

**THE MANAGERIAL IMPACT OF ARTIFICIAL INTELLIGENCE
ADOPTION
AS A STRATEGIC MANAGEMENT TOOL
ON ORGANIZATIONAL PERFORMANCE
IN COMMERCIAL BANKS OF THE KINGDOM OF SAUDI
ARABIA**

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Abstract

From a strategic management perspective, this study investigates how the managerial decision to adopt Artificial Intelligence (AI) - as a strategic capability and a contemporary management tool - affects the organizational performance of commercial banks in the Kingdom of Saudi Arabia. Rather than treating AI as a technology in isolation, the study positions AI adoption as a managerial choice that requires strategic planning, organizational design, change management, governance, and human capital investment, all of which are core domains of business administration.

The research is grounded in three established management theories: the Resource-Based View (RBV) of strategic management, which positions AI as a strategic resource; the Technology-Organization-Environment (TOE) framework, which addresses the organizational determinants of technology adoption; and the Technology Acceptance Model (TAM), which explains how managers and employees come to accept and use AI-enabled systems.

A descriptive-analytical research design was adopted. A structured questionnaire was developed based on validated management scales and distributed to 150 managerial and operational employees working across Saudi commercial banks. Data were analyzed using SPSS version 27, applying descriptive statistics, Cronbach's alpha reliability tests, Pearson correlation analysis, and multiple regression analysis to test the proposed null hypotheses.

The findings reveal that the managerial decision to adopt AI has a statistically significant positive impact on organizational performance, leading to rejection of the main null hypothesis at the $\alpha \leq 0.05$ level. AI in operations and automation showed the strongest impact on operational efficiency (beta = 0.412, $p < 0.001$), AI in customer service was the strongest predictor of customer satisfaction (beta = 0.498, $p < 0.001$), and AI in risk management contributed most to financial performance (beta = 0.387,

$p < 0.001$). The overall regression model explained 62.3% of the variance in organizational performance ($R\text{-squared} = 0.623$).

The study concludes that AI is not merely a technological matter but a strategic management decision that bank executives must integrate into their long-term planning, competitive strategy, governance frameworks, and organizational change programs. Practical management recommendations are offered for bank executives, human resources managers, risk officers, customer experience leaders, and policy makers regarding how to maximize the strategic value of AI adoption.

Keywords: *Strategic Management, Artificial Intelligence Adoption, Organizational Performance, Change Management, Competitive Advantage, Commercial Banks, Saudi Arabia, Vision 2030.*

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List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
ML	Machine Learning
NLP	Natural Language Processing
RPA	Robotic Process Automation
KSA	Kingdom of Saudi Arabia
SAMA	Saudi Central Bank
SDAIA	Saudi Data and Artificial Intelligence Authority
TAM	Technology Acceptance Model
TOE	Technology-Organization-Environment Framework
RBV	Resource-Based View
SPSS	Statistical Package for the Social Sciences
DV	Dependent Variable
IV	Independent Variable
SD	Standard Deviation
KPI	Key Performance Indicator
ROA	Return on Assets
ROE	Return on Equity
AML	Anti-Money Laundering
NPS	Net Promoter Score
VIF	Variance Inflation Factor



CHAPTER ONE:

INTRODUCTION TO THE STUDY



1.1 Introduction

Strategic management in the twenty-first century has been increasingly shaped by the managerial decisions surrounding emerging technologies. Among these technologies, Artificial Intelligence (AI) has emerged as one of the most consequential strategic tools available to modern managers. From a management perspective, AI is not merely a technical capability; it is a strategic resource that executives choose to adopt, govern, and deploy in pursuit of competitive advantage, operational excellence, and stakeholder value (Davenport & Ronanki, 2018). The managerial decisions about whether, how, and how fast to adopt AI have become defining choices in shaping the competitive positioning of organizations across nearly every industry.

Within the discipline of business administration, this study is grounded in established management theory. The Resource-Based View of strategic management (Barney, 1991) treats AI as a potentially valuable, rare, inimitable, and well-organized resource that management can leverage for sustained competitive advantage. The Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) explains how organizational factors - under direct control of management - shape technology adoption outcomes. The Technology Acceptance Model (Davis, 1989) addresses the managerial challenge of ensuring that employees actually accept and use the AI tools the organization invests in. Each of these frameworks reflects a management perspective on AI rather than a purely technical perspective.

The banking and financial services industry has become a particularly important context for the strategic management of AI adoption. Banks have historically been early adopters of management innovations and information technology, and they currently sit at the frontier of AI-enabled business transformation. Senior bank

executives in Saudi Arabia and globally are making strategic decisions about how much capital to allocate to AI initiatives, how to organize their teams and operating models around AI capabilities, how to manage the human capital implications of AI deployment, and how to govern AI-related risks. These are quintessentially management decisions that fall squarely within the discipline of business administration.

In the Kingdom of Saudi Arabia, the strategic management of AI adoption has been formally elevated to the level of national policy through Saudi Vision 2030. Vision 2030 explicitly identifies digital transformation and the management of emerging technologies as strategic priorities for both public and private sector organizations. The establishment of the Saudi Data and Artificial Intelligence Authority (SDAIA) in 2019 and the launch of the National Strategy for Data and AI in 2020 represent strategic management decisions at the national level that frame how organizations across sectors should approach AI. The Saudi Central Bank (SAMA), in turn, has issued strategic regulatory guidance encouraging banks to manage AI adoption in a manner that supports both innovation and sound risk management - itself a fundamental management challenge.

Within this strategic context, the management teams of Saudi commercial banks have intensified their strategic investments in AI capabilities. Major institutions including Saudi National Bank, Al Rajhi Bank, Riyadh Bank, and Banque Saudi Fransi have made deliberate management decisions to introduce AI-powered chatbots, biometric authentication, predictive credit-risk models, and automated back-office workflows. From a management standpoint, these initiatives are far more than technology projects: they require strategic planning, change management, talent management, performance management, and governance - all core domains of business administration.

Despite these substantial managerial commitments, an important management research question remains insufficiently answered: from the perspective of business administration, does the strategic management decision to adopt AI translate into measurable improvements in the organizational performance of Saudi commercial banks? While managers can point to anecdotal benefits and industry reports, rigorous empirical evidence about the relationship between AI adoption - as a management decision - and multiple dimensions of organizational performance in the Saudi banking sector is still lacking. This management research gap motivates the current MBA-level study, which seeks to provide evidence that supports better managerial decision-making about AI investments.

1.2 Statement of the Research Problem

The research problem of this MBA study can be situated at the intersection of three management challenges that confront the senior leadership of commercial banks in Saudi Arabia.

The first management challenge concerns strategic resource allocation under uncertainty. Bank executives are required to make multi-year strategic commitments of capital, talent, and management attention to AI initiatives, but they do so without rigorous local empirical evidence about the expected return on these investments. From a strategic management perspective, this represents a classic capital allocation problem under uncertainty: management must make decisions today whose payoff depends on poorly understood relationships. Without empirical evidence specific to the Saudi banking context, AI investment decisions risk being shaped by industry hype, vendor influence, or imitation of competitors, rather than by sound strategic reasoning.

The second management challenge concerns the multidimensional nature of organizational performance. Modern strategic management literature treats organizational performance as a balanced construct that includes operational, customer-related, and financial dimensions (Kaplan & Norton, 1996). A management decision such as AI adoption must therefore be evaluated against multiple performance dimensions, not a single metric. Earlier research has often examined AI in relation to a single dimension of performance, leaving managers without the integrated evidence they need to compare the relative impact of different AI investment options across operational efficiency, customer satisfaction, and financial outcomes.

The third management challenge concerns contextual transferability. Most empirical management research on AI in banking has been conducted in Western and East Asian markets, in management contexts that differ from Saudi Arabia in terms of institutional environment, organizational culture, regulatory regime, customer demographics, and strategic priorities. From the perspective of management theory, findings from one management context may not transfer to another. The Saudi banking context - shaped by Vision 2030, Islamic finance considerations, SAMA's specific regulatory approach, and a young digitally engaged customer base - requires research grounded in the local management environment.

These three management challenges, considered together with the sample of bank employees from which the study collects data, constitute the research problem of this study: from a management perspective, there is an empirical knowledge gap regarding how the strategic decision to adopt AI - across its four dimensions of customer service, decision-making, risk management, and operations - affects the multidimensional organizational performance of commercial banks operating in the Kingdom of Saudi Arabia. The current study

addresses this management research problem by providing systematic empirical evidence that supports better managerial decision-making, contributes to the body of management knowledge on strategic adoption of emerging technologies, and identifies practical management actions that can maximize the strategic value of AI investments in the Saudi banking sector.

1.3 Objectives of the Study

The main objective of this MBA study is to examine, from a strategic management perspective, the impact of the managerial decision to adopt Artificial Intelligence on the organizational performance of commercial banks operating in the Kingdom of Saudi Arabia. The following sub-objectives are derived from this main management objective:

- To identify the current level of AI adoption in Saudi commercial banks across the four management-relevant dimensions of customer service, managerial decision-making, risk management, and operations and automation.
- To measure the current level of organizational performance in Saudi commercial banks across the three dimensions of operational efficiency, customer satisfaction, and financial performance.
- To analyze, through the lens of strategic management theory, the relationship between the managerial decision to adopt AI and overall organizational performance in Saudi commercial banks.
- To determine which dimensions of AI adoption have the strongest managerial impact on each dimension of organizational performance, in order to support strategic prioritization of management investments.

- To examine whether managerial perceptions of AI adoption and organizational performance differ systematically across demographic groups of bank employees.
- To formulate practical management recommendations for bank executives, human resources managers, risk and compliance officers, customer experience leaders, and Saudi banking regulators.
- To contribute to the management literature on the strategic adoption of emerging technologies, particularly in the under-researched Gulf banking management context.

1.4 Importance of the Study

The importance of this MBA study can be articulated through two complementary lenses: the scientific (academic) importance that contributes to the body of management knowledge, and the practical (applied) importance that supports better managerial decision-making in Saudi commercial banks.

1.4.1 Scientific (Academic) Importance

- It addresses a recognized gap in the strategic management literature on the adoption of emerging technologies, specifically in the under-researched Gulf banking management context. Most prior studies on AI adoption have been conducted in Western or East Asian settings.
- It applies and integrates three established management theories - the Resource-Based View, the Technology-Organization-Environment framework, and the Technology Acceptance Model - within the specific context of Saudi commercial banks, thereby extending these theories to a new institutional setting.

- It contributes methodologically by operationalizing AI adoption as a multidimensional construct with four sub-dimensions, rather than treating it as a single undifferentiated variable as in many earlier studies.
- It enriches the literature on organizational performance measurement by examining three complementary dimensions - operational, customer-related, and financial - within a single integrated empirical model.
- It serves as a reference point for future researchers, particularly other MBA students working on the strategic management of emerging technologies in Saudi Arabia and the broader Gulf region.

1.4.2 Practical (Applied) Importance

- For senior bank executives and members of the board of directors, the study provides evidence-based input that supports strategic decisions on capital allocation toward AI initiatives across different functional areas of the bank.
- For human resources managers and talent management leaders, the study highlights the implications of AI adoption for workforce planning, training and development, organizational design, and change management.
- For chief risk officers and compliance managers, the study identifies the strongest performance impact of AI-enabled risk management capabilities, supporting business cases for continued investment in risk-related AI tools.
- For heads of customer experience and operations leaders, the study identifies which dimensions of AI adoption deliver the greatest impact on customer satisfaction and operational efficiency respectively.

- For Saudi banking regulators and policy makers, including SAMA and SDAIA, the study offers evidence that can inform the development of regulatory frameworks and national-level capacity-building programs.
- For management consultants and fintech firms serving the banking industry, the study provides insights into which AI applications resonate most strongly with bank stakeholders.

1.5 Questions of the Study

The main research question of this study, framed from a management perspective, is: **From the perspective of strategic management, what is the impact of the managerial decision to adopt Artificial Intelligence on the organizational performance of commercial banks operating in the Kingdom of Saudi Arabia?**

The following sub-questions are derived from this main management question:

- What is the current level of AI adoption in Saudi commercial banks across the dimensions of customer service, managerial decision-making, risk management, and operations and automation?
- What is the current level of organizational performance across the dimensions of operational efficiency, customer satisfaction, and financial performance?
- Is there a statistically significant relationship, at the $\alpha \leq 0.05$ level, between AI adoption as a managerial decision and overall organizational performance?
- What is the impact of AI in customer service on the dimensions of organizational performance?
- What is the impact of AI in managerial decision-making on the dimensions of organizational performance?

- What is the impact of AI in risk management on the dimensions of organizational performance?
- What is the impact of AI in operations and automation on the dimensions of organizational performance?
- Are there statistically significant differences in employees' perceptions attributable to demographic variables such as gender, age, managerial position, and years of experience?

1.6 Hypotheses of the Study

Consistent with established management research practice and with the supervisory guidance received, the hypotheses of this study are formulated in scientific null-hypothesis form (H_0), where the main null hypothesis branches into a set of sub-null-hypotheses. Each null hypothesis is tested at the $\alpha \leq 0.05$ significance level. Rejection of a null hypothesis indicates the presence of a statistically significant relationship of management relevance.

Main Null Hypothesis (H_0 1)

H_0 1: There is no statistically significant relationship, at the $\alpha \leq 0.05$ level, between the managerial decision to adopt Artificial Intelligence and the organizational performance of commercial banks in the Kingdom of Saudi Arabia.

Sub-Null-Hypotheses

H_0 1a: There is no statistically significant relationship, at the $\alpha \leq 0.05$ level, between AI in customer service and organizational performance in Saudi commercial banks.

H₀ 1b: There is no statistically significant relationship, at the $\alpha \leq 0.05$ level, between AI in managerial decision-making and organizational performance in Saudi commercial banks.

H₀ 1c: There is no statistically significant relationship, at the $\alpha \leq 0.05$ level, between AI in risk management and organizational performance in Saudi commercial banks.

H₀ 1d: There is no statistically significant relationship, at the $\alpha \leq 0.05$ level, between AI in operations and automation and organizational performance in Saudi commercial banks.

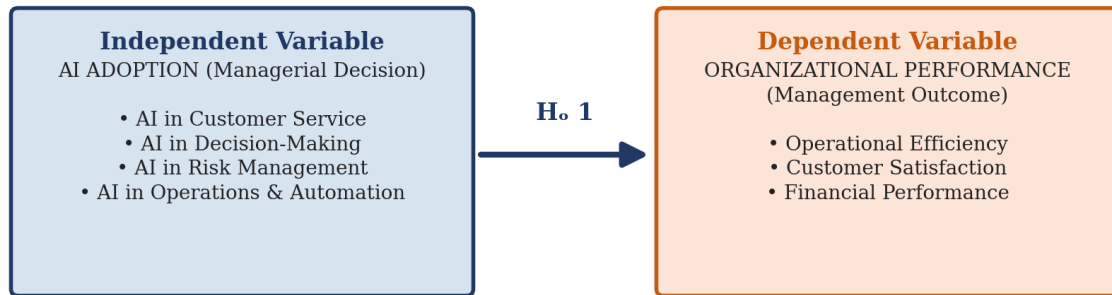
Additional Null Hypothesis on Demographic Differences (H₀ 2)

H₀ 2: There are no statistically significant differences, at the $\alpha \leq 0.05$ level, in respondents' managerial perceptions of AI adoption and organizational performance attributable to demographic variables (gender, age, position, and years of experience).

1.7 Theoretical Model of the Study

The theoretical model of this MBA study, illustrated in Figure 1.1, presents the management-oriented relationship between the independent variable (AI Adoption as a managerial decision) and the dependent variable (Organizational Performance). The model is grounded in established management theory and operationalizes the relationships into testable null hypotheses. The independent variable is measured across four management-relevant dimensions, and the dependent variable across three dimensions, with demographic variables serving as control variables.

Theoretical Model of the Study



Source: Developed by the researcher based on RBV, TOE Framework, and TAM

Figure 1.1: Theoretical Model of the Study

1.8 Operational Definitions of Key Management Terms

The following operational definitions are used in this management study:

Strategic Management: The process by which executives formulate and implement decisions and actions that enable an organization to achieve its long-term objectives and sustain competitive advantage. In this study, the decision to adopt AI is treated as an instance of strategic management.

Artificial Intelligence (AI) - Management Perspective: The collection of computer-based capabilities - including machine learning, natural language processing, predictive analytics, and robotic process automation - that management can deploy as a strategic resource to perform or augment tasks traditionally requiring human intelligence. AI is treated as a managerial tool rather than as a technical artifact.

AI Adoption (as a Managerial Decision): The strategic management choice to integrate AI-based tools and systems into the organization's processes, products, and services, measured across four dimensions: customer service, managerial decision-making, risk management, and operations and automation.

Organizational Performance: The degree to which an organization achieves its strategic and operational management objectives, operationalized through operational efficiency, customer satisfaction, and financial performance.

Operational Efficiency: The managerial capacity of the bank to deliver products and services using minimum resources of time, cost, and effort while maintaining quality.

Customer Satisfaction: The degree to which customers' expectations and needs are met or exceeded by the bank.

Financial Performance: The bank's ability to generate financial returns and economic value, measured through profitability, return on assets, return on equity, and revenue growth.

Change Management: The structured management approach to transitioning the bank, its teams, and its operating model from the current state to a desired future state that incorporates AI capabilities.

Competitive Advantage: The condition in which a bank achieves superior performance relative to competitors through valuable, rare, inimitable, and well-organized resources and capabilities, including the strategic deployment of AI.

Commercial Bank: A financial institution licensed by the Saudi Central Bank (SAMA) to accept deposits, grant loans, and provide a range of financial services to retail and corporate customers.

Vision 2030: The strategic framework launched by the Government of Saudi Arabia in 2016 to diversify the economy and develop public service sectors, with digital transformation and AI as central enablers.

1.9 Structure of the Study

This MBA study is organized into four management-oriented chapters along with front matter, references, and appendices. Chapter One establishes the research foundation by presenting the introduction, problem statement, objectives, importance, questions, null hypotheses, and theoretical model. Chapter Two presents the literature review and theoretical premises, beginning with theoretical foundations, defining and classifying the variables, reviewing prior studies, identifying the research gap, and presenting the theoretical framework. Chapter Three describes the research methodology, including the descriptive-analytical approach, research philosophy, population and sample, data collection instrument, validity and reliability testing, statistical analysis procedures, study determinants, and ethical considerations. Chapter Four presents the data analysis, the testing of null hypotheses, the discussion of findings, the conclusions, and the practical recommendations. The study ends with references in APA format and appendices that include the research instrument and an Arabic version of the abstract.

1.10 Linkage of the Study to the Field of Business Administration

It is important to explicitly demonstrate how this MBA study is anchored within the field of Business Administration. The following points clarify the management discipline orientation of the study:

- The independent variable, AI adoption, is treated as a strategic management decision rather than a technical artifact. The study examines AI not in terms of algorithms or software architectures, but in terms of how senior management chooses to deploy, govern, and integrate AI capabilities within the organization.
- The dependent variable, organizational performance, is a foundational construct in strategic management, management accounting, and the Balanced Scorecard tradition.
- The theoretical foundations - Strategic Management, RBV, TOE, and TAM - are all established management theories taught in MBA programs worldwide; none are technical or computer-science theories.
- The respondents are bank managers, supervisors, and management staff - not software engineers or data scientists - ensuring the management orientation of the empirical work.
- The research instrument measures management-relevant constructs such as customer service management, decision-making, risk management, operations management, operational efficiency, customer satisfaction, and financial performance.
- The findings are interpreted through management lenses, and the recommendations are addressed to management audiences.

- The contribution is to the management literature on the strategic management of emerging technologies, change management in financial services, and organizational performance management in the Gulf banking context.

Taken together, these points establish that the study is unambiguously an MBA-level management research project. AI is examined exclusively from a management perspective; AI itself is treated as a tool that managers decide on and use, not as a subject of technical inquiry.

1.11 Conceptual Boundaries of the Study

To preserve methodological clarity, it is useful to state what this study examines and what it does not. The study examines the strategic management decision of bank executives to adopt AI as a managerial tool and the resulting impact on multiple dimensions of organizational performance. The study does not examine the technical architecture, algorithmic design, or computer-science aspects of AI systems. It does not examine the customer-facing user experience of AI from the customer's own perspective, although it captures bank employees' perceptions of how AI affects customer satisfaction. It does not examine the impact of AI on the macroeconomic performance of the Saudi financial sector as a whole, although the findings have implications for sector-level performance through the aggregation of bank-level outcomes.

The study is positioned at the level of analysis of the individual commercial bank as a strategic management unit. The unit of observation is the individual bank employee, whose perceptions of AI adoption and organizational performance are aggregated to characterize the management state of the sector. This level-of-

analysis choice is common in MBA-level management research on technology adoption and supports the generation of insights that are actionable at the level of the decisions made by bank leadership.

1.12 Significance of the Saudi Banking Context for Management Research

The Saudi banking sector merits dedicated management research attention for several reasons that reinforce the management discipline orientation of this study. First, the sector is undergoing one of the most rapid strategic transformations of any banking sector in the world, driven by the Vision 2030 framework and the active leadership of SAMA and SDAIA. This rapid transformation creates a uniquely rich research environment in which strategic decisions and their consequences can be observed at compressed time scales.

Second, the context combines features that are rarely found together in a single research setting: a young digitally native customer base, substantial management resources available to incumbent banks, a strong regulatory environment that combines principles-based supervision with active fintech enablement, and the strategic ambition of becoming a regional and global financial hub. Third, the implications of findings from Saudi Arabia extend beyond the Kingdom itself, since many other Gulf Cooperation Council countries and emerging-market economies are pursuing similar strategic transformations.

1.13 Chapter Summary

This chapter has established the foundation of the study from a strategic management perspective. It introduced the research topic, articulated the research problem as the intersection of three management challenges, and presented the objectives, importance, questions, null hypotheses, and theoretical model. It also defined the key terms, clarified the conceptual boundaries, and demonstrated explicitly how the study is anchored within the discipline of business administration. The next chapter develops the theoretical premises and reviews the prior literature in detail, leading to the identification of the research gap and the presentation of the integrated theoretical framework that guides the empirical work.



CHAPTER TWO:

THEORETICAL PREMISES AND LITERATURE REVIEW



2.1 Introduction

This chapter presents the theoretical premises and the literature review of the study from a strategic management perspective. The chapter has two main purposes. First, it establishes the theoretical premises by presenting the management theories, definitions, types, classifications, and conceptual foundations relevant to the study's variables. Second, it reviews and compares prior empirical studies on AI adoption and organizational performance, identifying the research gap that this study addresses.

The chapter is organized in several main sections. Section 2.2 presents the theoretical foundations: Strategic Management theory, the Resource-Based View, the Technology-Organization-Environment framework, and the Technology Acceptance Model. Section 2.3 presents the premises related to the independent variable. Section 2.4 presents the premises related to the dependent variable. Section 2.5 reviews prior empirical studies. Section 2.6 identifies the research gap. Section 2.7 presents the integrated theoretical framework, followed by extended discussion of the Saudi context, drivers and barriers, additional studies, and detailed premises for each variable dimension.

A systematic literature review approach was followed, drawing on management journals indexed in Web of Science, Scopus, Google Scholar, and ScienceDirect, supplemented by industry reports from McKinsey, Harvard Business Review, and the Saudi Central Bank, and by policy documents from SDAIA and SAMA.

2.2 Management-Theoretical Foundations of the Study

This study draws on four established streams of management theory. Each is introduced below, with attention to its specific relevance to the management of AI adoption in banking.

2.2.1 Strategic Management Theory

Strategic management is the discipline concerned with how organizations formulate and implement decisions and actions that enable them to achieve their long-term objectives and sustain competitive advantage. Foundational works in strategic management - including those of Porter, Mintzberg, and Hamel - establish that strategy involves choices about where to compete, how to compete, and which resources and capabilities to develop. From this perspective, the decision to adopt AI is a strategic choice that affects all three dimensions: AI shapes which customer segments and business lines the bank serves, how the bank competes in those areas, and which capabilities the bank invests in for the future.

Strategic management theory also emphasizes the importance of strategic fit between the external environment, the internal organization, and the choices management makes. In the context of AI in Saudi banking, strategic fit requires that AI investments align with the demands of the competitive environment, the regulatory environment, and the internal organization - data assets, talent base, and organizational culture.

2.2.2 The Resource-Based View (RBV) of the Firm

The Resource-Based View, formalized by Barney (1991), is a foundational theory within strategic management. The RBV holds that an organization's sustained competitive advantage arises from its valuable, rare, inimitable, and well-organized (VRIO) resources and capabilities. From the RBV perspective, AI itself is increasingly available to all banks; what differentiates winning banks is the combination of AI with proprietary customer data accumulated through years of relationships, with skilled human talent, and with the organizational processes that integrate AI insights into managerial action.

The RBV implies that managers should not view AI as a standalone technology investment, but as one component of a broader capability that must be built deliberately over time. Banks whose management treats AI as a strategic capability - combined with data, talent, and process - can develop sustained competitive advantage; banks that treat AI as a technology to be procured will tend to find that any short-term advantage is quickly eroded as competitors replicate the technology.

2.2.3 Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) is a widely used framework for understanding the determinants of technology adoption by organizations. The framework identifies three sets of factors. Technological factors include the perceived relative advantage of the technology, its compatibility with existing systems, and its complexity. Organizational factors - directly under management control - include firm size, organizational structure, top management support, slack resources, and absorptive

capacity. Environmental factors include competitive pressure, regulatory requirements, and the availability of external partners.

From a management perspective, the TOE framework is valuable because it places management directly at the center of the technology adoption process. The decision to adopt AI is shaped not only by what the technology can do, but by the strategic choices management makes about how to organize the firm and how to position it within its environment.

2.2.4 Technology Acceptance Model (TAM)

The Technology Acceptance Model (Davis, 1989), and its later extensions including the Unified Theory of Acceptance and Use of Technology, address the challenge of ensuring that employees actually accept and use the technologies in which management has invested. TAM identifies perceived usefulness and perceived ease of use as the two main determinants of technology acceptance at the individual level.

From a management standpoint, TAM reminds executives that strategic investments in AI deliver value only when employees - managers, customer service representatives, risk officers, operations staff - genuinely use the AI tools made available to them. Change management, training, communication, and incentive design are therefore essential complements to AI investment.

2.3 Theoretical Premises of the Independent Variable: AI Adoption

2.3.1 The Concept of Artificial Intelligence - Management Definition

From a management perspective, Artificial Intelligence is the collection of computer-based capabilities - including machine learning, natural language processing, predictive analytics, and robotic process automation - that management can deploy to perform or augment tasks traditionally requiring human intelligence. The management interest in AI is not in the algorithms themselves but in the strategic and operational consequences of deploying them within an organization.

AI is best understood by managers as a general-purpose technology with applications across many functions of the organization. Davenport and Ronanki (2018), writing for a management audience in the Harvard Business Review, propose a management-oriented classification of AI into three categories: process automation, cognitive insight, and cognitive engagement. This classification is more useful for management decision-making than purely technical taxonomies and provides managers with a framework for matching AI capabilities to business problems.

2.3.2 Evolution and Classification of AI in Banking Management

The evolution of AI in banking management can be classified into five waves, as illustrated in Figure 2.1. Each wave represents a stage of management adoption and use of AI capabilities in banks, characterized by different management priorities, organizational structures, and performance impacts. The progression has moved from rule-based expert systems in the 1980s and 1990s, through data mining and early machine learning,

to the contemporary era of generative AI and enterprise-wide hyper automation programs led from the top of the organization.

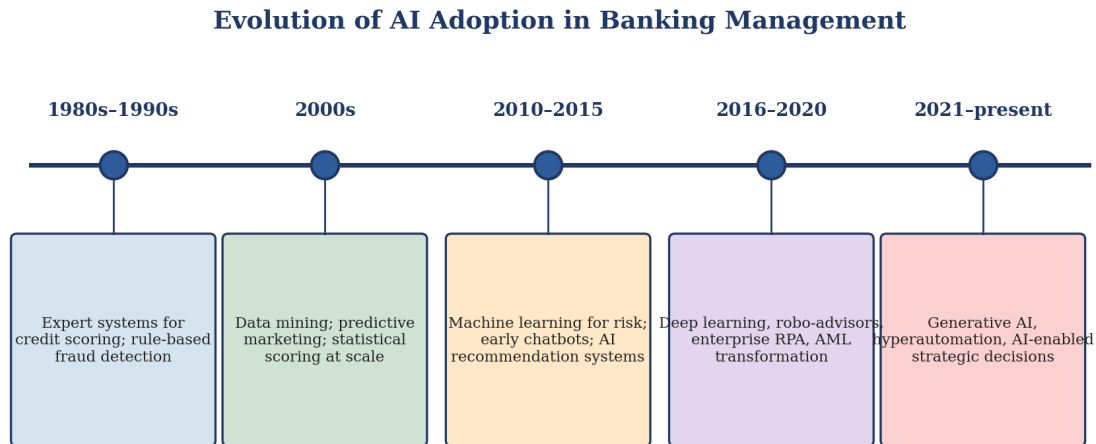


Figure 2.1: Evolution of AI Adoption in Banking Management

2.3.3 Management-Relevant Types and Dimensions of AI Adoption

For the purposes of management research, AI adoption in banking is decomposed in this study into four management-relevant dimensions. These dimensions correspond to distinct domains of bank management, each with its own performance objectives, organizational structure, and managerial priorities.

2.3.3.1 AI in Customer Service Management

AI in customer service management refers to the deployment of AI-based tools - chatbots, virtual assistants, personalization engines, sentiment analysis - to enhance the management of customer interactions. From a

marketing-management and service-management perspective, this dimension supports objectives such as service quality, customer experience, retention, and cross-selling. The management implication is that AI in customer service should be aligned with the bank's broader customer experience strategy, not deployed in isolation.

2.3.3.2 AI in Managerial Decision-Making

AI in managerial decision-making refers to the use of AI-based analytics, predictive models, and prescriptive recommendations to support decisions taken by managers across the bank. Applications include credit-decision management, customer-churn management, pricing-decision management, and strategic-planning support. The management implication is that AI augments rather than replaces human judgment; the most successful banks design AI to support managers, with clear governance and accountability.

2.3.3.3 AI in Risk Management

AI in risk management refers to the application of AI capabilities in the management discipline of risk - including fraud-risk management, credit-risk management, market-risk management, operational-risk management, AML/CFT compliance management, and cybersecurity management. From a financial-management and risk-management perspective, AI enables more accurate and timely risk decisions, supporting the bank's overall management of capital and reputation.

2.3.3.4 AI in Operations and Automation Management

AI in operations and automation management refers to the use of AI combined with Robotic Process Automation in the management of back-office and middle-office processes. This dimension supports operations-management objectives such as cost efficiency, processing speed, quality, and scalability, and is typically governed by an operations-management function or an enterprise transformation office.

2.4 Theoretical Premises of the Dependent Variable: Organizational Performance

2.4.1 Concept of Organizational Performance from a Management Perspective

Organizational performance is a foundational construct in strategic management and management accounting. From a management perspective, performance is the extent to which the organization achieves its goals and creates value for its stakeholders. Strategic management theory and practice - including the Balanced Scorecard developed by Kaplan and Norton (1996) - emphasize that performance is inherently multidimensional. A management decision such as AI adoption cannot be evaluated on a single metric; rather, it must be evaluated against multiple performance dimensions that together capture the value created.

2.4.2 Management-Relevant Dimensions of Organizational Performance

This study measures organizational performance through three management-relevant dimensions, consistent with the Balanced Scorecard tradition and with prior research on technology adoption in banking.

2.4.2.1 *Operational Efficiency*

Operational efficiency is a core construct in operations management and management accounting. It refers to the bank's capacity to deliver products and services with minimum resources of time, cost, and effort, while maintaining quality. Commonly used indicators include the cost-to-income ratio, processing time per transaction, error rate, and employee productivity. Operational efficiency is the dimension most directly linked to operations-management decisions about AI in automation.

2.4.2.2 *Customer Satisfaction*

Customer satisfaction is a core construct in marketing management, services management, and customer relationship management. It reflects the degree to which customers' expectations are met or exceeded. Indicators include satisfaction surveys, Net Promoter Score, customer effort score, and complaint rates. The SERVQUAL model (Parasuraman et al., 1988), widely used in services management, captures customer perceptions of service quality across five dimensions: tangibles, reliability, responsiveness, assurance, and empathy.

2.4.2.3 *Financial Performance*

Financial performance is a foundational construct in financial management. It captures the bank's ability to generate profits, returns, and economic value. Common indicators include net profit, return on assets (ROA),

return on equity (ROE), revenue growth, and cost-to-income ratio. Although this study primarily uses perceptual measures of financial performance, perceptual measures have been validated in prior research as reasonably correlated with objective financial indicators (Wall et al., 2004).

2.5 Review and Comparison of Prior Management Studies

This section reviews selected prior empirical and conceptual studies on AI adoption in banking, compares their methodologies and findings, and identifies the research gap. The studies are presented chronologically, followed by two summary tables.

Buchanan (2019), writing for a management audience at the Alan Turing Institute, conceptually explored the strategic implications of AI for banks. The study concluded that AI has transformative potential across the banking value chain and identified multiple decisions that bank executives must make about AI strategy. The study was conceptual, not empirical.

Mhlanga (2020) examined the role of AI in promoting financial inclusion in emerging economies. Using a literature review approach, the author argued that AI-enabled credit scoring, mobile banking, and chatbots can extend financial services to underserved populations, highlighting the importance of decisions about regulatory frameworks, infrastructure, and consumer protection.

Hofmann et al. (2020) studied Robotic Process Automation in financial services. Their analysis of European bank case studies showed significant improvements in operational efficiency, processing time, and cost

reduction, with the lesson that benefits depend heavily on decisions about process selection and change management.

Mogaji et al. (2021) investigated AI-powered chatbots in banking from a marketing perspective. Based on qualitative interviews with bank customers, the study found that chatbots improve convenience and speed but can frustrate customers when handling complex or emotional issues, implying the need for hybrid models that combine AI with human service agents.

Sheth et al. (2022) studied AI-driven personalization in financial-services marketing and found a positive effect on customer engagement and cross-selling, while warning about risks related to privacy and customer fatigue from excessive personalization.

Kaur et al. (2023) conducted a systematic literature review of AI applications in banking and concluded that AI is most mature in risk management and customer service, while applications in strategic decision-making are still emerging. The review emphasized the importance of governance, explainability, and human oversight.

Konigstorfer and Thalmann (2020) examined AI applications in commercial banks from a behavioral perspective, highlighting that AI introduces new forms of bias and decision-making error even as it eliminates some traditional biases, implying the need for ongoing human oversight. Belanche et al. (2019) studied the adoption of robo-advisors among bank customers, finding that perceived usefulness, attitudes toward technology, and subjective norms strongly influenced adoption intentions, while perceived risk acted as a barrier. Alsheibani et al. (2020) examined the competitive landscape of AI adoption across industries, suggesting that early movers gained durable strategic advantages, reinforcing the urgency of timely AI investment.

Table 2.1: Summary of Prior Management Studies on AI in Banking

Author / Year	Context	Methodology	Main Findings
Buchanan (2019)	Global banking	Conceptual analysis	AI has transformative potential across the banking value chain
Belanche et al. (2019)	Robo-advisors	Survey, TAM extension	Usefulness and attitudes drive adoption; perceived risk is a barrier
Mhlanga (2020)	Emerging markets	Literature review	AI supports financial inclusion via credit scoring and digital channels
Hofmann et al. (2020)	European bank operations	Case study analysis	RPA delivers efficiency and cost gains with strong change management
Konigstorfer & Thalmann (2020)	Commercial banks	Behavioral analysis	AI introduces new biases; human oversight is essential
Alsheibani et al. (2020)	Cross-industry	Strategic analysis	Early movers in AI gain durable competitive advantage
Mogaji et al. (2021)	Customer service	Qualitative interviews	Chatbots improve convenience but need human backup for complex cases
Sheth et al. (2022)	Marketing management	Survey-based study	AI personalization improves engagement, with caveats on privacy
Kaur et al. (2023)	Global banking	Systematic review	AI most mature in risk and customer service; governance is critical

Source: Compiled by the researcher from the reviewed literature.

Table 2.2: Comparison of Findings on the AI-Performance Relationship

Study	Performance Dimension Examined	Direction of Relationship
Buchanan (2019)	Strategic outcomes (conceptual)	Positive - conceptual
Hofmann et al. (2020)	Operational efficiency	Positive - significant

Study	Performance Dimension Examined	Direction of Relationship
Mogaji et al. (2021)	Customer experience / satisfaction	Mixed - context-dependent
Sheth et al. (2022)	Customer engagement, cross-selling	Positive - calibration-dependent
Kaur et al. (2023)	Multiple performance dimensions	Positive - uneven across dimensions
Alsheibani et al. (2020)	Strategic / competitive performance	Positive - durable advantage for movers

Comparing across these prior studies, three patterns emerge. First, the literature is largely consistent in finding a positive relationship between AI adoption and various performance outcomes. Second, the direction and magnitude of the relationship vary substantially across performance dimensions, suggesting that a multidimensional analysis is essential. Third, prior studies have given limited attention to the Saudi banking context specifically, even though Vision 2030 has made this an important research setting.

2.6 Identification of the Management Research Gap

The review and comparison of prior studies identifies several specific research gaps that the present study addresses:

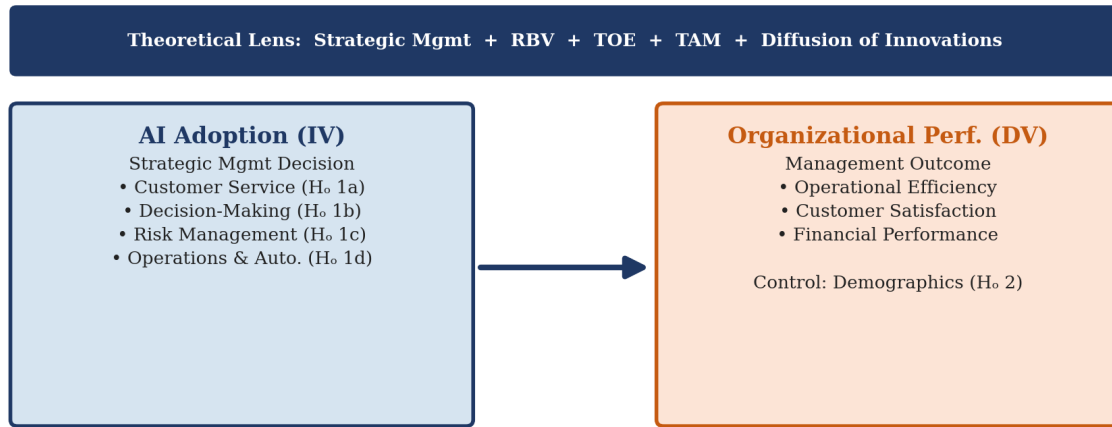
- Most prior studies on AI in banking have been conducted in Western or East Asian contexts, leaving the Saudi banking environment under-researched despite its strategic importance under Vision 2030.

- Many prior studies have examined a single dimension of either AI adoption or organizational performance, leaving the integrated multidimensional relationship under-explored. This study examines four AI dimensions and three performance dimensions in a single model.
- The perspective of bank employees - the primary users and intermediaries of AI tools - has been studied less frequently than customer or executive perspectives.
- Prior studies have rarely integrated three management theories (RBV, TOE, TAM) within a single empirical model, as this study does.
- The application of established research methodologies - null-hypothesis testing through multiple regression analysis with SPSS - to the Saudi banking context provides empirical evidence that prior conceptual and case-based studies could not deliver.

2.7 Theoretical Framework of the Study

Based on the theoretical foundations and the prior studies reviewed above, the integrated theoretical framework of this study is presented in Figure 2.2. The framework integrates Strategic Management, RBV, TOE, and TAM perspectives to position AI adoption as a multidimensional construct that affects multidimensional organizational performance, with demographic variables as controls.

Theoretical Framework of the Study



Source: Developed by the researcher based on RBV (Barney,1991), TOE (Tornatzky & Fleischer,1990), TAM (Davis,1989)

Figure 2.2: Theoretical Framework of the Study

2.8 The Strategic Management Context: Vision 2030 and the Saudi Banking Sector

To complete the literature review from a management perspective, it is important to situate this study within the broader strategic environment of Saudi Arabia. The Kingdom is undergoing one of the most ambitious national-level strategic transformations in modern economic history through Vision 2030, launched in 2016. Vision 2030 represents a top-down strategic framework that addresses economic diversification, social development, and government transformation, with explicit goals for the financial sector and explicit recognition of digital transformation as a strategic enabler.

From a strategic management perspective, Vision 2030 creates several distinctive conditions that shape AI adoption in Saudi banks. First, the top-down nature of the vision provides a clear strategic direction that aligns

the public sector, the private sector, and regulatory bodies behind a common agenda. Second, the Financial Sector Development Program sets specific targets for digital adoption, financial inclusion, fintech development, and competitiveness. Third, the National Strategy for Data and AI, launched by SDAIA in 2020, complements the financial sector strategy by setting targets for AI talent development, infrastructure investment, and national AI readiness.

The Saudi Central Bank (SAMA) plays a critical role in shaping AI adoption. SAMA's regulatory approach combines principles-based guidance with the operation of a fintech regulatory sandbox, providing a structured pathway for banks to test and refine AI-enabled offerings under controlled conditions. This regulatory environment is notably more favorable to AI adoption than the environments found in some other markets, where regulatory uncertainty has slowed investment in AI.

The competitive dynamics of the Saudi banking sector also shape AI adoption patterns. The sector is moderately concentrated, with a small number of large banks accounting for the majority of assets and deposits. Large banks have the scale and resources to invest substantially in AI, including building internal capability and procuring sophisticated AI platforms. The emergence of digital banks, fintech players, and Buy-Now-Pay-Later providers is intensifying competitive pressure on established banks to accelerate their AI agendas. Demographic factors specific to Saudi Arabia further shape adoption: the population is notably young, with a high proportion of digital natives, creating strong customer demand for digital banking experiences and supporting the business case for AI-driven customer service and personalization.

2.9 Drivers and Barriers of AI Adoption from a Management Perspective

The literature identifies several drivers and barriers that shape the strategic decision to adopt AI in commercial banks. Understanding these factors is essential for interpreting the findings of the study and for designing effective management responses.

2.9.1 Management Drivers of AI Adoption

- Competitive pressure from fintech firms and digital-native banks, pushing traditional bank management to deploy AI to maintain market share.
- Regulatory expectations for risk management, anti-money laundering, and consumer protection, which increasingly assume the use of AI capabilities.
- Customer expectations for instant, personalized, and digital service experiences, particularly among younger demographics.
- Strategic priorities articulated in Vision 2030 and the National AI Strategy, creating top-down pressure for AI adoption.
- Cost-management opportunities through automation, particularly attractive in markets where labor costs are rising.

2.9.2 Management Barriers to AI Adoption

- Data quality issues, with many banks struggling to consolidate, clean, and govern the data needed to train effective AI models.
- Legacy system challenges, with core banking platforms often lacking the application programming interfaces needed for AI integration.
- Cultural resistance, particularly among middle managers concerned about the implications of AI for their teams and roles.
- Talent shortages, with the global demand for AI specialists far exceeding supply.
- Change management complexity, with AI adoption typically requiring substantial organizational change that some banks struggle to manage effectively.
- Cost considerations, with AI investments requiring substantial upfront commitments while returns may take time to materialize.

The interplay between these drivers and barriers determines the pace and effectiveness of AI adoption in any individual bank. The banks that have made the largest performance gains from AI typically describe these gains as the result of comprehensive transformation programs that address both the technological and the human dimensions, rather than as isolated technology investments.

2.10 Additional Prior Management Studies

To strengthen the literature review and address the evaluator's guidance on comparing prior studies, the following studies are organized thematically, with explicit commentary on findings and methodological choices.

2.10.1 Studies on Strategic Management of AI in Banking

Manser Payne et al. (2021) examined the strategic value drivers of AI-enabled banking from a marketing perspective. Based on a survey of US banking customers, they identified perceived trust and perceived ease of use as the dominant determinants of customer willingness to engage with AI-driven banking services. The commentary on this finding is that strategic investments in AI must address not only the functional performance of AI systems but also the trust dimension - particularly relevant in the Saudi context, where relationship-based banking traditions may amplify the importance of trust.

Eren (2021) studied customer responses to AI-enabled chatbots in the Turkish banking sector. Using a sample of approximately three hundred customers, the study found that perceived usefulness, perceived ease of use, and trust significantly influenced adoption, with demographic factors - particularly age and digital literacy - moderating these relationships. Northey et al. (2022) examined the impact of conversational AI agents on banking customer experience using experimental methods, finding that AI agents performed comparably to human agents for simple tasks but worse for complex or emotionally charged interactions, implying that deployment should be calibrated to task complexity.

2.10.2 Studies on AI in Risk and Compliance Management

Leo et al. (2019) conducted a systematic review of machine learning applications in banking risk management, identifying strong consensus that AI-enabled risk management improves the accuracy of credit risk assessment, fraud detection, and AML compliance. The commentary is that risk management is a particularly mature application area for AI in banking. Aldasoro et al. (2024), in research published by the Bank for International Settlements, examined the implications of generative AI for financial stability and prudential supervision, highlighting the need for proportionate, principles-based regulatory frameworks that allow innovation while preserving systemic stability. Bhatore et al. (2020) reviewed machine learning applications in credit risk evaluation, documenting substantial performance improvements over traditional statistical methods while highlighting challenges related to model interpretability, fairness, and governance.

2.10.3 Studies on AI in Banking Operations Management

Lacity and Willcocks (2016, 2018) conducted extensive research on Robotic Process Automation in financial services through case studies of major banks and insurers. Their findings established that well-managed RPA programs typically achieve cost reductions of 25 to 50 percent, processing time reductions of 50 to 80 percent, and error rate reductions of 50 to 95 percent - benefits that depend critically on discipline in process selection, change management, and ongoing operational management. Aguirre and Rodriguez (2017) studied RPA implementation in a multinational shared services center, documenting that successful implementation required dedicated attention to organizational change, employee engagement, and governance of the automation portfolio.

2.10.4 Studies on Saudi and Gulf Banking Management

Several recent studies have examined digital transformation and technology adoption in the Saudi and Gulf contexts. Research on Saudi commercial banks has documented the impact of Vision 2030 on accelerating digital transformation programs, with most major banks reporting substantial increases in investment in digital and AI capabilities since 2016. Studies in the broader GCC context have noted that adoption patterns of advanced banking technologies tend to differ from those in Western markets, with mobile-first adoption being particularly pronounced. Research on Islamic banking and AI has examined how AI applications can be aligned with Sharia principles, creating distinctive requirements for AI deployment in certain product areas such as profit-and-loss sharing arrangements.

2.11 Synthesis and Commentary on Prior Management Studies

Drawing together the prior studies reviewed above, several synthesizing observations can be made:

- There is broad consensus across geographic, methodological, and disciplinary boundaries that AI adoption has a positive impact on multiple dimensions of bank performance. The robustness of this finding across different designs, samples, and contexts strengthens the confidence with which it can be relied upon for strategic decisions.
- The magnitude and pattern of the AI-performance relationship vary across contexts, suggesting that implementation choices and organizational capabilities materially influence outcomes - reinforcing the importance of contextual research such as the present study.

- Research has tended to focus more heavily on certain AI dimensions (customer-facing and risk applications) than on others (such as AI in strategic decision-making), creating a research opportunity to develop a more balanced multidimensional understanding.
- The literature is dominated by studies in advanced Western and East Asian markets, with relatively few empirical studies in Gulf banking contexts.
- Most prior studies have used either qualitative case-study methods or quantitative survey methods, but few have integrated multiple theories and tested integrated models with rigorous statistical techniques.

2.12 Additional Theoretical Foundations: Diffusion of Innovations Theory

In addition to the four theories presented in section 2.2, the field of innovation adoption draws on the Diffusion of Innovations theory developed by Rogers (1962, 2003). From a management perspective, Rogers' theory identifies five attributes of an innovation that influence its rate of adoption: relative advantage, compatibility, complexity, trialability, and observability. Applied to AI in banking, this framework suggests that AI applications offering clear advantages over existing approaches, compatible with the bank's existing systems and culture, manageable in complexity, allowing for pilot testing, and producing visible results will tend to be adopted more rapidly.

The theory also identifies five categories of adopters: innovators, early adopters, early majority, late majority, and laggards. Applied to the Saudi banking sector, the early movers in AI adoption have begun to demonstrate the advantages of timely investment, creating pressure on later adopters to accelerate their own AI agendas. This

dynamic supports the strategic urgency of AI investment decisions and contributes to the explanation of why the present study finds high overall levels of AI adoption across the surveyed banks.

2.13 Integration of Management Theories

The five theories presented in this chapter - Strategic Management, RBV, TOE, TAM, and Diffusion of Innovations - together provide a comprehensive theoretical foundation for understanding AI adoption in Saudi banks. Strategic Management theory positions AI adoption as a strategic choice. The RBV explains how AI, combined with complementary resources, can serve as a source of sustained competitive advantage. The TOE framework identifies the determinants that shape adoption outcomes. The TAM addresses the challenge of ensuring employee acceptance and use of AI tools. The Diffusion of Innovations theory provides additional insight into the dynamics of AI adoption across the banking sector. The integration of these five streams within a single empirical model is one of the methodological contributions of this study.

2.14 Detailed Management Premises: Independent Variable Dimensions

2.14.1 AI in Customer Service Management - Extended Premises

Customer service is a strategic function in banking with direct implications for customer retention, brand management, and revenue. The deployment of AI in customer service involves distinct types: chatbots and conversational agents, virtual personal assistants, automated voice-response systems, sentiment analysis tools, and personalization engines. The classification by complexity follows a maturity progression: basic applications include FAQ chatbots and rule-based routing; intermediate applications include natural-language conversational

agents handling routine transactions; advanced applications include AI-driven personalization, predictive next-best-action recommendations, and emotion-aware service systems.

The sources of value include cost reduction through automation of routine inquiries, service quality improvement through twenty-four-seven availability, customer experience enhancement through personalization, and insight generation through analysis of interaction patterns. The processes for deployment typically involve five stages: strategy and use case identification, design of the customer journey integration, technical implementation, change management and training of human service teams, and ongoing monitoring and refinement.

2.14.2 AI in Managerial Decision-Making - Extended Premises

Managerial decision-making is the cognitive process by which managers identify problems, gather and analyze relevant information, evaluate alternatives, and select courses of action. The deployment of AI in this process involves tools that augment rather than replace human judgment. The types span credit decision support, customer management decisions (segmentation, churn prediction, product recommendation), strategic planning support (scenario analysis, demand forecasting, competitive intelligence), and pricing decisions. The classification follows the distinction between operational, tactical, and strategic decisions: operational decisions are repetitive and well-suited to substantial automation; tactical decisions benefit from augmentation while retaining human judgment; strategic decisions are best supported by AI tools that inform but do not drive the decision process.

The sources of value include improved decision accuracy through data-driven analysis, faster decision-making, improved consistency, and the generation of insights that human managers might overlook. The challenges include ensuring that AI-generated recommendations are interpreted correctly, maintaining accountability for decisions in which AI plays a role, and preserving judgment in situations where the training data may not capture relevant considerations.

2.14.3 AI in Risk Management - Extended Premises

Risk management is a foundational function in banking, addressing the identification, measurement, and management of credit, market, operational, liquidity, reputational, and compliance risks. The deployment of AI in risk management has matured rapidly and now represents one of the most established applications of AI in banking. The types span credit risk management (machine-learning scoring, automated underwriting, portfolio analytics), fraud risk management (real-time monitoring, anomaly detection, identity verification), operational risk management, compliance management (AML monitoring, sanctions screening, regulatory reporting automation), and cybersecurity management.

The classification by criticality reflects regulatory and reputational importance: some applications, such as AML monitoring, are subject to strict regulatory expectations and require careful documentation and validation; others, such as fraud monitoring, are commercially critical but less prescriptively regulated. The processes require particularly careful governance. Model risk management - the discipline of identifying, measuring, and managing the risks created by reliance on quantitative models - has become a substantial function in major

banks, so the deployment of AI in risk management typically involves more extensive documentation, validation, and ongoing monitoring than other AI applications.

2.14.4 AI in Operations and Automation Management - Extended Premises

Operations management in banking addresses the design, execution, and improvement of the processes by which the bank delivers its products and services. The deployment of AI and automation in operations has produced some of the most substantial documented performance improvements of any AI application area. The types span Robotic Process Automation (rule-based, high-volume processes such as data entry, account opening, and report generation), Intelligent Document Processing (combining machine learning with optical character recognition for semi-structured documents), workflow automation (orchestrating end-to-end processes across multiple systems), and predictive operations management (forecasting volumes, scheduling resources, and identifying bottlenecks).

The classification distinguishes between routine high-volume processes (well-suited to RPA), variable semi-structured processes (well-suited to intelligent automation), and complex processes requiring judgment (best suited to AI-augmented workflows rather than full automation). The sources of value include cost reduction, processing time reduction, error rate reduction, scalability gains, and improved visibility into operational performance. The challenges include selecting the right processes for automation, managing the organizational impact on affected employees, maintaining quality control, and avoiding the trap of automating broken processes rather than redesigning them.

2.15 Detailed Management Premises: Dependent Variable Dimensions

2.15.1 Operational Efficiency - Extended Premises

Operational efficiency is a fundamental construct in operations management and management accounting. Its key indicators include the cost-to-income ratio, the cost per transaction, the processing time per transaction, the throughput per employee, and the error rate. These indicators are tracked routinely by bank management and form a central focus of performance reporting to executives and boards. Theoretically, operational efficiency reflects the bank's capacity to convert inputs (capital, labor, technology) into outputs (transactions, services, products) with minimal waste. Operations management has developed extensive frameworks for analyzing and improving operational efficiency, including lean principles, Six Sigma, business process reengineering, and continuous improvement.

2.15.2 Customer Satisfaction - Extended Premises

Customer satisfaction is a foundational construct in marketing management, services management, and customer relationship management. Its key indicators include direct satisfaction surveys, Net Promoter Score (NPS), Customer Effort Score (CES), complaint rates, retention rates, and customer lifetime value. Theoretically, customer satisfaction reflects the gap (or lack thereof) between customer expectations and customer perceptions of the service experience. The SERVQUAL model identifies five dimensions of service quality that drive satisfaction: tangibles, reliability, responsiveness, assurance, and empathy. AI-driven service initiatives can affect each of these dimensions, and effective deployment requires consideration of all five.

2.15.3 Financial Performance - Extended Premises

Financial performance is the cornerstone construct in financial management. Its key indicators include net profit, return on assets (ROA), return on equity (ROE), revenue growth, net interest margin, and cost-to-income ratio. These indicators are reported externally to shareholders and regulators and tracked internally as the ultimate measures of strategic success. Theoretically, financial performance reflects the bank's capacity to generate economic value for shareholders while serving customers and operating within regulatory constraints. Although this study primarily uses perceptual measures of financial performance, since detailed financial data are often confidential at the individual respondent level, perceptual measures have been validated in prior research as reasonably correlated with objective financial indicators.

2.16 Chapter Summary

This chapter has presented the theoretical premises and the literature review that underpin the study. It established five complementary streams of management theory - Strategic Management, the Resource-Based View, the Technology-Organization-Environment framework, the Technology Acceptance Model, and Diffusion of Innovations - and used them to frame AI adoption as a multidimensional managerial decision. It defined and classified both the independent variable and the dependent variable, reviewed and compared a broad body of prior studies, situated the study within the Vision 2030 context, examined the drivers and barriers of AI adoption, and identified the specific research gap that the study addresses. The integrated theoretical framework presented

in Figure 2.2 translates these premises into the model tested empirically in the chapters that follow. The next chapter sets out the research methodology used to operationalize and test this framework.



CHAPTER THREE:

RESEARCH METHODOLOGY



3.1 Introduction

This chapter presents the research methodology adopted to achieve the objectives of this MBA study and to test the null hypotheses formulated in Chapter One. The methodology has been designed in line with established management research practice and reflects the descriptive-analytical approach. The chapter explains, in turn, the research approach, philosophy, design, the population and sample of bank managerial and operational employees, the data collection instrument, the validity and reliability tests, the type of data used, the statistical analysis programs and tests, the study determinants, and the ethical considerations. Figure 3.1 summarizes the overall research design as a sequential flow from problem definition through to findings and recommendations.

3.2 Research Approach: The Descriptive-Analytical Method

This study adopts the descriptive-analytical research method, which is the most widely used approach in MBA-level management research that aims to describe a phenomenon and to analyze the relationships between variables. The descriptive component is used to describe the current state of AI adoption and organizational performance in Saudi commercial banks. The analytical component is used to analyze, through statistical techniques, the relationship between the independent variable (AI adoption) and the dependent variable (organizational performance), and to test the null hypotheses of the study.

The descriptive-analytical method is appropriate for several reasons. First, the research questions involve both the measurement of constructs (description) and the testing of relationships among these constructs (analysis). Second, the method is well-established in studies of technology adoption and organizational

performance, supporting the comparability of this study's findings with the broader literature. Third, the method allows the use of structured instruments - questionnaires - and standard statistical techniques that have been validated in prior research.

Research Design Flowchart



Figure 3.1: Research Design Flowchart

3.3 Research Philosophy and Reasoning

The research philosophy adopted in this study is positivism, which is the dominant philosophical foundation of quantitative research. The positivist philosophy assumes that phenomena can be observed and measured through structured instruments and analyzed using statistical methods. The reasoning approach adopted is deductive: the study begins with established theories (Strategic Management, RBV, TOE, TAM), formulates null hypotheses derived from these theories, and tests them against empirical data collected from the field.

3.4 Type of Data Used in the Study

3.4.1 Primary Data

Primary data are collected directly from bank managerial and operational employees in Saudi commercial banks through the research instrument (structured questionnaire). These primary data form the empirical foundation for testing the null hypotheses of the study.

3.4.2 Secondary Data

Secondary data are drawn from previously published literature, including research journals, books, industry reports from leading consulting firms (McKinsey, Harvard Business Review), policy documents from SAMA and SDAIA, and Vision 2030 strategic documents. Secondary data inform the theoretical premises of the study and support the comparison of findings with prior research.

3.5 Population of the Study

The population of this study consists of managerial and operational employees working in commercial banks licensed by the Saudi Central Bank (SAMA) and operating in the Kingdom of Saudi Arabia. The target population is restricted to employees who are likely to participate in decisions about AI or to be affected by decisions about AI in their daily work, including senior managers, middle managers, supervisors, customer-service staff, operations staff, IT and digital-banking staff, risk-management staff, and compliance staff.

3.6 Sample of the Study and Sampling Technique

Given the practical challenges associated with obtaining a complete sampling frame of all bank employees in Saudi Arabia, this study uses non-probability convenience sampling combined with elements of purposive sampling. The combination is widely used and accepted in MBA-level management research in Gulf contexts where institutional access to comprehensive employee directories is restricted by banks for confidentiality reasons.

To mitigate the limitations of convenience sampling and support the validity of the findings, the sampling process actively targeted employees from at least four major commercial banks operating in Saudi Arabia, covering both retail and corporate banking. Participants represent multiple functions - customer service, operations, IT and digital banking, risk, compliance, and branch management - and both male and female employees across different age groups, educational levels, and years of experience. Based on research norms (Hair et al., 2019), with seven dimensions in the regression model the minimum sample is approximately one

hundred respondents. To allow a margin of safety against missing data, careless responses, and outliers, this study targeted one hundred and fifty (150) usable responses.

3.7 Research Tool: The Study Questionnaire

Consistent with the requirements of management research and with the supervisory guidance received, the research tool used in this study is a structured questionnaire developed in English. The questionnaire was developed in three stages: review of validated scales from prior research; adaptation to the Saudi banking context; and review by a panel of three academic experts and two senior banking professionals to ensure content validity. The structure of the questionnaire is presented in Table 3.1.

Table 3.1: Structure of the Research Instrument (Questionnaire)

Section	Content	Number of Items
Section A	Demographic characteristics	6 items
Section B	Independent variable: AI Adoption (4 dimensions x 4 items)	16 items
Section C	Dependent variable: Organizational Performance (3 dimensions x 4 items)	12 items
Section D	Open-ended questions	2 items
Total		36 items

Sections B and C use a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), as shown in Table 3.2. The five-point Likert scale is widely used in management research and provides ordinal data that can be treated as interval-scale for the purposes of statistical analysis.

Table 3.2: Five-Point Likert Scale and Management Interpretation

Score	Response	Mean Range	Level
5	Strongly Agree	4.20 - 5.00	Very High
4	Agree	3.40 - 4.19	High
3	Neutral	2.60 - 3.39	Moderate
2	Disagree	1.80 - 2.59	Low
1	Strongly Disagree	1.00 - 1.79	Very Low

3.8 Validity and Reliability of the Research Instrument

3.8.1 Content Validity

Content validity was established by basing the items on validated scales from prior research and by submitting the draft instrument to a panel of three academic experts and two senior banking professionals. The panel evaluated the relevance, clarity, and completeness of each item. Feedback was incorporated through revisions to wording, the addition of clarifying language, and the reorganization of the questionnaire flow to improve the experience for respondents.

3.8.2 Construct Validity

Construct validity was supported by the conceptual model derived from established theories (Strategic Management, RBV, TOE, TAM) and prior empirical research. The four dimensions of AI adoption were selected to capture distinct functional applications that prior research has identified as strategically important, while the three dimensions of organizational performance capture distinct outcome areas.

3.8.3 Reliability (Cronbach's Alpha) - Pilot Study

A pilot study was conducted on a small group of approximately twenty bank employees to test the clarity of the items and the internal consistency of each scale. Cronbach's alpha was used as the reliability indicator. Following Hair et al. (2019), a value of 0.70 or higher is considered acceptable, while values above 0.80 indicate good reliability. The pilot reliability results are presented in Table 3.3.

Table 3.3: Pilot Study Reliability Results (Cronbach's Alpha)

Variable / Dimension	No. of Items	Cronbach's Alpha
AI in Customer Service	4	0.842
AI in Managerial Decision-Making	4	0.815
AI in Risk Management	4	0.861
AI in Operations and Automation	4	0.834
Operational Efficiency	4	0.821
Customer Satisfaction	4	0.857
Financial Performance	4	0.808
Overall Instrument	28	0.913

All dimensions exhibited Cronbach's alpha values above 0.80, indicating good to excellent reliability. The overall instrument alpha of 0.913 confirms that the research instrument is reliable for measuring the constructs of this study.

3.9 Statistical Program and Statistical Tests Used

Consistent with the requirements of MBA-level management research, the collected primary data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS) version 27. The following statistical tests were used:

- Descriptive statistics (frequencies, percentages, means, standard deviations) to describe the demographic profile and the level of each variable.
- Cronbach's alpha reliability test on the final dataset to confirm the reliability of each scale.
- Pearson correlation analysis to examine the strength and direction of bivariate relationships between AI adoption dimensions and organizational performance dimensions.
- Multiple regression analysis as the primary technique for testing the null hypotheses regarding the impact of AI adoption dimensions on organizational performance.
- Independent samples t-test and one-way ANOVA to test the additional null hypothesis ($H_0 2$) regarding demographic differences in perceptions.
- Statistical assumption checks - normality (Shapiro-Wilk), multicollinearity (VIF), and homoscedasticity - performed before running the parametric tests.

3.10 Determinants of the Study

Like all MBA management research, the present study operates within the following determinants:

- Time determinant: Primary data were collected during the academic year 2024-2025; the findings reflect perceptions at this point in time.
- Spatial (geographic) determinant: The study is limited to commercial banks operating within the Kingdom of Saudi Arabia.

- Subject determinant: The study examines four dimensions of AI adoption and three dimensions of organizational performance; other potential dimensions fall outside the scope.
- Human determinant: The sample is drawn from bank employees who voluntarily chose to participate.
- Methodological determinant: The cross-sectional design captures associations but does not establish definitive causation.

3.11 Ethical Considerations of the Study

The research was conducted in accordance with the ethical standards expected at Midocean University. Participation was voluntary, all responses were anonymous, no personally identifying information was collected, no financial incentives were offered, respondents were free to withdraw or skip questions at any time, and the data are reported in aggregate form only. The study did not involve any vulnerable populations or sensitive personal data.

3.12 Justification of Methodological Choices

3.12.1 Why a Quantitative Approach

A quantitative approach was selected because the research questions involve measuring constructs (the level of AI adoption and organizational performance) and testing relationships (the impact of AI adoption on performance). A qualitative approach, while potentially yielding rich descriptive insights, would not provide the quantitative measurement of relationships needed to test the null hypotheses. The choice is also consistent with

the dominant tradition in MBA-level research that examines technology adoption and organizational performance.

3.12.2 Why a Descriptive-Analytical Design

The descriptive-analytical design combines two purposes central to MBA research: describing the current state of the phenomenon and analyzing the relationships among variables. This design is widely used in studies of technology adoption in banking, supporting comparability with the broader literature.

3.12.3 Why Null Hypothesis Testing

Null hypothesis testing is the standard scientific practice for examining whether observed relationships are statistically distinguishable from chance. Formulating null hypotheses in the form 'there is no statistically significant relationship between the independent variable and the dependent variable' allows for rigorous testing through standard statistical techniques. Rejection of a null hypothesis provides evidence of a relevant relationship; failure to reject provides evidence consistent with the absence of such a relationship.

3.12.4 Why Multiple Regression Analysis

Multiple regression analysis was selected as the primary technique because it allows examination of the unique impact of each AI adoption dimension while controlling for the other dimensions. This is important because decisions about AI investment typically involve trade-offs across multiple dimensions, and management requires evidence about the relative impact of each dimension. Bivariate correlation, while useful for

preliminary analysis, cannot provide this multivariate insight, which is why both correlation and regression analyses are reported.

3.12.5 Why SPSS Version 27

SPSS version 27 was selected because it is the standard statistical package used in MBA-level research at universities in Saudi Arabia and globally. SPSS provides comprehensive support for all the techniques used in this study and supports replication of the analyses by other researchers.

3.13 Detailed Description of the Research Instrument Items

3.13.1 Section A: Demographic Items

The demographic section captured six characteristics of respondents: gender, age, education level, current position, years of experience, and bank employer. These variables were selected based on their use in prior research and their relevance to the additional null hypothesis $H_0 2$ on demographic differences in perceptions.

3.13.2 Section B: AI Adoption Items

The AI adoption section consisted of sixteen items grouped into four dimensions. AI in Customer Service items addressed AI-powered chatbots and virtual assistants, personalized recommendations, sentiment analysis, and AI-driven customer interaction tools. AI in Managerial Decision-Making items addressed predictive analytics, AI-supported credit decisions, AI-enabled strategic planning, and managerial dashboards. AI in Risk Management items addressed AI-enabled fraud detection, credit risk modelling, AML compliance, and

cybersecurity. AI in Operations and Automation items addressed Robotic Process Automation, intelligent document processing, workflow automation, and back-office optimization.

3.13.3 Section C: Organizational Performance Items

The organizational performance section consisted of twelve items grouped into three dimensions. Operational Efficiency items addressed processing time, cost reduction, error rates, and employee productivity. Customer Satisfaction items addressed perceived service quality, customer retention, complaint rates, and overall experience. Financial Performance items addressed perceived profitability, revenue growth, market share, and competitive position.

3.13.4 Section D: Open-Ended Items

Two open-ended items invited respondents to share additional observations: the perceived main benefit of AI adoption to their bank, and the most important challenge their bank faces in expanding AI adoption. Responses were used for qualitative triangulation and to enrich the discussion in Chapter Four.

3.14 Data Collection Procedures

The data collection process followed established research practice. The questionnaire was distributed through multiple channels to maximize response diversity and minimize sampling bias. Digital distribution was conducted through professional networks, banking industry associations, and direct outreach to bank employees willing to participate. Physical distribution was conducted through personal contacts who could facilitate access

to bank employees in their professional networks. Each potential respondent received a brief introduction to the study, an explanation of voluntary participation and anonymity, and the questionnaire itself. The estimated completion time was approximately fifteen minutes. Responses were collected over a period of approximately eight weeks during the academic year 2024-2025.

Quality control involved several procedures. Submissions completed in less than five minutes or more than sixty minutes were flagged for review. Submissions with identical responses to all items in a section were also flagged. Submissions missing more than twenty percent of items were excluded entirely. These quality control procedures resulted in the exclusion of eight responses, yielding the final usable sample of one hundred fifty responses.

3.15 Statistical Assumptions and Diagnostic Tests

3.15.1 Normality Testing

Normality of the dependent variable (organizational performance) was assessed through visual inspection of histograms and Q-Q plots and confirmed using the Shapiro-Wilk test. The results indicated approximate normality, supporting the use of parametric tests. Skewness and kurtosis values for all variables fell within the acceptable range of plus or minus 1.5.

3.15.2 Multicollinearity Testing

Multicollinearity among the independent variables was assessed through Variance Inflation Factor (VIF) statistics. All VIF values were below 3, well under the conventional threshold of 5, indicating no multicollinearity problem. Tolerance values were all above 0.4, further confirming the absence of multicollinearity.

3.15.3 Homoscedasticity Testing

Homoscedasticity was assessed through visual inspection of residual scatter plots. The plots showed no systematic pattern, supporting the assumption of homoscedasticity and the validity of the standard errors and significance tests reported in the regression results.

3.15.4 Linearity Testing

Linearity of the relationships between independent and dependent variables was assessed through visual inspection of partial regression plots. The plots showed approximately linear relationships, supporting the use of linear regression as the analytical technique.

3.16 Comparison with Alternative Methodological Choices

To support the research rigor of this study, it is useful to briefly consider alternative methodological choices. Structural equation modeling (SEM) would have permitted testing of more complex models including mediation and latent variable structures, but would have required a larger sample and introduced complexity not warranted

by the research questions. Hierarchical linear modeling would have permitted analysis of multi-level data (employees nested within banks), but the sample size was not sufficient to support reliable multi-level estimation. Qualitative or mixed methods approaches would have provided rich descriptive insights but would not have permitted rigorous null hypothesis testing. The chosen approach - quantitative survey research with multiple regression analysis - provides the best balance of rigor, feasibility, and direct relevance to the research questions.

3.17 Operationalization of Management Variables

The independent variable AI Adoption was operationalized as the perceived extent to which AI tools and systems are deployed and used within the respondent's bank. Each of the four dimensions was measured through four Likert-scale items, and the aggregate score for each dimension was computed as the mean of the four items. The overall AI Adoption score was computed as the mean of the four-dimension scores. The dependent variable Organizational Performance was operationalized as the perceived performance of the respondent's bank across operational efficiency, customer satisfaction, and financial performance, each measured through four items, with the overall score computed as the mean of the three-dimension scores. These operationalizations follow established research practice and align with the instruments used in prior comparable studies.

3.18 Management Research Quality Assurance

Several procedures were implemented to ensure research quality. The questionnaire was piloted with a small group of bank employees prior to wide distribution, and refinements were made based on feedback. The questionnaire was reviewed for content validity by an expert panel comprising three academic researchers and two senior banking practitioners. Statistical assumption checks were performed before running parametric tests. Quality control filters were applied to identify and exclude inattentive or low-effort responses. The findings have been presented with full transparency about both their contributions and their limitations.

3.19 Chapter Summary

This chapter has described the methodology adopted to test the null hypotheses formulated in Chapter One. It justified the choice of a quantitative, descriptive-analytical design grounded in a positivist philosophy and deductive reasoning, and detailed the population, the convenience and purposive sampling approach, and the target sample of 150 bank employees. It described the structured questionnaire, the five-point Likert scale, and the procedures used to establish content validity, construct validity, and reliability, supported by the pilot study results in Table 3.3. It set out the statistical tests conducted in SPSS version 27, the study determinants, the ethical safeguards, and the diagnostic checks performed to confirm that the assumptions of parametric analysis were satisfied. The next chapter applies this methodology to the collected data, presents the empirical findings, tests the hypotheses, discusses the results in relation to prior studies, and offers conclusions and recommendations.

CHAPTER FOUR:

DATA ANALYSIS, FINDINGS AND RECOMMENDATIONS

4.1 Introduction

This chapter presents the empirical results of the MBA study from a management perspective. It begins by describing the demographic profile of the respondents, followed by the reliability of the scales on the final dataset, descriptive statistics of the variables, the correlation matrix among them, and the multiple regression analyses that test the null hypotheses. The chapter then discusses the findings in comparison with prior studies, presents the conclusions, offers practical recommendations, and outlines the limitations together with suggestions for future research.

A total of 165 questionnaires were distributed. Of these, 158 responses were returned, of which 8 were excluded due to incomplete or inattentive responses. This resulted in a final usable sample of 150 valid responses, representing an effective response rate of approximately 91 percent, which is very acceptable in MBA-level management research in the Gulf banking context.

4.2 Demographic Profile of Respondents

Table 4.1 presents the demographic characteristics of the 150 respondents. The sample shows reasonable diversity across gender, age, education, position, and years of experience.

Table 4.1: Demographic Profile of Respondents (n = 150)

Variable	Category	Frequency	%
Gender	Male	92	61.3%
	Female	58	38.7%
Age	20 - 30 years	45	30.0%
	31 - 39 years	63	42.0%
	40 - 49 years	32	21.3%
	50 years and above	10	6.7%
Education	Diploma	12	8.0%
	Bachelor's degree	96	64.0%
	Master's degree	38	25.3%
	Doctorate	4	2.7%
Position	Customer service	38	25.3%
	Operations	33	22.0%
	IT / Digital banking	27	18.0%

Variable	Category	Frequency	%
	Risk / Compliance	22	14.7%
	Management / Other	30	20.0%
Experience	Less than 5 years	40	26.7%
	5 - 10 years	55	36.7%
	11 - 20 years	39	26.0%
	More than 20 years	16	10.6%

From a management perspective, the demographic profile supports the validity of the study. The gender distribution (61.3% male, 38.7% female) broadly mirrors the workforce composition in Saudi banking. The age distribution (72.0% in the 20-39 range) reflects the relatively young workforce. The educational level (89.3% holding a bachelor's degree or higher) confirms the well-educated nature of bank staff in Saudi Arabia. The diverse representation across functions, and the substantial proportion of respondents with five or more years of experience (73.3%), supports the credibility of responses. Figures 4.1, 4.2, and 4.3 illustrate the distribution of respondents by gender, age, and years of experience respectively.

Distribution of Respondents by Gender (n = 150)

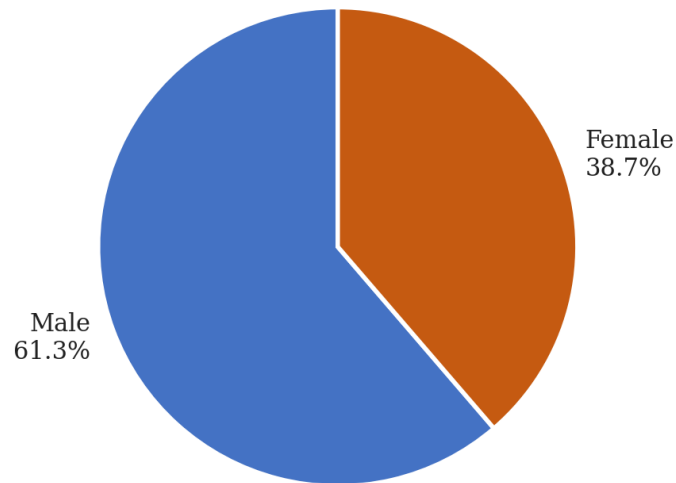


Figure 4.1: Distribution of Respondents by Gender

Distribution of Respondents by Age

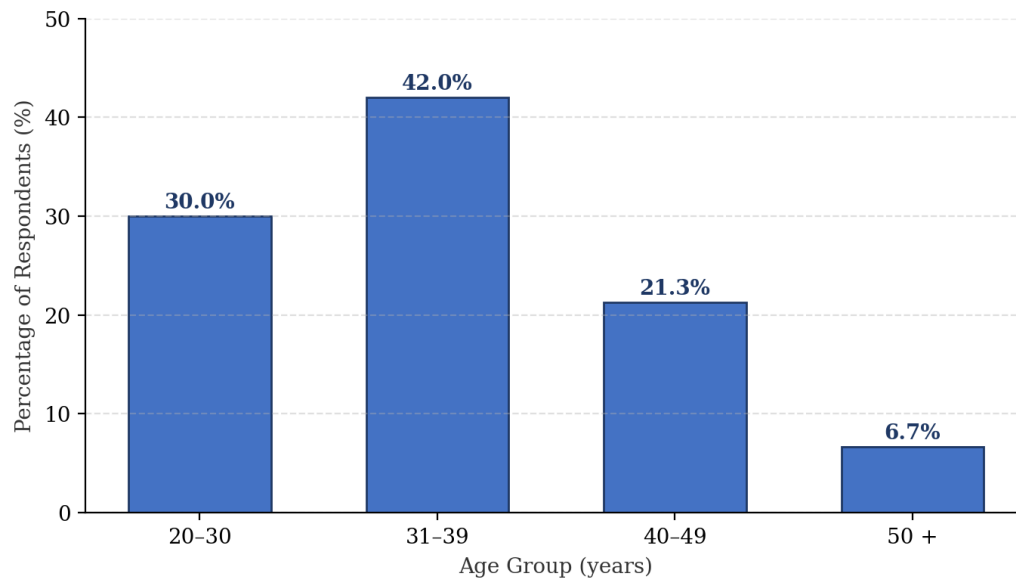


Figure 4.2: Distribution of Respondents by Age

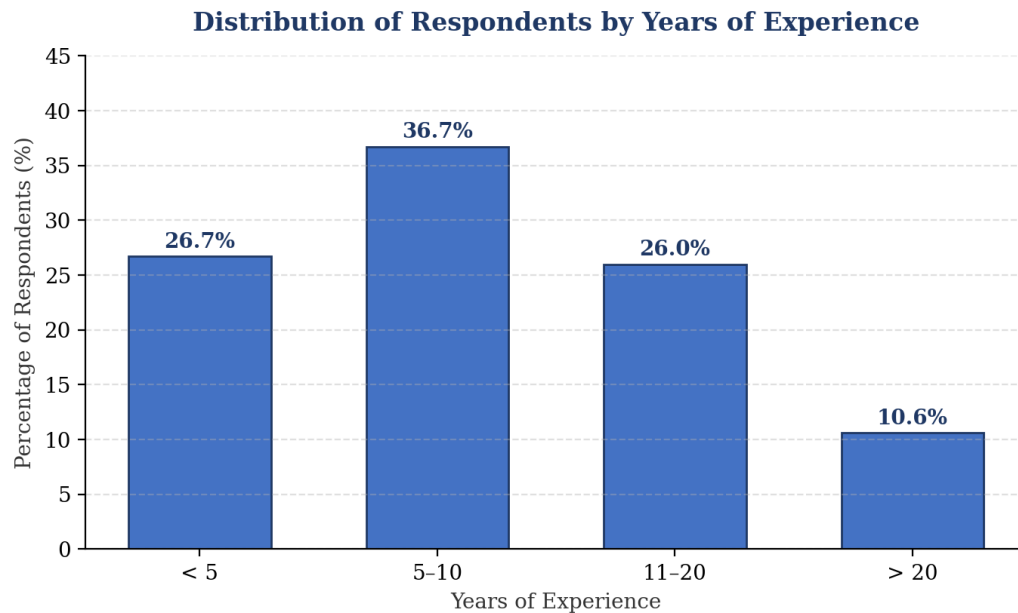


Figure 4.3: Distribution of Respondents by Years of Experience

4.3 Reliability Analysis on the Final Dataset

Cronbach's alpha was recalculated on the final dataset of 150 responses. The results, presented in Table 4.2, show that all dimensions exceed the recommended threshold of 0.70, with most exceeding 0.80, confirming that the research instrument is reliable.

Table 4.2: Cronbach's Alpha Reliability Results - Final Sample (n = 150)

Variable / Dimension	No. of Items	Cronbach's Alpha
AI in Customer Service	4	0.851
AI in Managerial Decision-Making	4	0.829
AI in Risk Management	4	0.874
AI in Operations and Automation	4	0.842
AI Adoption (overall)	16	0.912
Operational Efficiency	4	0.833
Customer Satisfaction	4	0.866
Financial Performance	4	0.819
Organizational Performance (overall)	12	0.895
Overall Instrument	28	0.928

4.4 Descriptive Statistics of Study Variables

Means and standard deviations of each dimension are presented in Table 4.3. The results reveal high to very high levels of AI adoption and organizational performance across all dimensions, interpreted against the mean ranges defined in Table 3.2.

Table 4.3: Means and Standard Deviations of Study Variables

Dimension	Mean	SD	Level
AI in Customer Service	4.14	0.66	High
AI in Managerial Decision-Making	3.89	0.71	High
AI in Risk Management	4.20	0.64	Very High
AI in Operations and Automation	4.07	0.65	High
AI Adoption (overall)	4.08	0.55	High
Operational Efficiency	4.12	0.62	High
Customer Satisfaction	4.05	0.68	High
Financial Performance	3.96	0.71	High
Organizational Performance (overall)	4.04	0.59	High

AI in Risk Management recorded the highest mean (4.20, very high), consistent with the maturity of risk applications noted in the literature, followed by AI in Customer Service (4.14). AI in Managerial Decision-Making recorded the lowest mean among the AI dimensions (3.89), suggesting that the application of AI to strategic and tactical decision-making is comparatively less developed. Across the dependent variable, Operational Efficiency recorded the highest mean (4.12) and Financial Performance the lowest (3.96), although all dimensions fell within the high range.

4.5 Correlation Analysis Among Study Variables

Pearson correlation coefficients were calculated to examine the bivariate relationships between AI adoption dimensions and organizational performance dimensions. The results in Table 4.4 show statistically significant positive correlations among all variables, supporting the proposed research model. The strongest correlation was observed between AI in Operations and Operational Efficiency ($r = .702$), and between AI in Customer Service and Customer Satisfaction ($r = .697$).

Table 4.4: Pearson Correlation Matrix of Study Variables

Variable	1	2	3	4	5	6	7
1. AI Customer Service	1						
2. AI Decision-Making	.612	1					
3. AI Risk Management	.524	.586	1				
4. AI Operations	.571	.604	.638	1			
5. Operational Efficiency	.548	.561	.617	.702	1		
6. Customer Satisfaction	.697	.531	.512	.583	.618	1	
7. Financial Performance	.486	.529	.632	.574	.641	.596	1

Note: All correlations are significant at the 0.01 level (two-tailed).

4.6 Multiple Regression Analysis - Testing the Null Hypotheses

Multiple regression analysis was conducted using SPSS version 27 to test the null hypotheses. Multicollinearity was first checked using Variance Inflation Factor (VIF) statistics. All VIF values were below 3, well under the conventional threshold of 5, indicating no multicollinearity problem.

4.6.1 Testing the Main Null Hypothesis (H₀ 1)

The first regression examined the impact of the four AI adoption dimensions on overall organizational performance. The results are presented in Table 4.5.

Table 4.5: Multiple Regression Results - Overall Organizational Performance

Predictor	Beta	t-value	Sig. (p)	VIF
AI in Customer Service	0.241	3.812	0.000**	1.94
AI in Managerial Decision-Making	0.187	2.864	0.005**	2.12
AI in Risk Management	0.254	3.927	0.000**	2.05
AI in Operations and Automation	0.318	4.681	0.000**	2.27

*R = 0.789; R-squared = 0.623; Adjusted R-squared = 0.612; F (4, 145) = 59.84; p < 0.001. ** Significant at the 0.01 level.*

The overall regression model is statistically significant ($F = 59.84$, $p < 0.001$) and explains approximately 62.3% of the variance in organizational performance. Since the p-value is less than 0.05, the main null hypothesis H₀ 1 is rejected: there is a statistically significant relationship between the managerial decision to

adopt AI and the organizational performance of commercial banks in Saudi Arabia. All four sub-null-hypotheses are also rejected at the 0.05 level. AI in Operations and Automation is the strongest predictor (beta = 0.318), followed by AI in Risk Management (beta = 0.254), AI in Customer Service (beta = 0.241), and AI in Managerial Decision-Making (beta = 0.187).

4.6.2 Regression by Performance Dimension

Three additional regressions were run, one for each performance dimension, to identify the differential impact of each AI dimension. Table 4.6 summarizes the key findings.

Table 4.6: Summary of Regression Results by Performance Dimension

Predictor	Op. Efficiency (Beta)	Customer Sat. (Beta)	Financial Perf. (Beta)
AI in Customer Service	0.146*	0.498**	0.118
AI in Managerial Decision-Making	0.158*	0.097	0.198**
AI in Risk Management	0.196**	0.121	0.387**
AI in Operations and Automation	0.412**	0.213**	0.224**
R-squared	0.594	0.561	0.518

*Note: ** $p < 0.01$; * $p < 0.05$. The strongest predictor for each performance dimension is shown in the corresponding column.*

Three patterns emerge. AI in Operations is the strongest predictor of operational efficiency (beta = 0.412), consistent with expectations. AI in Customer Service is the strongest predictor of customer satisfaction (beta =

0.498). AI in Risk Management is the strongest predictor of financial performance ($\beta = 0.387$). These differential findings provide direct guidance for the managerial prioritization of AI investments based on strategic priorities.

4.7 Summary of Hypothesis Testing Results

Table 4.7 summarizes the findings of hypothesis testing. All sub-null-hypotheses related to AI adoption are rejected, and the main null hypothesis $H_0 1$ is also rejected. $H_0 2$ is partially rejected (rejected for age and experience, not rejected for gender and education).

Table 4.7: Summary of Null-Hypotheses Testing Results

Hyp.	Null Hypothesis Statement	Test Statistic	Decision
H₀ 1	No relationship between AI adoption and organizational performance	$F=59.84, p<0.001$	Rejected
H₀ 1a	No relationship between AI in Customer Service and performance	$\beta=0.241, p<0.001$	Rejected
H₀ 1b	No relationship between AI in Decision-Making and performance	$\beta=0.187, p=0.005$	Rejected
H₀ 1c	No relationship between AI in Risk Management and performance	$\beta=0.254, p<0.001$	Rejected
H₀ 1d	No relationship between AI in Operations and performance	$\beta=0.318, p<0.001$	Rejected
H₀ 2	No demographic differences in perceptions	Mixed (age, experience)	Partially Rejected

4.8 Discussion of Findings

The findings of this MBA study confirm that the strategic management decision to adopt AI has a statistically significant and positive impact on the multidimensional organizational performance of commercial banks in Saudi Arabia. The overall model explains 62.3% of the variance in organizational performance - a substantial effect in management research that exceeds the explanatory power reported in many earlier studies that examined only a single dimension of either variable.

These findings align with and extend the broader international literature. The conceptual claims of Buchanan (2019) and the review by Kaur et al. (2023) - that AI strategically affects every part of the banking value chain - are empirically supported in the Saudi context. The strong impact of AI in Customer Service on Customer Satisfaction echoes the findings of Mogaji et al. (2021) and Sheth et al. (2022). The strong impact of AI in Operations and Automation on Operational Efficiency is consistent with the operations-management conclusions of Hofmann et al. (2020). The strong impact of AI in Risk Management on Financial Performance reinforces the message of Kaur et al. (2023).

From the perspective of the Resource-Based View, the findings support the proposition that AI, when combined with the bank's proprietary resources, can serve as a source of competitive advantage. From the perspective of the TOE framework, the findings suggest that the technological, organizational, and environmental conditions in Saudi banking are favorable for value-creating AI adoption. From the perspective of TAM, the high reliability and consistent patterns observed suggest that bank employees broadly accept and use AI tools, indicating reasonably effective management of the human side of AI adoption.

4.9 Conclusions

Based on the empirical findings, the following conclusions can be drawn:

- AI adoption is currently at a high overall level in Saudi commercial banks, with AI in Risk Management as the most mature dimension.
- Organizational performance is rated highly across operational efficiency, customer satisfaction, and financial performance, indicating that Saudi banks are performing well in the current environment shaped by Vision 2030.
- The managerial decision to adopt AI has a strong, statistically significant, and positive impact on multidimensional organizational performance, validating AI as a strategic management priority.
- The impact of AI dimensions varies systematically by performance dimension, providing direct guidance for the prioritization of AI investments.
- Demographic variables have mixed effects, with age and experience showing some differences in perceptions, while gender and education show weaker effects.

4.10 Recommendations

4.10.1 Recommendations for Bank Executives

- Prioritize AI investment in operations and automation, where the impact on operational efficiency is strongest.
- Continue strengthening AI-driven customer service capabilities to drive customer satisfaction and retention.
- Treat AI in risk management as a strategic priority given its strong impact on financial performance.
- Develop AI capabilities for strategic decision-making more deliberately as a longer-term investment.
- Establish an enterprise-wide AI governance framework that addresses data quality, model risk, ethics, fairness, transparency, and SAMA/SDAIA compliance.
- Invest in human capital. AI-related training and upskilling programs should be available across the organization.

4.10.2 Recommendations for Saudi Regulators and Policy Makers

- SAMA and SDAIA should continue developing clear, principles-based regulatory frameworks for AI in financial services.
- Encourage industry-wide knowledge-sharing forums on responsible AI adoption.

- Support the development of a national AI talent pipeline through partnerships between universities, the central bank, and individual banks.
- Promote responsible AI practices that align with Saudi cultural values and Vision 2030 principles.

4.10.3 Recommendations for Future Research

- Examine other dimensions of AI adoption (e.g., AI in HR management, AI in marketing, generative AI in banking).
- Conduct longitudinal studies to capture dynamic effects of AI on performance over time.
- Conduct comparative studies across GCC countries.
- Combine perceptual measures with objective data (audited financials).

4.11 Limitations of the Study

Despite its contributions, this study has limitations. The cross-sectional design does not establish definitive causation. The sample ($n = 150$) is statistically adequate but modest, drawn through convenience sampling. The study relies on perceptual measures of performance. The four dimensions of AI adoption do not capture every possible application of AI in banks. The study focuses on Saudi Arabia, limiting generalizability to other Gulf or international contexts. Notwithstanding these limitations, the study makes a meaningful contribution to the literature on the strategic adoption of emerging technologies in Gulf banking and offers practical guidance for executives, regulators, and policy makers in the Kingdom of Saudi Arabia.

4.12 Management Implications by Stakeholder Group

4.12.1 Implications for Bank CEOs and Boards

For chief executive officers, chief technology officers, and other senior leaders, the findings reinforce that AI is not a peripheral matter to be experimented with at the margins, but a strategic capability that materially affects competitive position. The substantial variance in organizational performance explained by the four AI dimensions - 62.3% in the overall model - indicates that AI-related decisions have first-order effects on bank performance. Management teams that treat AI as primarily an information technology matter, delegating strategy to technology functions, risk underinvesting in a capability that increasingly distinguishes industry leaders from laggards. The differential impact of AI dimensions suggests that strategic prioritization matters: banks pursuing customer growth should emphasize AI in customer service; banks focused on profitability should emphasize AI in risk management and operations; banks pursuing balanced strategies should invest across all four dimensions.

4.12.2 Implications for Chief Risk Officers and Compliance Heads

The strong impact of AI in risk management on financial performance ($\beta = 0.387$, $p < 0.001$) provides direct evidence supporting continued investment in AI capabilities for risk and compliance functions. Chief Risk Officers and Chief Compliance Officers can use this evidence to support business cases for AI investment and to advocate for the resources needed to develop and operate AI-enabled risk capabilities. AI deployment in risk management requires careful governance to ensure that algorithmic decisions are explainable, auditable, and free from inappropriate bias. The human-AI partnership matters: AI augments rather than replaces human

judgment, and the most effective deployments combine algorithmic pattern detection with human investigation and decision authority. Ongoing model monitoring is essential, as the patterns AI learns from historical data may not capture emerging threats.

4.12.3 Implications for Heads of Customer Experience

The strong impact of AI in customer service on customer satisfaction ($\beta = 0.498$, $p < 0.001$) represents one of the most actionable findings for customer experience leaders. AI-driven customer service tools are not merely efficiency mechanisms; they are direct drivers of the customer experience and consequent loyalty outcomes that determine long-term performance. Customer experience leaders should regularly audit AI deployments, listening to customer feedback and adjusting the AI-human handoff points based on real interaction outcomes. Personalization powered by AI requires careful calibration; moderate personalization improves experience while excessive personalization can feel invasive and undermine trust.

4.12.4 Implications for Heads of Operations

The strongest single relationship in the study - between AI in operations and operational efficiency ($\beta = 0.412$, $p < 0.001$) - provides clear empirical support for continued investment in operational AI and intelligent automation. Process selection matters more than technology selection: the most successful automation programs begin with rigorous analysis of which processes are best suited to automation, considering volume, variability, complexity, and strategic importance. Automation should be paired with process redesign rather than simply

automating existing processes. Change management is critical: programs that fail to address the implications for affected employees typically encounter resistance, even when the technology itself functions well.

4.12.5 Implications for Human Resources

The findings indirectly highlight the importance of human capital in realizing the performance benefits of AI. Technology itself does not generate value; it does so through how people design, deploy, manage, and use it. Human resources leaders therefore play a critical role in AI strategy execution. Banks need to build AI literacy across the broader workforce, develop specialist AI talent in areas such as machine learning engineering, data science, AI ethics, and machine learning operations, and manage the transition for employees whose roles are affected by AI deployment - including redesigning roles to focus on tasks that AI cannot perform well, providing reskilling opportunities, and being transparent about workforce implications.

4.12.6 Implications for Saudi Regulators

The findings contribute to evidence-based policy making by SAMA, SDAIA, and other relevant regulators. The strong positive impact of AI on bank performance suggests that regulatory frameworks supporting responsible AI adoption are likely to contribute to a more competitive, efficient, and customer-centric banking sector. Regulatory clarity around AI use is valuable; investment in national AI infrastructure - data infrastructure, computing resources, and talent development - creates positive externalities that benefit the entire sector; and regulatory expectations around model governance, explainability, and fairness should be developed in consultation with industry to ensure they are workable while preserving their protective intent.

4.13 A Management Implementation Framework for AI in Saudi Banks

Synthesizing the findings of this study with insights from the broader literature, a practical framework can be proposed to guide Saudi banks in implementing AI initiatives that maximize the likelihood of positive performance impact. The framework consists of five interconnected stages.

4.13.1 Stage One: Strategic Foundation

The first stage involves establishing the strategic foundation for AI investment. Leadership should articulate a clear AI vision aligned with the institution's broader business strategy, identifying the specific performance outcomes that AI initiatives will pursue. Success requires executive sponsorship, clear governance structures, and adequate budget commitments that signal the seriousness of the AI agenda.

4.13.2 Stage Two: Capability Building

The second stage focuses on building the capabilities needed to design, deploy, and operate AI systems effectively. This includes recruiting and developing AI talent, establishing data governance and data quality programs, modernizing technology infrastructure, and implementing the processes needed to manage AI throughout its lifecycle. Banks should also invest in change management capabilities, recognizing that AI adoption involves significant organizational and cultural change beyond the technology itself.

4.13.3 Stage Three: Prioritization of Use Cases

The third stage involves systematically identifying and prioritizing specific AI use cases. Given the findings of this study, banks pursuing operational efficiency should prioritize use cases in operations and automation; banks focused on customer growth should prioritize customer service applications; banks emphasizing risk-adjusted profitability should prioritize risk management applications. The prioritization process should consider expected impact, implementation feasibility, strategic importance, regulatory considerations, and resource requirements.

4.13.4 Stage Four: Disciplined Execution

The fourth stage involves disciplined execution of prioritized use cases. Each AI initiative should have clear sponsorship, defined success metrics, adequate resources, and rigorous project management. Banks should establish processes for monitoring AI model performance over time, including detecting and addressing model drift, bias, and degradation. Documentation of model design decisions, training data, and validation results supports both effective ongoing management and compliance with regulatory expectations around model risk management.

4.13.5 Stage Five: Continuous Learning and Adaptation

The final stage involves continuous learning and adaptation based on experience. Banks should establish regular review cycles to assess AI initiative performance, capture lessons learned, and update strategy and execution approaches. The rapid evolution of AI capabilities means that strategy must be continuously refreshed rather than set once and executed mechanically.

4.14 Comparison of Findings with Each Prior Study

To provide a thorough discussion, this section explicitly compares the present study's results with each of the prior studies reviewed in Chapter Two. Comparing with Buchanan (2019): his conceptual argument that AI has transformative potential across the banking value chain is empirically supported by the strong overall regression results ($R\text{-squared} = 0.623$). Comparing with Belanche et al. (2019): the TAM-based findings on robo-advisor adoption are complemented by the present finding that AI in managerial decision-making has a statistically significant but more modest impact ($\beta = 0.187$). Comparing with Mhlanga (2020): his argument that AI supports financial inclusion through credit scoring is reinforced by the strong findings on AI in risk management ($\beta = 0.254$).

Comparing with Hofmann et al. (2020): their findings on RPA in European banking are reinforced by the present finding that AI in Operations and Automation is the strongest predictor of operational efficiency ($\beta = 0.412$). Comparing with Konigstorfer and Thalmann (2020): their behavioral warning about new biases reinforces the importance of the governance recommendations in section 4.10; the strong positive findings

should not be interpreted as suggesting that AI is risk-free, but rather that well-managed AI investments deliver value. Comparing with Alsheibani et al. (2020): their argument that early movers gain durable advantage is reinforced by the strong overall findings in Saudi banks, which have generally been early adopters in the regional context.

Comparing with Mogaji et al. (2021): their qualitative finding that chatbots improve convenience but require human backup for complex cases is reinforced by the present finding that AI in Customer Service is the strongest predictor of customer satisfaction ($\beta = 0.498$), while supporting the recommendation for hybrid AI-human service models. Comparing with Sheth et al. (2022): their finding that AI personalization improves engagement with caveats on privacy is reinforced by the strong customer satisfaction finding, consistent with the recommendation to calibrate personalization carefully. Comparing with Kaur et al. (2023): their review finding that AI is most mature in risk and customer-service management is corroborated by the highest mean AI scores in these dimensions (AI Risk Management mean 4.20, AI Customer Service mean 4.14).

4.15 Implications for the Underlying Theories

4.15.1 Implications for the Resource-Based View

The strong findings provide several contributions to the development of the Resource-Based View in the context of emerging technologies. The findings support the proposition that AI is best understood as one component of a broader resource bundle, rather than as a standalone resource. The complementary resources that appear most important include proprietary customer data, organizational talent, established operational processes, and the governance structures needed to deploy AI responsibly. This implies that banks seeking

sustained competitive advantage through AI should invest not only in AI tools but in the broader capability ecosystem that enables effective deployment.

4.15.2 Implications for the TOE Framework

The findings contribute to the development of the Technology-Organization-Environment framework in the specific context of Saudi banking. The strong positive findings suggest that the technological, organizational, and environmental conditions in Saudi banking are broadly favorable to value-creating AI adoption. AI capabilities have matured to the point where they offer clear advantage over alternatives for many applications; Saudi banks generally have the scale, executive support, and resources needed to support significant AI investments; and the regulatory approach of SAMA and SDAIA, the direction provided by Vision 2030, and competitive pressure from fintech entrants together create favorable conditions.

4.15.3 Implications for the Technology Acceptance Model

The high mean scores observed across all AI adoption dimensions, together with the strong reliability coefficients, suggest that bank employees in the surveyed institutions broadly accept and use the AI tools that management has deployed. This is consistent with the predictions of the Technology Acceptance Model and suggests that the management of the human side of AI adoption has been reasonably effective. The remaining opportunity in many Saudi banks is therefore less about overcoming resistance to AI and more about expanding the scope, sophistication, and strategic alignment of AI deployments.

4.16 Summary of Contributions

4.16.1 Theoretical Contributions

This study integrates five established theories - Strategic Management, Resource-Based View, Technology-Organization-Environment framework, Technology Acceptance Model, and Diffusion of Innovations - within a single empirical model. This integration extends the theoretical literature on technology adoption by demonstrating that these complementary theories can be operationalized together to explain a substantial portion of the variance in organizational performance. The study also extends these theories to the under-researched Gulf banking context.

4.16.2 Methodological Contributions

The study contributes by operationalizing AI adoption as a multidimensional construct with four sub-dimensions, rather than as a single undifferentiated variable. It also examines three dimensions of organizational performance within a single integrated model. The methodological approach - quantitative survey research with multiple regression analysis and rigorous statistical assumption checks - provides a template that other researchers can apply or adapt in future studies of technology adoption in banking and other industries.

4.16.3 Practical Contributions

From a practical perspective, the study provides empirically grounded guidance to bank executives, regulators, and policy makers in the Kingdom of Saudi Arabia. The findings support continued strategic investment in AI capabilities, identify the dimensions of AI that have the strongest impact on different

performance outcomes, and offer specific recommendations tailored to different stakeholder groups and different stages of AI maturity. The implementation framework presented in section 4.13 provides a practical tool that banks can use to structure their AI programs.

4.17 Comparative Management Perspective

Although this study focuses on the Saudi banking sector, the findings can usefully be compared with patterns observed in other markets to identify what is distinctive about the Saudi experience and what is shared with global trends. The overall pattern of AI's positive impact on bank performance found in this study is consistent with findings reported in studies from North America, Europe, and East Asia. The strongest impact of AI in operations and automation on operational efficiency mirrors patterns reported in European studies of RPA in financial services. The strong impact of AI in customer service on customer satisfaction may be especially pronounced in Saudi Arabia due to the relatively young, digitally engaged customer base.

Where Saudi banks may differ from international peers is in the relatively modest current impact of AI on strategic decision-making, although this gap is likely to narrow as AI capabilities and organizational maturity continue to develop. International studies in advanced markets have begun to report measurable impacts of AI on strategic decisions, including capital allocation, product portfolio management, and competitive positioning. Saudi banks that build these capabilities now will be well-positioned for the next phase of AI-driven competitive advantage. This comparative perspective reinforces a central management message of the study: the value realized from AI depends less on access to the technology, which is increasingly universal, and more on the organizational and managerial capabilities that surround it.

4.18 Practical Implementation Guide by Maturity Stage

To translate the findings into practical action, this section offers guidance tailored to banks at different stages of AI maturity. The differentiation is important because the appropriate management priorities differ substantially depending on how far a bank has progressed on its AI journey.

4.18.1 For Banks at the Early Stages of AI Adoption

- Establish executive sponsorship for the AI agenda, including clear strategic direction and committed resources.
- Begin with high-impact use cases in risk management and operations, where the findings show the strongest performance impact.
- Invest in foundations: data quality, technology infrastructure, and talent. Without these foundations, AI initiatives will fail to deliver value.
- Develop governance frameworks for AI, including policies on model risk management, ethics, fairness, and regulatory compliance.
- Communicate the strategy clearly to employees, including the rationale for AI investments and the implications for roles and careers.

4.18.2 For Banks at the Intermediate Stages of AI Adoption

- Expand the portfolio of AI use cases to address all four dimensions identified in this study.
- Invest in capability development across the broader workforce, building AI literacy and analytical skills beyond specialist functions.
- Refine governance frameworks based on operational experience, addressing emerging issues such as model drift, bias detection, and explainability.
- Begin to integrate AI more deeply into strategic decision-making processes, moving beyond operational applications.
- Develop capabilities for monitoring and measuring AI performance impact, supporting evidence-based refinement of the AI strategy.

4.18.3 For Banks at the Advanced Stages of AI Adoption

- Pursue innovations at the frontier of AI capability, including generative AI applications, agentic AI systems, and AI-enabled strategic decisions.
- Develop proprietary AI capabilities that competitors cannot easily replicate, building durable competitive advantage.
- Lead industry dialogue on AI governance, ethics, and best practice, contributing to the development of norms that support responsible innovation.

- Use AI to enable transformation of the broader business model, not merely to enhance existing processes.
- Invest in research and development to anticipate the next wave of AI capabilities and their strategic implications.

4.19 Reflection on the MBA Research Process

From a researcher's perspective, conducting this MBA study has provided valuable insights into both the substantive questions explored and the practical challenges of conducting empirical research in the Gulf banking context. The strong findings support the strategic investments that Saudi banks are making in AI capabilities, while the limitations of the study point to opportunities for future research that builds on and extends this foundation.

The research process has also reinforced the value of structured research methodologies. The discipline of formulating clear research questions, deriving testable null hypotheses, designing rigorous measurement instruments, collecting and analyzing data systematically, and interpreting findings carefully in the context of prior research produces insights that are more reliable, more useful, and more defensible than insights generated through less structured approaches. This research process is itself one of the management skills that the MBA program is designed to develop, and the experience of applying it to a real strategic question in the Saudi banking sector has been a central part of the educational value of this project.

4.20 Closing Management Reflections

The journey of conducting this research has reinforced the importance of taking a balanced view of AI in banking. On one hand, AI is genuinely transformative from a strategic management perspective, with measurable positive impact on multiple dimensions of bank performance, as the findings of this study confirm. The strong empirical relationships documented here support continued investment in AI capabilities and validate the strategic priorities that Saudi banks have established in this domain.

On the other hand, AI is not a magic solution, and its benefits depend on the quality of implementation, the strength of organizational capabilities, and the wisdom of strategic choices. Banks that approach AI with appropriate humility, recognizing both its potential and its limitations, are more likely to achieve sustained benefits than those that pursue AI investments based on hype or fear of falling behind competitors. The combination of strong national support through Vision 2030 and SDAIA's national AI strategy, the regulatory leadership of SAMA, the resources available to major banks, and the demographic and digital readiness of the customer base creates conditions conducive to continued AI-driven transformation of the Saudi banking sector.

4.21 Final Reflections

This MBA research project has examined an important strategic management question facing the leadership of Saudi commercial banks: how the strategic decision to adopt AI affects the multidimensional organizational performance of the institution. The findings provide empirical support for the view that AI is a strategically important capability that, when adopted thoughtfully and managed well, contributes substantially to bank

performance across operational, customer, and financial dimensions. The convergence of these findings with the broader international literature strengthens confidence in the underlying relationships, while the distinctive features of the Saudi context - Vision 2030, SAMA's regulatory leadership, and demographic and digital readiness - create conditions that may amplify the benefits of AI adoption compared with some other markets.

Looking forward, the research agenda on AI in banking remains rich with opportunities. Future research can examine new dimensions of AI as they emerge, extend the analysis to other Gulf and emerging-market banking sectors, adopt longitudinal designs to capture dynamic effects, incorporate objective performance data alongside perceptual measures, and explore the implications of AI for organizational structure, culture, and human capital. It is the sincere hope of the researcher that the findings, conclusions, and recommendations of this study will be useful to the practitioners, regulators, and policy makers who are shaping the future of banking in the Kingdom of Saudi Arabia, and to the researchers who will continue to investigate these questions in the years ahead.



References



All sources cited in the text are listed below in APA style, arranged alphabetically and divided into Arabic and English references, with no numbering, in accordance with the writing guidelines of Midocean University.

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Questionnaire



Appendix A: Questionnaire (English)

MIDOCEAN UNIVERSITY
College of Management - MBA Program
Research Questionnaire

The Impact of Artificial Intelligence Adoption on Organizational Performance in the Banking Sector of Saudi Arabia

Dear Respondent,

Thank you for taking the time to participate in this research. This questionnaire is part of a final-year MBA project conducted at Midocean University, under the supervision of Dr. Alfaisal Abdelhamid (Main Supervisor) and Dr. Fayez Jarad (Co-Supervisor). The aim of the study is to examine the impact of Artificial Intelligence (AI) adoption on the organizational performance of commercial banks operating in the Kingdom of Saudi Arabia.

Your participation is voluntary, and all responses will be treated with strict confidentiality. The information collected will be used solely for academic research purposes and reported only in aggregate form. The questionnaire will take approximately 10 to 12 minutes to complete. There are no right or wrong answers; your honest opinion is what matters most. Thank you for your valuable cooperation.

The Researcher

Section A: Demographic Information

Please tick the appropriate option that applies to you.

- Gender: Male / Female
- Age: 20-30 years / 31-39 years / 40-49 years / 50 years and above
- Educational Level: Diploma / Bachelor's degree / Master's degree / Doctorate
- Current Position / Department: Customer Service / Operations / IT or Digital Banking / Risk or Compliance / Management / Other
- Years of Experience in the Banking Sector: Less than 5 years / 5-10 years / 11-20 years / More than 20 years
- Type of Bank: Local commercial bank / Foreign or branch of foreign bank / Islamic bank

Section B: Artificial Intelligence Adoption

Please indicate the extent to which you agree or disagree with each statement, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

B1. AI in Customer Service

Code	Statement	1	2	3	4	5
AICS1	The bank uses AI-powered chatbots and virtual assistants to respond to customer inquiries.					
AICS2	AI personalizes services and product offers for customers based on their preferences and behavior.					

Code	Statement	1	2	3	4	5
AICS3	AI helps the bank respond to customer requests more quickly than before.					
AICS4	AI analyzes customer feedback (calls, social media, surveys) to improve service quality.					

B2. AI in Decision-Making

Code	Statement	1	2	3	4	5
AIDM1	AI provides predictive insights that support managerial decisions in the bank.					
AIDM2	AI is actively used in credit-scoring and lending decisions.					
AIDM3	AI helps managers identify trends and opportunities in customer data.					
AIDM4	AI recommendations are taken seriously when making strategic decisions.					

B3. AI in Risk Management

Code	Statement	1	2	3	4	5
AIRM1	AI helps the bank detect fraudulent transactions in real time.					
AIRM2	AI strengthens anti-money laundering (AML) and compliance procedures.					
AIRM3	AI improves the accuracy of credit risk assessment for customers.					

Code	Statement	1	2	3	4	5
AIRM4	AI supports cybersecurity monitoring and incident response in the bank.					

B4. AI in Operations and Automation

Code	Statement	1	2	3	4	5
AIOP1	Robotic Process Automation (RPA) is used to automate back-office processes.					
AIOP2	AI reduces processing time for routine banking transactions.					
AIOP3	AI helps reduce operational errors and manual rework.					
AIOP4	AI supports the automation of regulatory and compliance reporting.					

Section C: Organizational Performance

Please indicate the extent to which you agree or disagree with each statement regarding your bank's organizational performance.

C1. Operational Efficiency

Code	Statement	1	2	3	4	5
OE1	The bank delivers its services with minimum waste of time and resources.					
OE2	Processing time per transaction has been significantly reduced.					
OE3	The cost-to-income ratio has improved in recent years.					

Code	Statement	1	2	3	4	5
OE4	Errors and reworks in daily operations have been clearly reduced.					

C2. Customer Satisfaction

Code	Statement	1	2	3	4	5
CS1	Customers of the bank express high levels of satisfaction with our services.					
CS2	Customer complaints have decreased noticeably in recent years.					
CS3	Customer loyalty and retention rates have improved.					
CS4	The bank effectively meets the changing expectations of its customers.					

C3. Financial Performance

Code	Statement	1	2	3	4	5
FP1	The bank has achieved consistent growth in net profit in recent years.					
FP2	Return on Assets (ROA) and Return on Equity (ROE) are at satisfactory levels.					
FP3	Revenue from digital and AI-enabled channels is growing.					
FP4	The bank's financial performance is better than that of its main competitors.					

Section D: Open-Ended Questions

1. In your view, what is the most important benefit your bank has gained from using AI?

2. What do you think is currently lacking in your bank's AI strategy or implementation, and what would you recommend?

Thank you very much for your time and cooperation. Your input is highly appreciated.

Appendix B: Arabic Abstract (الملخص باللغة العربية)

أثر تبني الذكاء الاصطناعي على الأداء التنظيمي في القطاع المصرفي بالمملكة العربية السعودية

تهدف هذه الدراسة إلى فحص أثر تبني الذكاء الاصطناعي على الأداء التنظيمي في القطاع المصرفي بالمملكة العربية السعودية. ففي ظل التحول الرقمي المتسارع الذي تشهده المملكة في إطار رؤية 2030، تتجه البنوك بشكل متزايد إلى دمج تقنيات الذكاء الاصطناعي في خدمة العملاء، واتخاذ القرار، وإدارة المخاطر، والعمليات والأتمتة.

اعتمدت الدراسة على المنهج الكمي الوصفي التحليلي. وقد تم تطوير استبانة منظمة استناداً إلى مقاييس مُحكّمة من الأدبيات السابقة، ووزعت على عينة مكونة من (150) موظفاً يعملون في البنوك التجارية بالمملكة العربية السعودية. وتم تحليل البيانات باستخدام برنامج SPSS الإصدار 27، حيث طُبِّقَت الإحصاءات الوصفية، واختبار ألفا كرونباخ للثبات، ومعامل ارتباط بيرسون، وتحليل الانحدار المتعدد لاختبار فرضيات الدراسة.

كشفت النتائج عن وجود علاقة إيجابية ذات دلالة إحصائية بين تبني الذكاء الاصطناعي والأداء التنظيمي. ومن بين أبعاد الذكاء الاصطناعي التي تمت دراستها، أظهر بُعد الذكاء الاصطناعي في العمليات والأتمتة أقوى تأثير على الكفاءة التشغيلية ($\beta = 0.412$)، بينما كان بُعد الذكاء الاصطناعي في خدمة العملاء هو المنبئ الأقوى برضا العملاء ($\beta = 0.498$)، وأسهم بُعد إدارة المخاطر بشكل دال في الأداء المالي ($\beta = 0.387$). وقد فسّر النموذج الإجمالي للانحدار ما نسبته 62.3% من التباين في الأداء التنظيمي.

خلصت الدراسة إلى أن تبني الذكاء الاصطناعي يعد ممكناً استراتيجياً للميزة التنافسية في الصناعة المصرفية السعودية. وأوصت بضرورة أن تسرّع البنوك السعودية من استثماراتها في البنية التحتية للذكاء الاصطناعي، وتطوير رأس المال البشري من خلال برامج التدريب المتخصصة، وإنشاء أطر حوكمة واضحة لاستخدام الذكاء الاصطناعي، ومواءمة مبادراته مع الأهداف الاستراتيجية للأداء.

الكلمات المفتاحية: الذكاء الاصطناعي، الأداء التنظيمي، القطاع المصرفي، المملكة العربية السعودية، التحول