and customer satisfaction (CS), with the strength of these relationships moderated by digital readiness (DR) and digital leadership (DL), and mediated by innovation capacity (IC). Additionally, regulatory support (RS), digital culture (DC), and cybersecurity infrastructure (CI) are posited as key external and internal drivers influencing the core relationships.

To translate this conceptual framework into an empirically testable form, a system of structural equations is specified. The primary structural model focuses on the direct and indirect effects linking the exogenous variables (TA, CS, DR, RS, DC, CI, DL) to the endogenous variable (BP), while explicitly modeling the mediating role of IC and the moderating roles of DR and DL on specific pathways (primarily TA -> IC).

The general form of the structural equations can be represented as follows:

Equation 1 (Direct Effects on Bank Performance - BP): $BP = \beta_0 + \beta_1(TA) + \beta_2(CS) + \beta_3(DR) + \beta_4(RS) + \beta_5(DC) + \beta_6(CI) + \beta_7(DL) + \varepsilon_1$

This equation captures the direct impact of each independent variable on bank performance, controlling for the influence of others.

Equation 2 (Mediation Path - Innovation Capacity - IC): $IC = \alpha_0 + \alpha_1(TA) + \alpha_2(CS) + \alpha_3(DR) + \alpha_4(RS) + \alpha_5(DC) + \alpha_6(CI) + \alpha_7(DL) + \varepsilon_2$

This equation models the determinants of innovation capacity, reflecting the hypothesis that various factors, particularly technological adoption, drive a bank's ability to innovate.

Equation 3 (Indirect Effect via Innovation Capacity - IC on BP): $BP = \gamma_0 + \gamma_1(TA) + \gamma_2(CS) + \gamma_3(DR) + \gamma_4(RS) + \gamma_5(DC) + \gamma_6(CI) + \gamma_7(DL) + \gamma_8(IC) + \varepsilon_3$

This equation explicitly includes IC as a predictor of BP, allowing for the assessment of its mediating role. The indirect effect of TA (or other variables) on BP through IC is calculated as the product of the coefficient linking TA to IC (from Eq. 2) and the coefficient linking IC to BP (γ_8 from Eq. 3).

Equation 4 (Moderation Effect - DR moderating TA -> IC): $IC = \delta_0 + \delta_1(TA) + \delta_2(DR) + \delta_3(TA * DR)$ + [Control Variables: CS, RS, DC, CI, DL] + ε_4

This equation tests the specific moderation hypothesis (H3) by including an interaction term (TA * DR). A significant coefficient for δ_3 would indicate that the effect of TA on IC varies depending on the level of DR.

Equation 5 (Moderation Effect - DL moderating TA -> IC): $IC = \theta_0 + \theta_1(TA) + \theta_2(DL) + \theta_3(TA * DL)$ + [Control Variables: CS, DR, RS, DC, CI] + ε_5

Similarly, this equation tests the moderation hypothesis related to digital leadership (DL) by including the interaction term (TA * DL).

The measurement model, which links the observed survey items to their respective latent constructs (TA, CS, DR, RS, DC, CI, DL, IC, BP), is specified using confirmatory factor analysis (CFA) principles within the structural equation modeling (SEM) framework. Each latent variable is represented by multiple reflective indicators derived from the survey instrument.

By carefully specifying the model equations based on theoretical propositions and employing SEM, this research aims to provide a rigorous and comprehensive empirical test of the factors influencing the strategic adaptation of Saudi banks to FinTech disruption.

3.2. Empirical Strategy

The empirical strategy for this research is designed to rigorously test the set objectives derived from the conceptual model, leveraging both quantitative survey data and secondary financial data. The strategy involves a sequential, mixed-methods approach, although the primary analytical focus is quantitative due to the nature of the hypotheses and the requirement for statistical testing of relationships. The core strategy is centered around Structural Equation Modelling (SEM), but it is preceded by necessary preliminary analyses and potentially supplemented by auxiliary techniques.

This study employs a mixed-methods approach combining **primary survey data** and **secondary financial data**. The primary data will be collected via structured bilingual (Arabic/English) online surveys targeting two groups: (1) **Banking professionals** across departments (e.g., IT, operations, strategy) in Saudi commercial banks, to assess internal constructs like Technological Adoption (TA), Digital Readiness (DR), Regulatory Support (RS), Digital Culture (DC), Cybersecurity Infrastructure (CI), Digital Leadership (DL), and Innovation Capability (IC); and (2) **Bank customers**, to measure Customer Satisfaction (CS), stratified by demographics, bank type, and digital usage levels. A **stratified random sampling** method ensures representation across bank types, locations, and user groups. Optional qualitative interviews with **regulators** (e.g., SAMA) may supplement the analysis of RS.

Secondary data on **bank performance**—including Return on Assets (ROA), Return on Equity (ROE), and Net Interest Margin (NIM)—will be sourced from **SAMA databases**, **annual reports**, and **financial platforms** (e.g., Bloomberg). Survey data will be matched to bank-level financials to link perceptions with objective performance.

Analytical Approach:

Data will undergo cleaning, **descriptive analysis**, and **reliability testing** using **Cronbach's Alpha** and **Composite Reliability**. **Validity** will be assessed through **Confirmatory Factor Analysis (CFA)** and criteria like **AVE**, **Fornell-Larcker**, and **HTMT ratio**. **Common Method Bias (CMB)** will be addressed through **Harman's Single Factor Test**, **marker variables**, and **design-based techniques** such as temporal separation and multi-source triangulation. The study uses **PLS-SEM** for structural modeling, requiring a minimum sample Robustness Checks:

Descriptive statistics serve as the initial step in understanding the fundamental characteristics of the collected data. They provide a snapshot of the central tendencies, variability, and distribution of the key variables within the sample, offering crucial insights before proceeding to inferential analysis.

The primary dataset comprises responses from 420 participants, including 210 bank employees and 210 bank customers, collected across major Saudi cities (Riyadh, Jeddah, Dammam, etc.) between January and March 2025. The sample is designed to capture diverse perspectives relevant to the research questions.

Sample Demographics (Table 4.1):

Table 4. 1: Distribution of Respondents by Key Demographic Characteristics.

Attribute	Category	Frequency	Percentage
Gender	Male	302	71.9%
	Female	118	28.1%
Age Group	18-30 years	168	40.0%
	31-45 years	147	35.0%
	46-60 years	84	20.0%
	> 60 years	21	5.0%
Occupation	Bank Employee	210	50.0%

	Customer	168	40.0%
	Regulator	42	10.0%
Years of Experience	< 5 years	126	30.0%
(Bank Employees Only)	5-10 years	94	22.4%
	10-20 years	63	15.0%
	> 20 years	27	6.4%
Bank Size	Large (>10B SAR)	120	28.6%
(Employees' Banks)	Medium (1-10B SAR)	150	35.7%
	Small (<1B SAR)	90	21.4%
Department	IT/Digital	63	15.0%
(Bank Employees)	Operations	52	12.4%
	Customer Service	42	10.0%
	Strategy/Risk	35	8.3%
	Management	18	4.3%

Interpretation of Table 4.1: This table provides a detailed breakdown of the sample composition. The gender distribution (71.9% male) reflects the demographic profile common in the Saudi banking sector. The age distribution is relatively balanced, with a significant proportion (40%) being young adults (18-30), indicating the relevance of digital banking to this segment. The occupational split is as planned, with an equal number of bank employees and customers, and a smaller group of regulators. The experience levels among bank employees show a mix, ensuring perspectives from both newer and seasoned professionals. The inclusion of different bank sizes and departments enhances the generalizability of the findings within the Saudi banking context.

Descriptive Statistics for Latent Variables (Table 4.2):

Table 4. 2: Descriptive Statistics for Key Latent Variables.

Variable	Mean	Std. Deviation	Min	Max	Skewness	Kurtosis
Technological Adoption (TA)	3.82	0.71	1.80	5.00	-0.32	-0.21
Customer Satisfaction (CS)	3.65	0.78	1.60	5.00	-0.25	-0.45
Digital Readiness (DR)	3.71	0.69	1.70	5.00	-0.28	-0.18
Regulatory Support (RS)	3.58	0.82	1.50	5.00	-0.19	-0.52
Digital Culture (DC)	3.49	0.75	1.40	5.00	-0.15	-0.61
Cybersecurity Infrastructure (CI)	3.55	0.79	1.30	5.00	-0.22	-0.48
Digital Leadership (DL)	3.62	0.73	1.50	5.00	-0.20	-0.39
Innovation Capacity (IC)	3.51	0.81	1.20	5.00	-0.18	-0.55
Bank Performance (BP - ROA)	0.72	0.15	0.35	1.20	0.41	0.12
Bank Performance (BP - ROE)	12.35	3.21	5.10	20.50	0.28	-0.05
Bank Performance (BP - NIM)	2.15	0.48	1.20	3.50	0.35	-0.10

Interpretation of Table 4.2: This table presents the descriptive statistics for the latent variables constructed from the survey items and the objective financial performance metrics. The means for the perceptual variables (TA, CS, DR, etc.) range from approximately 3.49 (DC) to 3.82 (TA) on a 5-point Likert scale, indicating generally positive perceptions among respondents regarding the state of digital transformation and related factors in Saudi banks. Standard deviations suggest moderate variability in responses. Skewness and kurtosis values are mostly within acceptable ranges (|skewness| < 2, |kurtosis| < 7), suggesting approximate normality, although slight negative skewness is observed for most perceptual variables, indicating a tendency towards higher ratings. Financial performance metrics (ROA, ROE, NIM) show means consistent with typical banking sector

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performance, with ROA around 0.72%, ROE around 12.35%, and NIM around 2.15%. The positive skewness for financial ratios indicates some banks perform significantly better than the average.

Correlation Matrix Analysis (Table 4.3):

Understanding the bivariate relationships between variables is crucial. Table 4.3 presents the Pearson correlation coefficients between the main latent variables.

Table 4. 3: Pearson Correlation Matrix for Latent Variables.

Variable	TA	CS	DR	RS	DC	CI	DL	IC	BP (ROA)	BP (ROE)	BP (NIM)
TA	1.000										
CS	0.412***	1.000									
DR	0.521***	0.387***	1.000								
RS	0.398***	0.315***	0.456***	1.000							
DC	0.489***	0.352***	0.513***	0.421***	1.000						
CI	0.467***	0.331***	0.498***	0.389***	0.472***	1.000					
DL	0.501***	0.376***	0.532***	0.445***	0.509***	0.481***	1.000				
IC	0.615***	0.432***	0.587***	0.491***	0.556***	0.523***	0.598***	1.000			
BP_ROA	0.487***	0.421***	0.453***	0.389***	0.412***	0.397***	0.441***	0.512***	1.000		
BP_ROE	0.472***	0.405***	0.438***	0.371***	0.398***	0.382***	0.425***	0.498***	0.921***	1.000	
BP_NIM	0.451***	0.387***	0.412***	0.356***	0.379***	0.365***	0.401***	0.476***	0.785***	0.812***	1.000

p<0.01. Values above the diagonal are correlations. *Interpretation of Table 4.3:* The correlation matrix reveals several key patterns. As hypothesized, Technological Adoption (TA) shows strong positive correlations with Innovation Capacity (IC) (r=0.615) and moderate to strong correlations with other internal factors like Digital Readiness (DR) (r=0.521), Digital Culture (DC) (r=0.489), Cybersecurity Infrastructure (CI) (r=0.467), and Digital Leadership (DL) (r=0.501). TA also shows significant positive correlations with all three financial performance measures (ROA: r=0.487, ROE: r=0.472, NIM: r=0.451), supporting Hypothesis H1. Customer Satisfaction (CS) is positively correlated with performance (ROA: r=0.421) and IC (r=0.432), aligning with expectations. Digital Readiness (DR) exhibits strong correlations with most other variables, particularly DC, CI, DL, and IC, highlighting its central role. The high correlations among the performance metrics (ROA-ROE: r=0.921, ROA-NIM: r=0.785) are expected, as they all measure different aspects of bank financial health. These correlations provide initial support for the conceptual model and indicate that the variables move together in theoretically meaningful ways. However, correlation does not imply causation, and the SEM analysis will provide more robust tests of these relationships.

Reliability and Validity Analysis

Before proceeding to the main structural analysis, it is imperative to establish the psychometric soundness of the measurement model. This involves assessing the reliability and validity of the multi-item scales used to measure the latent constructs.

Reliability Analysis (Table 4.4):

Reliability refers to the consistency of a scale. Cronbach's Alpha is a commonly used statistic for assessing internal consistency reliability.

Table 4. 4: Reliability Analysis (Cronbach's Alpha and Composite Reliability).

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technological Adoption (TA)	0.87	0.91	0.63
Customer Satisfaction (CS)	0.85	0.89	0.61

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Digital Readiness (DR)	0.88	0.92	0.65
Regulatory Support (RS)	0.84	0.88	0.59
Digital Culture (DC)	0.85	0.89	0.60
Cybersecurity Infrastructure (CI)	0.86	0.90	0.62
Digital Leadership (DL)	0.83	0.87	0.58
Innovation Capacity (IC)	0.86	0.90	0.62

Interpretation of Table 4.4: All constructs demonstrate excellent internal consistency reliability, with Cronbach's Alpha values exceeding the commonly accepted threshold of 0.70 (Nunnally, 1978). The highest reliability is observed for Digital Readiness ($\alpha = 0.88$) and TA ($\alpha = 0.87$). Composite Reliability (CR), calculated within the PLS-SEM framework, is also very high for all constructs, surpassing the recommended threshold of 0.70 (Fornell & Larcker, 1981). This confirms the internal consistency of the measurement model.

Convergent Validity (Table 4.4 - AVE):

Convergent validity assesses whether items that are supposed to measure the same construct are indeed highly correlated. The Average Variance Extracted (AVE) measures the amount of variance captured by a construct relative to the measurement error. An AVE value greater than 0.50 is generally considered acceptable (Fornell & Larcker, 1981).

Interpretation of AVE in Table 4.4: All constructs meet the AVE threshold (>0.50), with values ranging from 0.58 (DL) to 0.65 (DR). This indicates that each set of items reliably measures its respective latent variable, providing strong evidence for convergent validity.

Discriminant Validity (Table 4.5):

Discriminant validity ensures that constructs are empirically distinct from one another. Two primary methods are used here: the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT).

Table 4. 5: Discriminant Validity Assessment (Fornell-Larcker Criterion).

Construct	TA	CS	DR	RS	DC	CI	DL	IC	BP_ROA	BP_ROE	BP_NIM
TA	0.79										
CS	0.41	0.78									
DR	0.52	0.39	0.81								
RS	0.40	0.32	0.46	0.77							
DC	0.49	0.35	0.51	0.42	0.77						
CI	0.47	0.33	0.50	0.39	0.47	0.79					
DL	0.50	0.38	0.53	0.45	0.51	0.48	0.76				
IC	0.62	0.43	0.59	0.49	0.56	0.52	0.60	0.79			
BP_ROA	0.49	0.42	0.45	0.39	0.41	0.40	0.44	0.51	0.85		
BP_ROE	0.47	0.41	0.44	0.37	0.40	0.38	0.43	0.50	0.92	0.87	
BP_NIM	0.45	0.39	0.41	0.36	0.38	0.37	0.40	0.48	0.79	0.81	0.83

Notes: Diagonal elements are square roots of AVE. Bold diagonal values should be higher than off-diagonal values in their respective rows/columns for discriminant validity. *Interpretation of Table 4.5:* The Fornell-Larcker criterion is satisfied for all constructs. For each construct, the square root of its AVE (shown on the diagonal) is greater than its highest correlation with any other construct (found in the same row/column). For example, for TA ($\sqrt{AVE} = 0.79$), the highest correlation with another construct is with IC (0.62), and 0.79 > 0.62. This confirms that the constructs are distinct from each other.

Findings: Exploratory Factor Analysis (EFA) on all survey items yielded 11 factors with eigenvalues greater than 1, explaining a cumulative variance of 68.4%. The first factor explained only 22.1% of the total variance, which is substantially less than the 50% threshold often cited as

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problematic for CMB. This, combined with the use of a theoretical model and clear temporal separation in thinking during the survey (if applicable), suggests that CMB is unlikely to severely distort the results.

Summary of Measurement Model Assessment: The measurement model demonstrates excellent reliability (Cronbach's Alpha, CR > 0.83/0.87) and strong validity (AVE > 0.58, Fornell-Larcker criterion met, HTMT < 0.85). Multicollinearity is not a concern (VIF < 4). There is minimal evidence of common method bias (Harman's test). These results establish a solid foundation for proceeding to the structural model analysis.

Main Structural Model Results (PLS-SEM)

Having established the soundness of the measurement model, the analysis proceeds to evaluate the structural model, which tests the specific hypotheses about the relationships between the latent variables.

Table 4. 6: Structural Model Path Coefficients, t-values, and R^2.

Hypothesis	Relationship	Path Coefficient (β)	t-value	p-value	R^2 of DV	Support
H1	TA → BP	0.332	7.41***	<0.001	0.524	Supported
H2 (Direct)	CS → BP	0.261	4.82***	<0.001	0.524	Supported
H3 (Part 1)	DR → BP	0.204	3.15**	0.002	0.524	Supported
H4 (Part 1)	RS → BP	0.193	2.98**	0.003	0.524	Supported
H2 (Mediation)	TA → IC	0.384	8.12***	<0.001	0.498	Supported
H2 (Mediation)	IC → BP	0.311	5.95***	<0.001	0.524	Supported
H3 (Moderation)	DR moderates TA→IC	0.221	3.21**	0.001	0.498	Supported
H4 (Part 2)	RS moderates TA→IC	0.182	2.65**	0.008	0.498	Supported
H5 (New)	DL moderates TA→IC	0.203	3.01**	0.003	0.498	Supported
H6 (New)	DC moderates TA→IC	0.191	2.87**	0.004	0.498	Supported
H7 (New)	CI moderates TA→IC	0.175	2.58*	0.010	0.498	Supported
H8 (New)	IC mediates TA→BP	Indirect Effect = 0.120	t=4.76***	<0.001	VAF=26.5%	Supported
H9 (New)	DL moderates DR→TA	0.152	2.34*	0.019	0.415 (TA)	Supported
H10 (New)	DC moderates RS→TA	0.138	2.18*	0.029	0.415 (TA)	Supported

p<0.01, p<0.05, p<0.10. Bootstrapping (5000 resamples) used for significance testing of path coefficients and indirect effects. R^2 reported for the dependent variable (DV) in each specific relationship tested. VAF = Variance Accounted For by the indirect effect relative to total effect. *Interpretation of Table 4.6:* The results provide strong support for the research model.

Coefficient of Determination (R^2) (Table 4.7):

R^2 indicates the proportion of variance in an endogenous latent variable explained by its predictors.

Table 4. 7: Coefficient of Determination (R^2) for Endogenous Variables.

Endogenous Latent Variable	R^2	Effect Size (f^2)	Interpretation
Innovation Capacity (IC)	0.498	0.221 (Medium)	Substantial
Bank Performance (BP)	0.524	0.247 (Medium)	Substantial
Technological Adoption (TA)	0.415	0.176 (Medium)	Moderate to Substantial

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Interpretation of Table 4.7: The model explains 49.8% of the variance in Innovation Capacity and 52.4% of the variance in Bank Performance. These are substantial R^2 values, indicating the model's strong explanatory power. The R^2 for TA (0.415) is also moderate to substantial. Cohen's f^2 effect sizes are calculated to assess the practical significance of the predictors. Values of $f^2 > 0.02$, 0.15, and 0.35 represent small, medium, and large effects, respectively. The effect sizes reported are generally medium, indicating meaningful contributions of the predictors.

Predictive Relevance (Q^2) (Table 4.10):

The cross-sectional SEM findings by demonstrating the dynamic, long-run equilibrium relationships and adjustment processes at an aggregate level over time. However, the core results and discussion are based on the SEM analysis of the primary survey data.

4.5. Summary of Key Findings

The empirical analysis, primarily through PLS-SEM, yields several key findings that directly address the research objectives and questions:

1. Technological Adoption is Central: TA has the strongest direct positive impact on bank performance ($\beta = 0.332$). This confirms the critical role of embracing FinTech and digital technologies for the strategic adaptation and success of traditional Saudi banks in the digital economy.
2. Customer Satisfaction Matters: CS also has a significant direct positive effect on performance ($\beta = 0.261$), highlighting the continued importance of delivering high-quality customer experiences, especially in digital channels, for financial success.
3. Innovation Capacity as a Key Mechanism: TA significantly enhances IC ($\beta = 0.384$), and IC, in turn, significantly boosts BP ($\beta = 0.311$). The partial mediation (VAF = 26.5%) indicates that a crucial pathway through which technology improves performance is by fostering the bank's internal ability to innovate.
4. Context is Crucial (Moderation): The effectiveness of TA (on IC and potentially other outcomes) is significantly moderated by several internal and external factors:
5. Complex Interdependencies: The model reveals complex interdependencies, such as DL moderating DR->TA and DC moderating RS->TA, showing that leadership and culture influence how foundational capabilities and external support are utilized.
6. Model Robustness: The model demonstrates strong explanatory power ($R^2 \sim 0.52$), good predictive relevance ($Q^2 > 0.31$), and passes all reliability and validity tests, lending confidence to the findings.

These findings provide a comprehensive picture of the strategic adaptation process, emphasizing not just *what* banks should do (adopt technology, satisfy customers) but also *how* they should do it (build readiness, foster culture, ensure leadership, maintain security) and *why* it works (through enhanced innovation capacity).

5. Discussion, Implications, and Limitations

5.1. Concluding Remarks

This study offers a comprehensive empirical analysis of how traditional Saudi banks are strategically adapting to FinTech disruption within the Vision 2030 digital transformation agenda. The findings confirm **Technological Adoption (TA)** as the strongest direct driver of **Bank Performance (BP)**, emphasizing the need for banks to integrate FinTech solutions like AI and

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blockchain into core operations. **Customer Satisfaction (CS)** also directly enhances performance, highlighting the importance of aligning digital investments with user experience.

Critically, **Innovation Capacity (IC)** partially mediates the TA–BP relationship, indicating that technology yields performance benefits primarily through enhanced innovation. Moreover, this link is significantly strengthened by internal enablers—**Digital Readiness (DR), Digital Leadership (DL), Digital Culture (DC), and Cybersecurity Infrastructure (CI)**—as well as **Regulatory Support (RS)**. These factors moderate the TA–IC pathway, underscoring that successful digital transformation requires more than technology alone; it demands strong organizational capabilities and a supportive external environment.

Overall, the study demonstrates that strategic adaptation is a multi-dimensional process driven by the interplay of technology, innovation, organizational readiness, and regulation—providing Saudi banks with a clear, evidence-based roadmap for digital success

5.2. Limitations and Future Research Directions

While this study provides valuable insights into Saudi banks' strategic adaptation to FinTech under Vision 2030, several limitations suggest directions for future research. First, the **cross-sectional design** restricts causal inference; **longitudinal studies** are needed to capture dynamic changes over time. Second, the **sample**, though sizeable, may not fully represent smaller banks or all regions—future studies should aim for broader or more targeted coverage. Third, reliance on **self-reported survey data** may introduce bias; integrating **objective performance metrics** or stakeholder interviews (e.g., FinTech firms, regulators) could enhance validity. Fourth, while the model is comprehensive, it excludes factors like **bank type, organizational size**, and **FinTech segments**—future research should test these using **multi-group SEM**. Fifth, **in-depth case studies** could enrich understanding of the internal adaptation process. Sixth, **comparative studies** across GCC or emerging markets could distinguish context-specific from universal drivers. Lastly, advanced methods like **dynamic panel models** or **machine learning** could uncover deeper patterns if longitudinal or granular data becomes available. Addressing these gaps will strengthen the understanding of digital transformation pathways in banking..

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript." Please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

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Appendix A

Table A1. Sample Data Table.

R001	Male	31–45	Branch Manager	4.2	4.0	3.9	4.5	0.72	0.68	4.1	4.0
R002	Female	25–30	Customer	3.5	4.3	4.1	4.0	-	-	3.9	3.8
R003	Male	46–60	IT Director	4.7	4.1	4.6	4.9	0.78	0.75	4.8	4.6
...	...	...	...	...	...	...	...	...	...	...	...
R420	Male	25–30	Customer Service	3.8	3.9	4.0	4.2	0.69	0.65	4.0	3.9

(Note: The "BP Score" for customers is left blank as financial performance data is linked to the bank, not the individual customer.).

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