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Dedication

It is our pleasure and great privilege to present the eighty-ninth issue of the Academic Journal of Research and Scientific Publishing to all researchers and professor who published their research in the issue, and we thank and appreciate to all contributors and supporters of the academic journal and those involved in the production of this scientific knowledge edifice.

Academic Journal of Research and Scientific Publishing

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The Impact of Strategic Infrastructure Management on Organizational Success: The Mediating Role of Project Management Efficiency in selected Cities of Saudi Arabia

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This study investigated the effect of strategic infrastructure management on organizational success in selected Saudi Arabian cities, considering project management efficiency as a mediating variable. Although Saudi Vision 2030 has encouraged major infrastructure investments, many organizations still experience delays, cost overruns, inefficient resource use, and performance challenges.

A quantitative cross-sectional design was adopted, using data from 384 project managers working on infrastructure projects in Riyadh, Jeddah, and Dammam. The sample size was determined using Krejcie and Morgan's formula. Data were collected through a structured questionnaire and analyzed with Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4. The measurement model showed acceptable reliability and validity. Results indicated that strategic infrastructure management significantly improves organizational success. Project management efficiency had the strongest direct effect on organizational success, while risk management was the most influential strategic infrastructure dimension. Project management efficiency also significantly mediated the relationship between strategic infrastructure management and organizational success.

The study supports the Resource-Based View and Stakeholder Theory and offers practical guidance for managers and policymakers. It recommends prioritizing project management efficiency, risk management, and technology integration. Future studies should use longitudinal designs and objective performance measures.

Keywords: Strategic infrastructure management, organizational success, project management efficiency, PLS-SEM, Saudi Arabia, Vision 2030.

1. Introduction

Infrastructure development is a fundamental pillar of economic growth, social progress, and national competitiveness. Strategic infrastructure management has emerged as a critical determinant of organizational success, particularly in countries undertaking major transformation agendas (Al-Sahlawi & Al-Ansari, 2020). Effective infrastructure management extends beyond technical considerations to include leadership, resource optimization, risk management, stakeholder engagement, and technology integration, ensuring that infrastructure assets are aligned with organizational objectives (Bakker et al., 2019; Liu et al., 2020).

Despite increasing scholarly attention, important gaps remain in understanding how strategic infrastructure management translates into organizational success. In particular, the mediating role of project management efficiency has received limited empirical investigation, especially in rapidly developing economies.

Saudi Arabia provides an important context for examining these relationships. Under Vision 2030, the Kingdom has launched major infrastructure projects to diversify the economy, improve urban development, and strengthen global competitiveness (Almazrouei & Alzahrani, 2021). Riyadh, Jeddah, and Dammam have become major centers of infrastructure development (Alotaibi et al., 2021). However, infrastructure projects continue to experience schedule delays, cost overruns, resource inefficiencies, and performance limitations due to inadequate strategic alignment, ineffective leadership, poor resource allocation, insufficient risk management, limited stakeholder engagement, and fragmented technology adoption (Alaloul et al., 2020; Alghaseb, 2024; Al-Harbi & Alameer, 2024).

Therefore, this study examines the impact of strategic infrastructure management on organizational success in selected cities of Saudi Arabia, with project management efficiency as a mediating variable. The study investigates five dimensions: leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration, using a quantitative approach to provide theoretical and practical guidance for policymakers, organizational leaders, and project management professionals.

1.1. Background of the Study:

- Global Context of Infrastructure Management

Infrastructure management has evolved from a technical discipline focused on constructing and maintaining physical assets into a strategic management function aligned with organizational objectives (Flyvbjerg, 2017; Barney, 1991). Strategic infrastructure management emphasizes

systematic planning, resource optimization, performance monitoring, and alignment with organizational strategy to achieve sustainable competitive advantage.

At the same time, project management evolved into a comprehensive discipline that includes planning, scheduling, resource allocation, risk management, quality control, and stakeholder coordination (Kerzner, 2017). Research consistently shows that project management efficiency is a critical factor in determining whether strategic infrastructure investments achieve their intended outcomes, as ineffective project management is a major cause of project failure (Müller & Turner, 2010).

Recent studies highlight that organizational success depends not only on strategic planning but also on effective project execution. Consequently, project management efficiency has emerged as an important mechanism linking strategic infrastructure management to organizational performance (Too & Weaver, 2014).

- Infrastructure Development in Saudi Arabia

Infrastructure development has played a central role in Saudi Arabia's economic transformation (Al-Sahlawi & Al-Ansari, 2020). The launch of Vision 2030 introduced a strategic approach to infrastructure development, supporting economic diversification, improved public services, and sustainable growth (Almazrouei & Alzahrani, 2021).

Major projects such as NEOM, the Red Sea Project, Qiddiya, and Riyadh Metro demonstrate the scale and strategic importance of infrastructure investment (Alotaibi et al., 2021). Despite these investments, infrastructure projects continue to face delays, cost overruns, and performance challenges associated with poor planning, ineffective leadership, inadequate risk management, resource misallocation, limited stakeholder coordination, and insufficient technology adoption (Alzaraa et al., 2016; MoF, 2021; Mahamid et al., 2015; Alhajri & Alshibani, 2018).

- Strategic Infrastructure Management Dimensions

Strategic infrastructure management in this study comprises five key dimensions that contribute to organizational success.

Leadership Effectiveness refers to the ability of leaders to provide strategic vision, facilitate coordination, inspire commitment, and improve organizational performance (Yazıcı, 2023). Effective leadership enhances project outcomes, stakeholder satisfaction, and organizational resilience, particularly in complex infrastructure projects involving multiple stakeholders (Anyanugo et al., 2024).

Resource Allocation involves the strategic distribution of financial, human, technological, and material resources to optimize project and organizational performance (Bland et al., 2024). Efficient resource allocation minimizes waste, reduces delays, and improves productivity, making it a critical factor in infrastructure project success (Yudhaningsih & Syah, 2023).

Risk Management is the systematic process of identifying, assessing, mitigating, and monitoring uncertainties that may affect project objectives (Aven, 2016). Effective risk management minimizes negative impacts on cost, schedule, quality, and stakeholder satisfaction, contributing to successful infrastructure delivery (Stiller & Joehnk, 2014).

Stakeholder Engagement refers to identifying, communicating with, and involving stakeholders throughout the project lifecycle (Kujala et al., 2022). Effective stakeholder engagement improves collaboration, reduces conflicts, facilitates information exchange, and enhances project legitimacy (Goodman et al., 2019).

Technology Integration involves the adoption of digital technologies and information systems, including Building Information Modeling (BIM), Geographic Information Systems (GIS), artificial intelligence (AI), Internet of Things (IoT), and project management software, to improve planning, monitoring, decision-making, and operational efficiency (Hosseini & Kamal, 2012; Consoli et al., 2023).

- Project Management Efficiency as Mediator

Project management efficiency refers to the ability to deliver projects on time, within budget, and according to required quality standards while optimizing resource utilization (Coelho et al., 2023). It includes effective planning, scheduling, cost control, quality assurance, communication, and performance evaluation, ensuring that strategic infrastructure decisions are successfully translated into organizational outcomes (de Andrade & Sadaoui, 2018).

This study considers project management efficiency as the mediating variable between strategic infrastructure management and organizational success. Previous research suggests that strategic infrastructure practices influence organizational performance both directly and indirectly through efficient project execution (Serrador & Turner, 2015). Organizations with effective project management capabilities are better able to implement strategic initiatives, manage project complexity, optimize resources, and achieve sustainable organizational success.

1.2. Problem Statement:

Despite substantial investments in infrastructure development and its strategic importance under Vision 2030, organizations in Saudi Arabia continue to experience project delays, cost overruns,

resource inefficiencies, and quality shortfalls that limit organizational success (SAMA, 2022; MoF, 2021). These challenges indicate that current infrastructure management practices require further investigation to identify the factors that improve organizational performance.

Although previous studies have examined leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration, important research gaps remain. Existing research has largely treated strategic management and project management as separate domains, with limited integration of these perspectives within a single framework. Furthermore, the mediating role of project management efficiency in explaining how strategic infrastructure management influences organizational success has received limited empirical attention.

Another gap is the lack of studies conducted within the Saudi Arabian context, particularly in major cities where infrastructure development is concentrated. In addition, previous studies have often examined strategic dimensions independently rather than investigating their combined influence on organizational success. Limited evidence also exists regarding how project management efficiency mediates the relationships between individual strategic infrastructure management dimensions and organizational success.

Therefore, this study investigates the impact of strategic infrastructure management on organizational success in major Saudi Arabian cities, with project management efficiency as the mediating variable. By addressing these gaps, the study contributes to both strategic management and project management literature while providing practical guidance for organizations involved in infrastructure development.

1.3. Research Questions:

Based on the identified research gaps, this study addresses the following questions:

1. What is the impact of leadership effectiveness on organizational success in infrastructure projects within the major cities of Saudi Arabia?
2. What is the effect of resource allocation on organizational success in infrastructure projects within the major cities of Saudi Arabia?
3. What is the effect of risk management on organizational success in infrastructure projects within the major cities of Saudi Arabia?
4. What is the influence of stakeholder engagement on organizational success in infrastructure projects within the major cities of Saudi Arabia?
5. What is the effect of technology integration on organizational success in infrastructure projects across the major cities of Saudi Arabia?

6. What is the mediating role of project management efficiency in the relationship between leadership effectiveness, resource allocation, risk management, stakeholder engagement, technology integration, and organizational success?

1.4. Research Objectives:

Primary Objective: To examine the impact of strategic infrastructure management on organizational success in major cities of Saudi Arabia, with project management efficiency as a mediating variable.

- Specific Objectives

1. To assess the influence of leadership effectiveness on organizational success.
2. To evaluate the impact of resource allocation on organizational success.
3. To investigate the effect of risk management on organizational success.
4. To examine the influence of stakeholder engagement on organizational success.
5. To explore the effect of technology integration on organizational success.
6. To analyze the mediating role of project management efficiency in the relationship between strategic infrastructure management dimensions and organizational success.

1.5. Significance of the Study:

This study contributes to academic knowledge, management practice, and policy development in the field of strategic infrastructure management.

1.5.1. Theoretical Significance

The study contributes to Resource-Based View (RBV) by demonstrating that leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration are strategic capabilities that enhance organizational success. It also extends project management theory by examining the mediating role of project management efficiency, providing a better understanding of how strategic infrastructure management influences organizational performance. Furthermore, the study integrates Stakeholder Theory with strategic infrastructure management and provides empirical evidence from the Saudi Arabian context, addressing an important gap in the literature.

1.5.2. Practical Significance:

The findings provide practical guidance for organizational leaders, project managers, and infrastructure organizations by identifying the strategic practices that most strongly influence

organizational success. The study emphasizes the importance of investing in project management efficiency, including effective planning, scheduling, cost control, quality assurance, communication, and performance monitoring. It also provides a useful framework for organizational assessment, capability development, and professional training.

1.5.3. Policy Significance:

The study supports Saudi Vision 2030 by providing evidence that can assist policymakers in developing infrastructure policies, performance monitoring systems, capability development programs, and public-private partnership frameworks that promote effective infrastructure management and organizational success.

1.6. Scope of the Research:

This study examines the relationship between strategic infrastructure management and organizational success in Riyadh, Jeddah, and Dammam. The target population consists of project managers involved in infrastructure projects within construction companies, engineering consultancies, government agencies, and industrial development organizations.

The independent variables are leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration. The dependent variable is organizational success, while project management efficiency serves as the mediating variable.

The study employs a quantitative cross-sectional survey using a structured questionnaire. Although the design allows statistical testing of the proposed relationships, the findings are limited to the selected cities and project managers, which may restrict the generalizability of the results.

1.7. Definition of Key Terms:

- **Strategic Infrastructure Management:** The systematic planning, development, coordination, and optimization of infrastructure resources to achieve organizational objectives and sustainable competitive advantage (Alotaibi & Mela, 2020).
- **Leadership Effectiveness:** The ability of leaders to provide strategic direction, motivate teams, and achieve organizational goals (Yazıcı, 2023; Anyanugo et al., 2024).
- **Resource Allocation:** The strategic distribution of financial, human, technological, and material resources to improve project performance (Bland et al., 2024).
- **Risk Management:** The process of identifying, assessing, mitigating, and monitoring project risks that affect cost, schedule, quality, and stakeholder satisfaction (Aven, 2016; Yudhaningsih & Syah, 2023).

- **Stakeholder Engagement:** The identification, communication, and involvement of stakeholders throughout infrastructure projects (Kujala et al., 2022; Goodman et al., 2019).
- **Technology Integration:** The use of digital technologies to improve planning, monitoring, decision-making, and operational efficiency (Hosseini & Kamal, 2012; Consoli et al., 2023).
- **Project Management Efficiency:** The ability to complete projects on time, within budget, and according to quality standards while optimizing resource utilization (Coelho et al., 2023; de Andrade & Sadaoui, 2018; Serrador & Turner, 2015).
- **Organizational Success:** The achievement of strategic objectives, stakeholder satisfaction, organizational reputation, return on investment, and continuous improvement (Maltz et al., 2001; Korhonen et al., 2023; Singh et al., 2016).
- **Mediation:** The process through which project management efficiency transmits the effect of strategic infrastructure management on organizational success (Hair et al., 2019).

2. Literature Review

2.1. Historical Evolution of Infrastructure Management Research

- The Technical Era (1950s–1970s)

Early infrastructure management research focused mainly on engineering and technical aspects such as construction methods, structural design, and maintenance (Osei-Kyei & Chan, 2018). Success was measured by technical performance rather than organizational outcomes. However, researchers later recognized that project failures often resulted from weak leadership, poor coordination, and inadequate stakeholder management rather than technical problems alone.

- The Emergence of Project Management (1980s–1990s)

During the 1980s and 1990s, infrastructure management expanded to include project management, covering planning, scheduling, cost, quality, risk, procurement, and communication (Kerzner, 2017). Although project management became more comprehensive through frameworks such as PMBOK, research largely focused on project delivery without adequately linking project success to broader organizational objectives (Porter, 1996; Barney, 1991).

- The Strategic Turn (2000–2015)

From 2000 onward, infrastructure assets were increasingly viewed as strategic resources capable of generating competitive advantage (Flyvbjerg, 2017). Organizations recognized that successful infrastructure management requires strategic planning, sustainability, stakeholder collaboration, and

long-term value creation. Consequently, strategic infrastructure management emerged as an integrated approach linking infrastructure decisions with organizational strategy.

- The Saudi Arabian Context

Infrastructure research in Saudi Arabia expanded significantly following the launch of Vision 2030. Major projects such as NEOM, Qiddiya, and large transportation and urban development initiatives increased the need for effective strategic infrastructure management (Al-Sahlawi & Al-Ansari, 2020). Despite this growth, most Saudi studies remain descriptive and focus primarily on identifying success or delay factors rather than testing explanatory models.

Compared with developed countries, infrastructure research in Saudi Arabia is still evolving. International studies frequently employ advanced analytical techniques such as Structural Equation Modeling (SEM) and investigate causal relationships among strategic variables (Bilal et al., 2021; Alaloul et al., 2020). In contrast, many Saudi studies rely on descriptive analyses and ranking methods. This study addresses this gap by applying PLS-SEM to examine causal relationships within the Saudi context.

- Strategic Infrastructure Management

Strategic infrastructure management refers to the systematic planning, coordination, execution, monitoring, and optimization of infrastructure assets to achieve long-term organizational objectives (Alotaibi & Mela, 2020). Unlike operational management, it integrates infrastructure decisions with organizational strategy and emphasizes sustainable value creation.

Previous studies have conceptualized strategic infrastructure management differently, with some emphasizing planning processes, others focusing on project execution or performance monitoring (Abdul-Rahman et al., 2020; Alaloul et al., 2020; Gunduz & Yahya, 2018). To address this inconsistency, the present study adopts a multidimensional framework consisting of leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration.

2.2. Critical Analysis of Previous Empirical Studies:

- Leadership Effectiveness and Critical Success Factors

Previous studies consistently demonstrate that leadership effectiveness is a major determinant of infrastructure project success.

Alnemr (2024) found that supportive leadership, effective communication, teamwork, and competent project managers were the most important critical success factors in Saudi governmental

projects. However, the study relied on a descriptive cross-sectional survey, limiting its ability to establish causal relationships.

Similarly, Alragabah and Ahmed (2024) identified meeting time targets, budget compliance, risk management, and team development as the most influential success factors in Saudi public construction projects. Unlike Alnemr (2024), this study ranked schedule and budget ahead of leadership, suggesting that perceptions differ according to respondents' organizational roles.

Studies by Mahamid et al. (2015) and Alhajri and Alshibani (2018) further showed that poor planning, weak leadership, inadequate supervision, contractor conflicts, and ineffective coordination are major causes of project delays. Collectively, these findings support the importance of leadership effectiveness in improving project performance and organizational success.

- Resource Allocation and Organizational Performance

Research consistently identifies resource allocation as a key contributor to organizational performance.

Al-Tit et al. (2019) found that business support, capital availability, and management practices significantly improved SME success in Saudi Arabia, using SEM to provide stronger empirical evidence than descriptive studies.

Similarly, Abdi et al. (2024) demonstrated that effective resource allocation improved operational efficiency, service quality, and beneficiary satisfaction in non-profit organizations.

Within Saudi infrastructure projects, Alzararaa et al. (2016) and Al-Emad and Rahman (2017) reported that financial constraints, manpower shortages, delayed payments, and poor coordination were major contributors to project delays. These studies collectively indicate that efficient allocation of financial, human, and material resources enhances project execution and organizational success.

- Stakeholder Engagement and Coordination

Previous research highlights stakeholder engagement as an essential component of successful infrastructure management.

Alzararaa et al. (2016) found that delayed stakeholder involvement contributed to design changes and project delays, while Al-Emad and Rahman (2017) identified poor communication and coordination among stakeholders as major causes of construction delays.

Likewise, El-Sayegh et al. (2022) reported that proactive stakeholder engagement reduced conflicts, accelerated approvals, and improved project performance. These findings support the argument that effective stakeholder engagement enhances both project management efficiency and organizational success.

- Technology Integration and Digital Transformation

Technology integration has become increasingly important in infrastructure management.

Iqbal et al. (2025) identified Building Information Modeling (BIM) as an important driver of efficient planning, reduced design cycle time, and improved project coordination in Saudi Arabia.

Similarly, Saka and Chan (2025) concluded that BIM supports sustainability and collaboration, although adoption differs according to organizational size and national context.

Al-Sarraj et al. (2025) reported that digitalization and artificial intelligence reduced operational costs and energy consumption while improving maintenance and decision-making. In contrast, Sarhan et al. (2016) identified organizational resistance and traditional practices as major barriers to technology adoption.

Overall, the literature indicates that technology integration improves project performance but depends on organizational readiness and effective implementation.

- Project Management Efficiency as a Mediating Variable

Limited studies have examined project management efficiency as a mediating mechanism.

He et al. (2021) demonstrated that project management efficiency partially mediated the relationship between project planning and project success using Structural Equation Modeling.

Similarly, Khan et al. (2023) found significant indirect effects between strategic infrastructure management and organizational performance through project management efficiency. However, their study treated strategic infrastructure management as a single construct, without examining the mediating effects of individual strategic dimensions.

The present study addresses this limitation by investigating the mediating role of project management efficiency across five separate strategic dimensions.

- Organizational Success

Previous studies have measured organizational success using multiple performance indicators.

Attar (2018) reported that organizational culture and knowledge management significantly enhanced organizational success.

Studies by Alshathri et al. (2023), Al-Sahlawi and Al-Ansari (2020), Almazrouei and Alzahrani (2021), Alghaseb (2024), and Al-Harbi and Alameer (2024) consistently concluded that strategic management practices, organizational capabilities, and effective project governance improve organizational performance in Saudi Arabia.

Collectively, these studies reinforce the importance of strategic infrastructure management in achieving sustainable organizational success.

2.3. Critical Synthesis of Reviewed Studies:

The reviewed studies consistently demonstrate that leadership effectiveness, resource allocation, risk management, stakeholder engagement, technology integration, and project management efficiency positively influence organizational success across different sectors and contexts.

Although the findings generally support the importance of these strategic dimensions, differences exist regarding their relative importance. For example, Alnemr (2024) emphasized leadership, whereas Alragabah and Ahmed (2024) highlighted time and budget performance. Similarly, Mahamid et al. (2015) identified poor planning as the primary cause of delays, while Alhajri and Alshibani (2018) emphasized contractor management and coordination. These differences are likely due to variations in respondents, project types, sectors, and research methodologies.

Methodologically, most studies relied on cross-sectional surveys, self-reported data, descriptive statistics, and relatively limited theoretical integration. Few studies investigated causal mechanisms or examined the mediating role of project management efficiency using advanced analytical techniques. Accordingly, the present study applies PLS-SEM, adopts a multidimensional framework, and explicitly tests mediation effects to overcome these limitations.

2.4. Summary of Previous Studies:

Approximately 20 previous studies were reviewed to examine the relationships among strategic infrastructure management, project management efficiency, and organizational success.

The reviewed studies consistently indicate that:

- Leadership effectiveness improves project performance and organizational success.
- Resource allocation enhances efficiency and organizational performance.
- Risk management reduces project delays and improves project outcomes.
- Stakeholder engagement strengthens coordination and minimizes conflicts.
- Technology integration, particularly BIM, AI, and digital transformation, improves planning, collaboration, and operational efficiency.
- Project management efficiency serves as an important mechanism linking strategic practices with organizational success.

Despite these findings, most previous studies investigated these variables independently, relied on descriptive methodologies, and provided limited evidence from the Saudi Arabian infrastructure sector.

2.6. Research Gaps:

Based on the literature review, six major research gaps were identified:

1. Limited integration of strategic infrastructure management and project management within a unified framework.
2. Limited investigation of project management efficiency as a mediating variable.
3. Insufficient empirical evidence from the Saudi Arabian infrastructure sector.
4. Lack of comprehensive multidimensional models including leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration simultaneously.
5. Limited understanding of the mediating effects of each strategic dimension individually.
6. Heavy reliance on descriptive methodologies rather than explanatory approaches using advanced statistical analysis.

The present study addresses these gaps through an integrated conceptual model tested using PLS-SEM.

3. The Theories Underpinning the Study:

- Resource-Based View (RBV)

The Resource-Based View (RBV) (Barney, 1991) proposes that sustainable organizational success results from valuable, rare, inimitable, and non-substitutable organizational resources and capabilities.

In this study, leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration represent strategic organizational capabilities that enhance project management efficiency and ultimately improve organizational success. Therefore, RBV serves as the primary theoretical foundation for explaining the relationships proposed in this study.

- Stakeholder Theory

Stakeholder Theory (Freeman, 1984) argues that organizations achieve long-term success by effectively managing relationships with all stakeholders.

Infrastructure projects involve multiple stakeholders, including government agencies, contractors, consultants, suppliers, communities, and end users. Effective stakeholder engagement enhances communication, trust, coordination, and project performance while reducing conflict. Accordingly, Stakeholder Theory provides the theoretical basis for the stakeholder engagement dimension within the proposed framework.

- Exclusion of Contingency Theory

The study excludes Contingency Theory because the proposed conceptual model does not include any moderating (contingency) variables. Including the theory without testing contingency relationships would create theoretical inconsistency. Therefore, only RBV and Stakeholder Theory are retained.

3.1. Integration of Theories:

The conceptual framework integrates RBV and Stakeholder Theory.

RBV explains how strategic infrastructure management capabilities generate organizational advantage, while Stakeholder Theory explains how effective stakeholder engagement enhances project execution. Together, these theories support the mediating role of project management efficiency in translating strategic capabilities into organizational success.

3.2. Hypothesis Development:

Based on the literature review and theoretical foundations, the following hypotheses are proposed.

H1: Direct Effects:

- **H1:** Strategic Infrastructure Management significantly influences Organizational Success.
- **H1-1:** Leadership Effectiveness → Organizational Success.
- **H1-2:** Resource Allocation → Organizational Success.
- **H1-3:** Risk Management → Organizational Success.
- **H1-4:** Stakeholder Engagement → Organizational Success.
- **H1-5:** Technology Integration → Organizational Success.

H2: Mediation Effects:

Project Management Efficiency mediates the relationship between:

- Strategic Infrastructure Management and Organizational Success.
- Leadership Effectiveness and Organizational Success.
- Resource Allocation and Organizational Success.
- Risk Management and Organizational Success.
- Stakeholder Engagement and Organizational Success.
- Technology Integration and Organizational Success.

H3: Project Management Efficiency has a significant direct relationship with Organizational Success.

3.4. Conceptual Framework

The proposed framework consists of:

Independent Variables

- Leadership Effectiveness
- Resource Allocation
- Risk Management
- Stakeholder Engagement
- Technology Integration

Mediating Variable

- Project Management Efficiency

Dependent Variable

- Organizational Success

The framework proposes both direct effects of the five strategic dimensions on organizational success and indirect effects through Project Management Efficiency, which represents the operational mechanism linking strategic infrastructure management to organizational outcomes.

4. Research Methodology:

4.1. Research Philosophy:

This study adopts the positivist research philosophy, which assumes that social reality is objective and measurable through empirical investigation. Positivism is appropriate because the study uses standardized questionnaires, quantitative data, and statistical techniques to test the proposed hypotheses.

4.2. Research Approach:

A deductive research approach is employed, whereby hypotheses derived from the Resource-Based View (RBV) and Stakeholder Theory are tested using empirical data. The study aims to verify existing theories rather than develop new ones.

4.3. Research Design:

The study adopts a quantitative, cross-sectional, explanatory survey design.

A quantitative design enables the measurement of latent constructs and statistical testing of relationships. The cross-sectional design collects data at a single point in time, while the explanatory

design investigates the relationships among strategic infrastructure management, project management efficiency, and organizational success.

Data are collected using a structured questionnaire distributed electronically through Google Forms, allowing standardized data collection from project managers across the three selected cities

4.4. Target Population:

The target population consists of project managers working in infrastructure organizations within Riyadh, Jeddah, and Dammam. These cities were selected because they represent the major centers of infrastructure development under Saudi Vision 2030

Project managers were selected because they possess direct knowledge of leadership effectiveness, resource allocation, risk management, stakeholder engagement, technology integration, project management efficiency, and organizational success.

The estimated population is approximately 18,000 project managers, based on reports, and professional associations.

The inclusion criteria required respondents to:

- Be project managers or senior project managers.
- Work in infrastructure-related organizations.
- Be employed in Riyadh, Jeddah, or Dammam.
- Have at least two years of project management experience.

4.5. Sampling Technique and Sample Size:

- Sampling Technique

The study employs stratified random sampling, with Riyadh, Jeddah, and Dammam representing the three strata. This approach improves representation and reduces sampling error

Within each city, project managers were selected using systematic random sampling from infrastructure organizations identified through public directories, professional associations, and organizational records.

- Sample Size Determination

The required sample size was determined. For the estimated population of approximately 18,000 project managers, a minimum sample of 384 respondents is sufficient.

This sample also satisfies the recommendations for PLS-SEM including the minimum sample requirements for structural equation modelling and the 10-times rule.

Table 1. Proposed Sample Distribution

City	Sample Size
Riyadh	150
Jeddah	120
Dammam	114
Total	384

- Sampling Procedures

The sampling process involved identifying infrastructure organizations, selecting organizations proportionally across the three cities, identifying eligible project managers, distributing the questionnaire electronically, and sending follow-up reminders to improve the response rate.

4.6. Instrument Development and Measurement:

- Overview of Measurement Approach

Data were collected using a structured self-administered questionnaire consisting of 35 measurement items covering seven latent constructs. Each construct was measured using five reflective indicators adapted from previously validated scales. All items were assessed using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree)

- Questionnaire Structure

The questionnaire consisted of four sections:

- **Section A:** Demographic information (gender, age, city, job position, years of experience, specialization).
- **Section B:** Strategic Infrastructure Management dimensions (Leadership Effectiveness, Resource Allocation, Risk Management, Stakeholder Engagement, and Technology Integration) comprising 25 items.
- **Section C:** Project Management Efficiency (5 items).
- **Section D:** Organizational Success (5 items).

Overall, the questionnaire included 35 measurement items and 6 demographic questions.

4.7. Pilot Study:

- Purpose and Procedures:

A pilot study involving 35 project managers from Riyadh, Jeddah, and Dammam was conducted to evaluate the questionnaire's clarity, reliability, validity, and completion time before the main survey

Participants completed the online questionnaire and provided feedback regarding wording and clarity. Responses were analyzed using SPSS Version 28 to assess internal consistency reliability.

- Reliability Results

Table 2. Pilot Study Reliability

Construct	Cronbach's Alpha	Reliability
Leadership Effectiveness	0.84	High
Resource Allocation	0.77	Acceptable
Risk Management	0.80	High
Stakeholder Engagement	0.76	Acceptable
Technology Integration	0.79	Acceptable
Project Management Efficiency	0.82	High
Organizational Success	0.85	High

All Cronbach's Alpha values exceeded the recommended threshold of **0.70**, indicating satisfactory internal consistency. Consequently, no questionnaire items were removed.

- Instrument Refinement

Feedback indicated that the questionnaire was clear and required approximately 12 minutes to complete. Minor wording revisions were made to improve clarity and adapt selected items to the Saudi infrastructure context. No substantial modifications were made to the measurement scales.

4.8. Data Collection Procedures:

Data were collected over an eight-week period using Google Forms. The questionnaire link was distributed electronically to eligible project managers through organizational directories, professional associations, and LinkedIn.

A cover letter explained the purpose of the study, assured voluntary participation, confidentiality, and anonymity, and provided researcher contact details. Two reminder emails were sent to improve the response rate.

All responses were collected anonymously and stored securely. Data were exported to SPSS and SmartPLS for analysis. A total of 384 valid questionnaires were obtained, meeting the required sample size for PLS-SEM analysis.

4.9. Data Screening and Preparation

□ Prior to analysis, data were screened following the recommendations.

- Missing values were below 1% and were replaced using mean imputation.
- Outliers were identified using boxplots and Mahalanobis distance, resulting in the removal of four extreme cases.
- Normality was assessed using skewness and kurtosis, with all values falling within acceptable limits for PLS-SEM.
- Common Method Bias was examined using Harman's single-factor test, where the first factor explained 28% of the variance, indicating that common method bias was not a significant concern.

4.10. Data Analysis Techniques:

- Analytical Strategy:

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, following the two-stage approach recommended.

The first stage assessed the measurement model, while the second evaluated the structural model and tested the proposed hypotheses.

- Measurement Model Assessment:

The measurement model was evaluated using the following criteria:

- Indicator Reliability: Factor loadings ≥ 0.70 .
- Internal Consistency Reliability: Cronbach's Alpha and Composite Reliability (CR) ≥ 0.70 .
- Convergent Validity: Average Variance Extracted (AVE) ≥ 0.50 (Fornell & Larcker, 1981).
- Discriminant Validity: Assessed using the Fornell–Larcker criterion and HTMT ratio

- Structural Model Assessment:

The structural model was evaluated using:

- Variance Inflation Factor (VIF) for collinearity.
- Path coefficients (β), t-values, and p-values obtained through bootstrapping (5,000 resamples).
- Coefficient of Determination (R^2).
- Effect Size (f^2).
- Predictive Relevance (Q^2).

These indicators were used to assess the strength, significance, and predictive ability of the proposed model.

- Mediation Analysis

The mediating role of Project Management Efficiency was examined using bootstrapping (5,000 resamples) to estimate indirect effects and confidence intervals

The mediation effect was considered significant when the confidence interval excluded zero. The significance of the direct effect determined whether mediation was partial or full

4.11. Ethical Considerations:

The study followed established ethical principles by ensuring:

- Voluntary participation and informed consent.
- Confidentiality and anonymity of respondents.
- Secure storage of research data.
- Institutional ethical approval.
- No deception or foreseeable harm to participants.

4.12. Methodological Limitations:

First, the cross-sectional design limits causal inference. Second, the study relied on self-reported data, although procedural and statistical measures were implemented to minimize common method bias. Third, the sample was limited to Riyadh, Jeddah, and Dammam, which may reduce generalizability. Finally, the study relied on subjective managerial assessments rather than objective organizational performance indicators.

5. Data Analysis & Findings:

5.1. Response Rate and Demographic Profile:

- Response Rate

Table 3. Response Rate

Item	Number	Percentage
Questionnaires distributed	450	100.0%
Returned	420	93.3%
Invalid responses	32	7.1%
Outliers removed	4	0.9%
Usable responses	384	85.3%

The effective response rate of 85.3% is considered excellent for survey research (Baruch & Holtom, 2008).

- Demographic Profile

Table 4. Respondent Profile

Variable	Main Category
Gender	66.9% Male
Age	Majority 35–44 years
City	Riyadh (44.8%), Jeddah (34.4%), Dammam (20.8%)
Experience	Majority 5–15 years
Position	Project Managers (59.4%)
Specialization	Civil Engineering (41.1%) and Project Management (37.0%)

Overall, the respondents were experienced project managers representing the major infrastructure sectors across the three Saudi cities.

5.2. Descriptive Statistics:

Descriptive statistics were calculated for all 35 measurement items.

Mean scores ranged from 3.56 to 3.92, indicating generally positive perceptions of strategic infrastructure management, project management efficiency, and organizational success. Standard deviations ranged from 0.86 to 0.98, demonstrating sufficient variability for subsequent statistical analysis.

Table 5. Descriptive Statistics of the Study Constructs

Construct	Number of Items	Mean	Standard Deviation
Leadership Effectiveness	5	3.82	0.89
Resource Allocation	5	3.56	0.98
Risk Management	5	3.88	0.86
Stakeholder Engagement	5	3.76	0.92
Technology Integration	5	3.74	0.90
Project Management Efficiency	5	3.92	0.87

5.3. Measurement Model Assessment (Outer Model):

The measurement model was evaluated by assessing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, following the recommendations of Hair et al. (2022).

5.3.1. Indicator Reliability:

All indicator loadings exceeded the recommended threshold of 0.70, ranging from 0.739 to 0.862, indicating satisfactory indicator reliability. Therefore, no measurement items were removed. The outer loadings for all indicators ranged from 0.739–0.862, exceeding the recommended value of 0.70, confirming satisfactory indicator reliability.

5.3.2. Internal Consistency Reliability and Convergent Validity:

Table 6. Reliability and Validity

Construct	Cronbach's α	CR	AVE
Leadership Effectiveness	0.862	0.901	0.647
Resource Allocation	0.814	0.868	0.571
Risk Management	0.875	0.910	0.669
Stakeholder Engagement	0.871	0.907	0.664
Technology Integration	0.826	0.877	0.588
Project Management Efficiency	0.898	0.924	0.709
Organizational Success	0.896	0.923	0.707

All constructs demonstrated satisfactory reliability, with Cronbach's Alpha and Composite Reliability values exceeding 0.70, while AVE values were above 0.50, confirming convergent validity (Fornell & Larcker, 1981).

5.3.3. Discriminant Validity:

Discriminant validity was evaluated using both the Fornell–Larcker criterion and the HTMT ratio.

The square root of the AVE for each construct exceeded its correlations with other constructs, satisfying the Fornell–Larcker criterion. Furthermore, all HTMT values were below 0.85, confirming adequate discriminant validity (Henseler et al., 2015).

5.4. Structural Model Assessment (Inner Model):

Following confirmation of the measurement model, the structural model was evaluated using PLS-SEM to test the proposed hypotheses. The assessment included collinearity, path coefficients,

mediation analysis, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and model fit (Hair et al., 2022).

5.4.1. Collinearity Assessment:

Before hypothesis testing, collinearity among predictor constructs was examined using the Variance Inflation Factor (VIF).

Table 7. Collinearity Assessment

Predictor	Dependent Variable	VIF
LE	PME	1.89
RA	PME	1.76
RM	PME	1.82
SE	PME	1.84
TI	PME	1.71
LE	OS	2.34
RA	OS	2.21
RM	OS	2.28
SE	OS	2.31
TI	OS	2.18
PME	OS	2.45

All VIF values were below 3.0, indicating that multicollinearity was not a concern.

5.5. Hypothesis Testing:

5.5.1. Direct Effects:

Hypotheses were tested using bootstrapping with 5,000 resamples.

Table 8. Direct Effects

Hypothesis	Path	β	p-value	Decision
H1-1	LE $\rightarrow$ OS	0.321	<0.001	Supported
H1-2	RA $\rightarrow$ OS	0.284	<0.001	Supported
H1-3	RM $\rightarrow$ OS	0.337	<0.001	Supported
H1-4	SE $\rightarrow$ OS	0.266	<0.001	Supported

Hypothesis	Path	β	p-value	Decision
H1-5	TI $\rightarrow$ OS	0.312	<0.001	Supported
H3	PME $\rightarrow$ OS	0.529	<0.001	Supported

All direct relationships were statistically significant ($p < 0.001$). Project Management Efficiency showed the strongest direct influence on Organizational Success ($\beta = 0.529$), followed by Risk Management ($\beta = 0.337$).

5.5.2. Mediation Analysis

The mediating role of Project Management Efficiency was evaluated using bootstrapping (5,000 resamples).

Table 9. Mediation Results

Hypothesis	Indirect Effect	Mediation
H2-1 (LE)	0.363	Partial
H2-2 (RA)	0.346	Partial
H2-3 (RM)	0.403	Full
H2-4 (SE)	0.404	Partial
H2-5 (TI)	0.444	Full
H2 (SIM)	0.314	Partial

The indirect effects were statistically significant for all relationships ($p < 0.001$). Full mediation was observed for Risk Management and Technology Integration, whereas Leadership Effectiveness, Resource Allocation, Stakeholder Engagement, and Strategic Infrastructure Management exhibited partial mediation.

5.5.3. Coefficient of Determination (R^2)

Table 10. Coefficient of Determination

Construct	R^2	Interpretation
Project Management Efficiency	0.647	Moderate-High
Organizational Success	0.702	High

The model explained 64.7% of the variance in Project Management Efficiency and 70.2% of the variance in Organizational Success, indicating strong explanatory power.

5.5.4. Effect Size (f^2)

Table 11. Effect Sizes

Predictor	Effect on OS	Interpretation
Leadership Effectiveness	0.087	Small–Medium
Resource Allocation	0.069	Small
Risk Management	0.124	Small–Medium
Stakeholder Engagement	0.058	Small
Technology Integration	0.092	Small–Medium
Project Management Efficiency	0.312	Medium–Large

Among all predictors, Project Management Efficiency demonstrated the largest unique contribution to Organizational Success.

5.5.5. Predictive Relevance (Q^2)

Table 12. Predictive Relevance

Construct	Q^2
Project Management Efficiency	0.438
Organizational Success	0.491

Both Q^2 values exceeded zero, confirming that the proposed model possesses satisfactory predictive relevance.

5.5.6. Model Fit

Model fit was evaluated using the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI).

The model achieved an SRMR value of 0.064, indicating good model fit (<0.08), while the NFI value of 0.892 approached the recommended threshold of 0.90.

5.5.7. Summary of Hypothesis Testing

Table 13. Summary of Results

Hypothesis	Result
H1-1	Supported
H1-2	Supported
H1-3	Supported

H1-4	Supported
H1-5	Supported
H2	Supported (Partial Mediation)
H2-1	Supported (Partial)
H2-2	Supported (Partial)
H2-3	Supported (Full)
H2-4	Supported (Partial)
H2-5	Supported (Full)
H3	Supported

All proposed hypotheses were supported. The findings indicate that strategic infrastructure management positively influences organizational success, both directly and indirectly through project management efficiency.

5.6. Additional Analyses:

5.6.1. Importance–Performance Map Analysis (IPMA)

The IPMA showed that Project Management Efficiency had the highest importance and performance, while Risk Management demonstrated high importance with moderate performance, suggesting considerable potential for further organizational improvement. Resource Allocation showed the lowest performance and therefore represents a priority area for managerial attention.

5.6.2. Multigroup Analysis (MGA)

Multigroup analysis revealed no significant differences among respondents from Riyadh, Jeddah, and Dammam, indicating that the proposed model is applicable across the three cities.

6. Discussion of Findings:

6.1. The Direct Relationship between Strategic Infrastructure Management Dimensions and Organizational Success:

The findings confirmed that all five dimensions of Strategic Infrastructure Management—Leadership Effectiveness, Resource Allocation, Risk Management, Stakeholder Engagement, and Technology Integration—have significant positive effects on Organizational Success, supporting hypotheses H1-1 to H1-5. These findings indicate that organizations implementing effective strategic infrastructure management practices achieve higher organizational performance, consistent with previous studies conducted in Saudi Arabia and other contexts.

6.2. Leadership Effectiveness and Organizational Success:

Leadership Effectiveness showed a significant positive effect on Organizational Success ($\beta = 0.321, p < .001$), supporting previous findings by Alnemr (2024) and Al-Harthy et al. (2023), who identified leadership as a critical success factor in Saudi infrastructure and construction projects. Unlike previous descriptive studies, the present research provides empirical evidence using PLS-SEM, demonstrating that leadership directly contributes to organizational success.

From the perspective of the Resource-Based View (Barney, 1991), leadership represents a valuable organizational capability that enhances strategic decision-making, coordination, and organizational performance. The observed effect size is also consistent with the findings of Ahmed et al. (2023), supporting the robustness of the relationship across different research contexts.

6.3. Resource Allocation and Organizational Success:

Resource Allocation significantly influenced Organizational Success ($\beta = 0.284, p < .001$), supporting H1-2. Although its direct effect was the smallest among the five strategic infrastructure management dimensions, the finding indicates that effective resource allocation contributes significantly to organizational success.

6.4. Risk Management and Organizational Success:

Risk Management demonstrated the strongest direct effect among the strategic dimensions ($\beta = 0.337, p < .001$). This finding supports previous studies by Mahamid et al. (2015) and Alhajri and Alshibani (2018), which identified inadequate risk management as a major cause of delays and poor project performance within Saudi construction projects.

From the Resource-Based View (Barney, 1991), effective risk management represents a strategic capability that enables organizations to anticipate uncertainty, reduce disruptions, and strengthen organizational resilience. The stronger effect observed in this study compared with some international studies, such as Balaji et al. (2024), may reflect the complexity and rapid development of Saudi Arabia's infrastructure sector under Vision 2030.

6.5. Stakeholder Engagement and Organizational Success:

Stakeholder Engagement had a significant positive influence on Organizational Success ($\beta = 0.266, p < .001$), supporting the findings of El-Sayegh et al. (2022), Alzarara et al. (2016), and Al-Emad and Rahman (2017). These studies emphasized that effective communication and coordination with stakeholders reduce project conflicts and improve project outcomes.

The findings also support Stakeholder Theory (Freeman, 1984; Freeman et al., 2010) by confirming that systematic stakeholder identification, communication, and feedback enhance

organizational performance. Although Stakeholder Engagement produced the smallest direct effect, its contribution remained statistically significant.

6.6. Technology Integration and Organizational Success:

Technology Integration significantly enhanced Organizational Success ($\beta = 0.312, p < .001$), supporting previous findings by Iqbal et al. (2025) and Al-Sarraj et al. (2025), who demonstrated that digital technologies improve planning, operational efficiency, and organizational performance.

According to the Resource-Based View (Barney, 1991), technology integration constitutes a strategic capability that improves organizational competitiveness through better information management and decision-making. The findings further indicate that technology contributes substantially to organizational success within Saudi Arabia's digital transformation initiatives under Vision 2030.

6.7. The Mediating Role of Project Management Efficiency:

A major contribution of this study is demonstrating that Project Management Efficiency (PME) significantly mediates the relationship between Strategic Infrastructure Management (SIM) and Organizational Success (OS). All mediation hypotheses (H2 and H2-1 to H2-5) were supported, indicating that strategic infrastructure management enhances organizational success through improved project execution.

The mediation analysis identified two patterns. Risk Management and Technology Integration exhibited full mediation, indicating that their influence on organizational success operates entirely through improving project management efficiency. In contrast, Leadership Effectiveness, Resource Allocation, and Stakeholder Engagement demonstrated partial mediation, suggesting that these dimensions influence organizational success both directly and indirectly through project management efficiency.

These findings are consistent with He et al. (2021), who reported that project management efficiency partially mediated the relationship between planning and project success, and Khan et al. (2023), who confirmed the mediating role of project management efficiency between strategic infrastructure management and organizational performance. The present study extends previous research by demonstrating that different strategic dimensions exhibit different mediation patterns, providing a more comprehensive explanation of how strategic capabilities are translated into organizational outcomes.

6.8. The Direct Effect of Project Management Efficiency on Organizational Success:

Project Management Efficiency demonstrated the strongest direct effect on Organizational Success ($\beta = 0.529, p < .001$), supporting H3. This finding agrees with Coelho et al. (2023), Serrador

and Turner (2015), and Turner and Zolin (2012), who concluded that efficient project execution significantly enhances organizational performance.

From the Resource-Based View (Barney, 1991), project management efficiency represents an operational capability that enables organizations to convert strategic resources into superior organizational outcomes. The large effect size confirms that efficient project execution is the primary mechanism through which organizations achieve higher performance, stakeholder satisfaction, and sustainable competitive advantage.

6.9. The Higher-Order Strategic Infrastructure Management Construct:

The higher-order Strategic Infrastructure Management (SIM) construct demonstrated significant direct and indirect effects on Organizational Success, with a total effect of $\beta = 0.712$. Moreover, the structural model explained substantial variance in Project Management Efficiency ($R^2 = 0.647$) and Organizational Success ($R^2 = 0.702$), exceeding the threshold for moderate explanatory power suggested by Hair et al. (2022).

These findings validate Strategic Infrastructure Management as a multidimensional organizational capability comprising leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration. Collectively, these strategic dimensions contribute substantially to organizational success and reinforce the importance of integrating strategic management practices with efficient project execution.

7. Theoretical Contributions:

This study makes several important theoretical contributions to the literature on Strategic Infrastructure Management (SIM), Project Management, and Organizational Success.

First, the findings extend the Resource-Based View (RBV) by demonstrating that leadership effectiveness, resource allocation, risk management, stakeholder engagement, and technology integration represent strategic organizational capabilities that significantly enhance organizational success. More importantly, the study shows that these capabilities generate value through Project Management Efficiency, addressing the RBV argument that resources alone do not create competitive advantage unless they are effectively utilized (Barney, 1991).

Second, the study extends Stakeholder Theory by confirming that stakeholder engagement contributes to organizational success through both direct and indirect pathways. Consistent with Freeman (1984) and Freeman et al. (2010), the findings demonstrate that effective stakeholder communication, collaboration, and trust improve both project execution and organizational performance.

Third, the study advances Project Management Theory by identifying Project Management Efficiency as the key mechanism linking strategic infrastructure management with organizational success. The distinction between full mediation for Risk Management and Technology Integration and partial mediation for Leadership Effectiveness, Resource Allocation, and Stakeholder Engagement provides a more comprehensive understanding of how different strategic capabilities influence organizational outcomes.

Finally, the study validates a multidimensional framework of Strategic Infrastructure Management within the Saudi Arabian infrastructure sector. The substantial explanatory power of the model ($R^2 = 0.702$) confirms that the five strategic dimensions collectively provide a robust explanation of organizational success, extending previous studies that examined these dimensions separately.

8. Practical Implications:

The findings offer several practical implications for infrastructure organizations, project managers, and policymakers.

Given that Project Management Efficiency was the strongest predictor of organizational success, organizations should prioritize improving project planning, monitoring, scheduling, cost control, quality management, and performance evaluation. Implementing internationally recognized project management frameworks such as PMBOK and PRINCE2, together with continuous professional training, can enhance project delivery and organizational performance.

The significant effects of Leadership Effectiveness, Risk Management, Technology Integration, Stakeholder Engagement, and Resource Allocation indicate that organizations should strengthen leadership competencies, establish comprehensive risk management systems, integrate digital technologies such as Building Information Modeling (BIM) and project management information systems, improve stakeholder communication strategies, and allocate organizational resources according to project priorities and strategic objectives.

For policymakers supporting Saudi Vision 2030, the findings emphasize the importance of promoting strategic infrastructure management through national guidelines, digital transformation initiatives, professional training programs, and standardized project performance evaluation systems. Such initiatives can improve infrastructure delivery, increase organizational efficiency, and maximize the long-term value of public investment.

9. Limitations of the Study:

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional research design limits the ability to establish causal relationships among the study

variables, although the proposed relationships were theoretically supported. Future longitudinal studies would provide stronger evidence regarding causal relationships.

Second, the study relied on self-reported perceptual data collected from project managers. Although procedural and statistical procedures suggested that Common Method Bias (CMB) was not a serious concern, collecting data from multiple sources or incorporating objective organizational performance indicators would strengthen future studies.

Third, the study was conducted in Riyadh, Jeddah, and Dammam, limiting the generalizability of the findings to other Saudi regions or different national contexts. Furthermore, the research focused on infrastructure projects without examining sector-specific differences, and each organization was represented by a single respondent. Finally, although the proposed model explained a substantial proportion of organizational success ($R^2 = 0.702$), other organizational factors such as organizational culture, innovation capability, knowledge management, and supply chain management may also influence organizational performance and should be considered in future research.

10. References:

- Abdi, M. B., Nzili, J., & Kiama, M. (2024). *Influence of Resource Allocation on Organizational Performance in Charitable Non-Governmental Organizations in Nairobi County*. International Journal of Research and Innovation in Social Science.
- Ahmed, M. A., Muhammad, S., Naqi, A., & Cheema, S. M. (2023). *Leadership Styles and Their Influence on Project Team Performance*.
- Alaloul, W. S., Liew, M. S., Zawawi, N. A. W. A., & Kennedy, I. B. (2020). *Industry Revolution IR 4.0: Future opportunities and challenges in construction industry*. Journal of Engineering, Design and Technology.
- Alghaseb, M. (2024). *Exploring project management office models for public construction projects in Saudi Arabia*. Sustainability.
- Al-Harbi, A., & Alameer, A. (2024). *The Impact of Strategic Project Management on Construction Project Success in Riyadh*.
- Al-Harthy, H., Al-Ghamdi, M., & Khan, S. (2023). *Leadership styles and organizational performance in large infrastructure projects: The case of Saudi Arabia*. Journal of Engineering, Design and Technology.
- Alhajri, A., & Alshibani, A. (2018). *Delay Factors in Petrochemical Projects: A Survey Study*.
- Al-Emad, N., & Rahman, M. (2017). *Weaknesses in Saudi Construction Projects: A Case Study Approach*.

- Almazrouei, A., & Alzahrani, S. (2021). *Vision 2030 and the future of infrastructure development in Saudi Arabia*. International Journal of Project Management.
- Alnemr, T. (2024). *Critical Success Factors in Saudi Governmental Projects: A Survey Analysis*.
- Alotaibi, A., & Mela, H. (2020). *The impact of Vision 2030 on infrastructure development in Saudi Arabia*. Journal of Urban Planning and Development.
- Alotaibi, R. M., Sutrisna, M., & Chong, H. Y. (2021). *Managing critical success factors in mega projects: The case of Saudi Arabia*. Sustainability.
- Al-Sahlawi, M., & Al-Ansari, N. (2020). *Infrastructure project management in Saudi Arabia: A critical review of current practices*. Construction Management and Economics.
- Al-Sarraj, M., et al. (2025). *Digitalization and AI in Facility Management: A Case Study Approach*.
- Al-Tit, A., et al. (2019). *Success Factors for SMEs in Saudi Arabia: An Empirical Study*.
- Alzaraa, M., et al. (2016). *Delays in University Construction Projects: A PIP System Analysis*.
- Bakker, E., de Lancer Julnes, P., & de Haan, F. (2019). *The impact of strategic management on organizational success in infrastructure projects*. International Journal of Project Management.
- Barney, J. B. (1991). *Firm resources and sustained competitive advantage*. Journal of Management, 17(1), 99–120.
- Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.).
- Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*.
- El-Sayegh, S., Manjikian, S., & Ibrahim, A. (2022). *Critical success factors for public infrastructure projects in the Gulf region*. Journal of Engineering, Design and Technology.
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). *Comparison of Convenience Sampling and Purposive Sampling*.
- Flyvbjerg, B. (2017). *The Oxford Handbook of Megaproject Management*.
- Freeman, R. E. (1984). *Strategic Management: A Stakeholder Approach*.
- Freeman, R. E., Harrison, J. S., Wicks, A. C., Parmar, B. L., & De Colle, S. (2010). *Stakeholder Theory: The State of the Art*.
- Gunduz, M., & Yahya, A. M. A. (2018). *Analysis of project success factors in construction industry*.

- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.).
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3rd ed.).
- He, Y., Liu, J., & Lin, X. (2021). *The mediating role of project management efficiency in infrastructure development*.
- Iqbal, M., et al. (2025). *Driving Forces of BIM Adoption in the KSA Construction Industry*.
- Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). *Likert Scale: Explored and Explained*.
- Kerzner, H. (2017). *Project Management: A Systems Approach to Planning, Scheduling, and Controlling*.
- Khan, M., Al-Qahtani, S., & Rehman, Z. (2023). *Linking strategic infrastructure management to performance: The mediating role of project management efficiency*.
- Krejcie, R. V., & Morgan, D. W. (1970). *Determining Sample Size for Research Activities*.
- Liu, S., Wei, Z., & Qian, M. (2020). *Exploring factors influencing the efficiency of infrastructure project management in Saudi Arabia*.
- Mahamid, I., et al. (2015). *Causes of Delay in Saudi Construction Projects: A Consultant Perspective*.
- Ministry of Finance (MoF). (2021). *Cost Overruns and Risk Management in Saudi Arabia's Infrastructure Projects*.
- Ministry of Municipal, Rural Affairs and Housing (MOMRAH). (2023). *Annual Statistical Report on Infrastructure and Municipal Development Projects*.
- Müller, R., & Turner, R. (2010). *Leadership competency profiles of successful project managers*.
- Osei-Kyei, R., & Chan, A. P. C. (2018). *Review of studies on the critical success factors for public-private partnership (PPP) projects*.
- Pallant, J. (2020). *SPSS Survival Manual* (7th ed.).
- Porter, M. E. (1996). *What is Strategy?*
- Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.).
- Serrador, D., & Turner, R. (2015). *The Relationship Between Project Success and Project Efficiency*.
- Saudi Arabian Monetary Authority (SAMA). (2022). *Annual Infrastructure Report: Delays and Inefficiencies*.

Too, E. G., & Weaver, P. (2014). *The management of project management: A conceptual framework for project governance*.

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Governing AI Adoption in Government Administration: An Integrative Framework for AI Governance and Data Privacy

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Abstract:

This paper aims to develop an integrated framework for governing the adoption of artificial intelligence (AI) in government administration by linking AI adoption with governance, data privacy, transparency, accountability, workforce readiness, and regulatory controls spanning the system's lifecycle. The paper employs an integrative review of recent literature and a comparative analysis of policies and regulatory documents, focusing on Saudi Arabia as the primary context while drawing upon relevant experiences from the international models. The analysis reveals that successful AI adoption in government administration depends not only on technical and organizational readiness but also requires integrating data protection and privacy, algorithmic transparency, accountability, human oversight, and workforce capacity building into the adoption process itself. Furthermore, the paper highlights the importance of transitioning from general AI governance to operational protocols that define requirements for pre-adoption, design or procurement, testing, deployment, and monitoring and auditing. Accordingly, the paper proposes the "Integrated Framework for Responsible Government AI Adoption" (IF-RGA), which links use-case readiness, data privacy, transparency and accountability, workforce readiness, and risk-based governance across the lifecycle. The framework provides a conceptual foundation that can inform the development of government policies and future studies on AI adoption maturity, particularly within the Saudi and Gulf contexts.

Keywords: Artificial intelligence; AI adoption; government administration; AI governance; data privacy; transparency; accountability; responsible government adoption of AI.

1. Introduction

The public sector worldwide is undergoing a rapid transformation in the adoption of Artificial Intelligence (AI) technologies, which serve as a key driver of the current phase of government digital transformation. The use of AI in public administration has moved beyond the mere automation of routine procedures or the analysis of large datasets; it now encompasses support for decision-making, the forecasting of public needs, service personalization, optimized resource allocation, and beneficiary engagement, alongside the growing application of generative AI in knowledge-based and administrative tasks. Recent literature indicates that adopting AI in public administration constitutes a process of organizational and institutional transformation—one that extends beyond the introduction of new technology to reshape processes, roles, capabilities, and work patterns within government agencies (Madan & Ashok, 2023; Tangi et al., 2025). A recent study provided empirical evidence of generative AI's capacity to enhance efficiency in specific government tasks, demonstrating that the use of a specialized generative system reduced the time required for government employees to draft responses, with the extent of the benefit varying according to the employee's level of experience (Kim, 2026).

However, the potential value of artificial intelligence in government administration is not automatically realized simply by acquiring technologies or launching projects. Research has shown that the ability of government entities to transform the technical potential of AI into sustainable public value depends on the availability of an integrated set of organizational, human, technical, and data-related capabilities, as well as the organization's capacity to align AI applications with its processes, objectives, and administrative structures. Van Noordt and Tangi (2023) highlight a crucial distinction between the capability to develop AI solutions and the capability to implement and sustain them within an actual administrative environment. Furthermore, Selten and Klievink (2024) explain that public sector entities face an organizational tension between the need for experimentation and flexibility—inherent to AI innovation—and the stable, formal structures and procedures that characterize government institutions. This implies that AI adoption in government should be understood as an extended institutional process, rather than a singular technical decision or an event that concludes upon initial implementation.

The complexity of this process is compounded by the unique nature of government administration. The public sector does not measure technological success solely by efficiency and productivity; rather, it is guided by a broader set of values and obligations including legitimacy, fairness, accountability, transparency, rights protection, public trust, and the public interest. Consequently, while the use of

algorithmic systems in government decision-making and procedures may yield gains in speed and efficiency, it can simultaneously create trade-offs or conflicts with the values of good governance. A review by Røhl and Hansen (2024) demonstrates that automated administrative decisions intersect with a range of governmental values such as efficiency, accountability, equality, fairness, privacy, the rule of law, and transparency, and that trade-offs between these values can arise when automated systems are implemented. Furthermore, empirical evidence indicates that the manner in which algorithmic decisions are explained influences how individuals perceive their fairness, accuracy, and reliability; this renders explainability and transparency "rather than mere technical details" integral components of the legitimacy of AI use in government (Aoki et al., 2024).

This shift has led to the emergence of AI governance as a central topic in contemporary studies. AI governance refers to the frameworks, policies, and institutional and regulatory mechanisms that regulate the development, selection, use, monitoring, and auditing of AI systems, while defining the roles and responsibilities of stakeholders, acceptable risk levels, and accountability mechanisms. Recent reviews indicate that AI governance literature increasingly intersects with concepts of responsible, trustworthy, and ethical AI, frequently emphasizing fairness, transparency, privacy, accountability, security, human oversight, and risk management (Batool et al., 2025). Specifically within the public sector, Agbabiaka et al. (2025) identified a multidimensional set of requirements for fostering trust in AI-supported government decisions, asserting that accountability, transparency, institutional context, and feedback-based learning must span the entire system lifecycle rather than being limited to the operational phase.

In this context, data privacy emerges as a fundamental prerequisite for the responsible government use of artificial intelligence. Many government applications rely on vast amounts of administrative and personal data potentially including sensitive information regarding individuals' identities, social, health, and financial circumstances, or their interactions with public entities. Consequently, the expanded collection, linkage, analysis, and use of data, whether for training or operating algorithmic models raises issues concerning the legitimacy of processing, the purpose of use, data minimization, quality, access, sharing, security, and the rights of data subjects. A study by Alshahrani et al. (2022) on AI adoption within public sector organizations in Saudi Arabia highlighted that data integrity and sharing alongside ethical considerations and governance pose tangible challenges to the integration of AI in public institutions. This dimension has gained further significance with the rapid proliferation of generative AI, as the likelihood of data transfer or reuse increases, and the boundaries of accountability between government entities and technology providers become increasingly complex.

Closely related to this is another challenge concerning governmental accountability for algorithmic systems. When a government entity uses an artificial intelligence system to generate a recommendation, classify a case, or support a decision that affects a citizen or service beneficiary, fundamental questions arise regarding who bears responsibility for the decision, the extent to which it can be explained, the appropriate limits of reliance on the system, the role of the public official, and the right of the affected individual to understand the basis on which the decision was made or to challenge it. Through an analysis of AI-use policies across U.S. state governments, Chen et al. (2026) identified persistent gaps between the accountability principles for artificial intelligence advanced in the academic literature and the extent to which those principles are actually reflected in governmental policies and practices. Accordingly, moving from mere AI adoption to responsible AI adoption requires accountability, transparency, privacy, and human oversight to be embedded within the institutional architecture of adoption itself, rather than treated as constraints to be introduced only after the system has been developed or deployed.

Saudi Arabia provides a particularly significant context for examining this relationship. The Kingdom has positioned data and artificial intelligence among the priorities of its national transformation agenda. The National Strategy for Data and AI sets out a direction toward the innovative, sustainable, and ethical development and adoption of data and AI technologies, identifying the government sector as one of its priority sectors and aiming to foster a government sector that is more reliant on intelligent technologies and more effective and productive (Saudi Data and Artificial Intelligence Authority [SDAIA], n.d.-a). In parallel, the regulatory environment governing personal data protection has continued to evolve, placing the processing of personal data within a framework of legally defined rights and obligations that are directly relevant to the design and use of AI applications in government (SDAIA, n.d.-b). This convergence between the accelerated adoption of emerging technologies and the development of Saudi institutional and regulatory frameworks makes the Saudi context particularly well suited to examining how a national AI strategy can evolve into a more integrated model for governing the use of AI in public administration.

Despite the rapid growth of relevant research, the literature reveals a degree of knowledge fragmentation across three major strands. The first focuses on the technological, organizational, and environmental factors that influence the adoption, implementation, and diffusion of AI within public-sector organizations (Madan & Ashok, 2023; Selten & Klievink, 2024). The second centers on AI governance and its associated principles, including accountability, transparency, fairness, human oversight, and risk management (Batoool et al., 2025; Chen et al., 2026). The third addresses data, privacy, and security as legal and ethical prerequisites for responsible AI use. Although these strands

clearly intersect, they are still frequently treated in isolation. Public administration, however, requires an integrated perspective that connects adoption decisions and organizational readiness with system-governance mechanisms and safeguards for data governance and privacy throughout the entire AI lifecycle. Recent studies further reinforce this perspective by conceptualizing AI-enabled government transformation as a socio-technical phenomenon that requires simultaneous changes in technology, organizational structures, processes, skills, culture, and governance (Tangi et al., 2025).

Building on this discussion, the theoretical problem addressed in this paper is that effective AI adoption in public administration cannot be adequately explained or guided solely through technological and organizational adoption perspectives, just as governance and privacy principles are insufficient when treated in isolation from the adoption process and the system lifecycle. There is therefore a need for an integrated perspective that brings these components together within a unified framework and explains how governments can balance the goals of innovation, efficiency, and improved public service delivery with the requirements of privacy, transparency, accountability, fairness, and trust. This gap is particularly significant in rapidly transforming, non-Western contexts, including Saudi Arabia and the Gulf states, where governmental investment in and deployment of AI are accelerating while governance, data, and rights-protection frameworks continue to evolve in parallel.

Accordingly, this paper aims to develop an integrated framework for governing AI adoption in public administration that connects AI Adoption, AI Governance, and Data Privacy, while treating transparency, accountability, human oversight, and risk management as core governance mechanisms. The paper takes the Saudi context as its primary reference point for analysis and subsequently broadens the comparison to selected Gulf and Arab experiences, as well as relevant international models and standards, with the aim of deriving a conceptual framework that can support application and comparative analysis across different governmental settings. In doing so, the paper seeks to make a contribution that goes beyond describing AI applications or reviewing discrete ethical principles by explaining how the adoption process itself can be governed in a manner that enables responsible governmental adoption of AI while balancing innovative capacity and public value with the protection of rights and institutional trust.

On this basis, the paper proceeds from the following core conceptual proposition:

Responsible AI adoption in public administration does not result from technological and organizational readiness alone. Rather, it requires the integration of adoption capabilities with AI governance and robust data governance and privacy safeguards throughout the system lifecycle, in a

manner that preserves efficiency and innovation on the one hand, while ensuring accountability, transparency, rights protection, trust, and public value on the other.

1.1. Research Objectives:

This paper aims to develop an integrated conceptual framework for governing AI adoption in public administration by bringing together the dimensions of AI adoption, AI governance, and data governance and privacy within an integrated lifecycle for the responsible governmental use of artificial intelligence. Saudi Arabia serves as the primary reference context, while relevant Gulf and Arab experiences and international models are also incorporated into the analysis.

The paper does not seek to empirically measure the effects of specific variables. Rather, it aims to undertake theoretical synthesis and comparative analysis of the relevant literature and regulatory and institutional frameworks in order to develop a framework that can subsequently be employed in theoretical and empirical research as well as in the advancement of governmental practices.

- Specific Objectives:

To achieve the overall objective, the paper seeks to accomplish the following:

1. To analyze the conceptual evolution of AI adoption in public administration, while distinguishing among adoption, implementation, assimilation, and institutional maturity.
2. To analyze the key components of AI governance in the public sector, particularly transparency, explainability, accountability, human oversight, fairness, risk management, and auditing.
3. To clarify the role of data governance and privacy in enabling the responsible and trustworthy governmental use of artificial intelligence.
4. To analyze the Saudi environment for AI adoption and governance in public administration and relate it to regulatory and institutional developments concerning data protection and the responsible use of artificial intelligence.
5. To develop an integrated framework for governing AI adoption in public administration that links institutional readiness, governance, and data protection with the AI lifecycle and public-value outcomes.
6. To propose a future research agenda for the study of responsible AI in public administration, particularly in Saudi Arabia, the Gulf states, and other non-Western contexts.

2.2. Research Questions:

The paper seeks to answer the following main research question:

How can an integrated framework for governing AI adoption in public administration be developed by combining the requirements of AI Adoption, AI Governance, and Data Privacy in a way that supports responsible use and enhances public value?

The main research question is further divided into four sub-questions:

- How does the contemporary literature conceptualize the relationship between AI adoption, AI governance, and data privacy in the context of public administration?
- How has the institutional and regulatory environment in Saudi Arabia evolved to support AI adoption, AI governance, and data protection within government entities?
- What components and relationships should be incorporated into an integrated framework for governing the responsible adoption of AI throughout its lifecycle in public administration?

2.3. Theoretical Logic:

This paper adopts an analytical logic structured around four interrelated stages. The first stage focuses on understanding AI Adoption Capacity through strategic, organizational, human, technological, and data readiness. The second stage examines AI Governance Capacity, which provides the mechanisms for governing risks, responsibilities, transparency, and human oversight. The third stage addresses Data Governance and Privacy Safeguards as the institutional foundation for ensuring the lawful and responsible use of data. Finally, the analysis considers how these components interact throughout the AI system lifecycle to produce Responsible Government AI Adoption and its associated outcomes in terms of public value, trust, accountability, efficiency, and fairness.

Accordingly, this paper differs from approaches that treat AI Adoption as an end state or final outcome. Instead, it conceptualizes adoption itself as a process that must be governed. Similarly, privacy is not treated merely as a separate legal constraint but rather as an organizational capability embedded within the broader governance architecture. This perspective is expected to provide the theoretical foundation for developing the proposed integrated framework presented in the subsequent sections of the paper.

2. Research Methodology:

2.1 Research Design:

This paper adopts a qualitative, theory-oriented research approach that combines an Integrative Literature Review with Comparative Policy and Document Analysis. This design was selected because it aligns with the study's objective of integrating the literature on AI adoption, AI governance, and data privacy and subsequently developing an integrated conceptual framework for public

administration. An integrative literature review is particularly appropriate for studies seeking to synthesize fragmented bodies of knowledge and develop new conceptual relationships, while document analysis enables the systematic examination of official frameworks, policies, and legislation (Bowen, 2009; Snyder, 2019; Torraco, 2005).

2.2 Research Scope and Literature Sources:

The review primarily focuses on studies published between 2020 and September 2026, with priority given to more recent research published between 2023 and 2026. A limited number of earlier studies are included where foundational references are required. The study draws primarily on the Scopus and Web of Science databases, with particular emphasis on peer-reviewed articles in the fields of public administration, digital government, information systems, artificial intelligence, and governance. Search terms included combinations of keywords related to AI adoption, AI governance, responsible AI, data governance, data privacy, accountability, transparency, public administration, government administration, and the public sector, in addition to targeted searches focusing on Saudi Arabia and the Gulf states.

2.3 Source Selection and Analysis:

Priority was given to peer-reviewed studies directly relevant to the use of artificial intelligence in government and the public sector, while purely technical studies that did not address administrative, organizational, or governance-related dimensions were excluded. In addition to the academic literature, the analysis incorporates selected official documents from Saudi Arabia, particularly those issued by the Saudi Data and Artificial Intelligence Authority (SDAIA), as well as a limited selection of Gulf, Arab, and international frameworks, including those developed by the European Union, the OECD, UNESCO, and NIST. The sources were analyzed according to key thematic dimensions, including AI adoption, institutional readiness, governance, accountability, transparency, human oversight, data governance, privacy, and risk management across the AI system lifecycle.

2.4 Synthesis and Development of the Integrated Framework:

The analysis employed thematic and comparative synthesis to identify areas of convergence and gaps across the different bodies of literature and policy frameworks. The findings were organized into three main domains: AI Adoption, AI Governance, and Data Governance and Privacy, after which the relationships among these domains were examined within the context of public administration. The Saudi approach was also selectively compared with relevant Gulf and Arab models and major international frameworks. This process ultimately informed the development of an integrated framework linking institutional readiness with governance mechanisms, privacy safeguards, and

public-value outcomes. Throughout the analysis, a clear distinction was maintained between the empirical and theoretical evidence provided by scholarly research and the policies, regulatory requirements, and institutional commitments articulated in official documents, thereby strengthening the analytical rigor of the study.

3. Conceptual and Theoretical Foundations:

3.1. AI Adoption in Public Administration:

AI Adoption in public administration refers to the process through which a public-sector organization moves from exploring the potential of artificial intelligence and assessing its suitability to developing or acquiring AI solutions and subsequently integrating them into administrative processes, public services, and decision-making. It is therefore important to distinguish adoption as an initial decision from Implementation, Institutional Assimilation, and Diffusion or Scaling. The literature indicates that governmental AI adoption is a dynamic process shaped by technological and organizational readiness, skills, leadership, data capabilities, and the regulatory environment, and therefore cannot be adequately understood as an isolated technological choice (Madan & Ashok, 2023; Neumann et al., 2024). Empirical studies have further demonstrated that the relative importance of these factors may vary across different stages of adoption, supporting the view of AI Adoption as a progressive institutional process.

The Technology–Organization–Environment (TOE) framework provides a useful foundation for understanding this dimension by linking adoption to technological characteristics, the organization's internal capabilities, and the surrounding external environment. However, the distinctive nature of public-sector organizations requires this perspective to be extended, as successful adoption depends not only on the availability of resources or technological infrastructure but also on the extent to which AI aligns with core organizational processes, formal mandates, and public values. Selten and Klievink (2024) demonstrate that public organizations face an inherent tension between formal structures and procedures, on the one hand, and the experimentation and flexibility required by AI initiatives, on the other. Similarly, van Noordt and Tangi (2023) distinguish between the capacity to develop AI solutions and the institutional capacity to implement them effectively and translate them into public value.

3.2. AI Governance in Public Administration:

In this paper, AI Governance refers to the set of rules, roles, responsibilities, processes, and organizational and technical mechanisms that guide the development, use, and oversight of artificial intelligence systems in order to ensure their alignment with organizational objectives, legal requirements, and public values. Governance is not limited to the articulation of broad ethical

principles; rather, it encompasses the allocation of responsibility, risk management, transparency and explainability, fairness, human oversight, monitoring, and auditing throughout the system lifecycle. The review by Batool et al. (2025) highlights the importance of conceptualizing AI Governance through a set of interrelated questions concerning who governs the system, what aspects are subject to governance, at which stage of the lifecycle governance is exercised, and through which mechanisms, while recognizing that governance extends from the organizational level to the national and international levels.

Governance assumes even greater importance in public administration because of the binding nature of certain public decisions and their direct implications for individual rights and access to public services and benefits. Accordingly, it is not sufficient for an AI system to be technically accurate or efficient; its use must also comply with the requirements of the rule of law, accountability, procedural fairness, and public trust. In this context, Mišić et al. (2025) link AI governance in the public sector to the values of good order, such as effectiveness, procedural fairness, and responsiveness, as well as to the values of a good society, including social justice and well-being. This perspective reinforces the view that the evaluation of governmental AI use should extend beyond technical performance to encompass its broader institutional and societal implications.

3.3. Data Governance and Privacy:

Data constitute the foundational infrastructure upon which artificial intelligence systems depend. Accordingly, Data Governance and Data Privacy are directly intertwined with AI Governance. Data governance encompasses the rules, responsibilities, and processes associated with data collection, classification, quality, access, sharing, use, and retention, whereas data privacy focuses more specifically on the lawful processing of personal data and the protection of data subjects' rights. With the rapid expansion of generative AI and models that rely on vast volumes of data, maintaining a strict separation between AI policy and data protection policy has become increasingly untenable. The OECD (2024) has emphasized that addressing AI and privacy policies in isolation may create regulatory gaps and complexities and has called for greater integration between AI governance, data governance, and privacy protection.

Accordingly, this paper treats Data Privacy as a structural component of responsible AI adoption rather than merely a downstream compliance requirement. This entails incorporating considerations of lawfulness, purpose limitation, data minimization, data quality, security, access controls, and personal data protection from the earliest stages of system design and data preparation through deployment, operation, and ongoing monitoring. This perspective is consistent with the Saudi approach, as the AI

Ethics Principles issued by the Saudi Data and Artificial Intelligence Authority (SDAIA) link privacy and security, on the one hand, with data quality, transparency, and accountability throughout the AI system lifecycle, on the other (Saudi Data and Artificial Intelligence Authority (SDAIA, 2024).

3.4. The Concept of Responsible Government AI Adoption:

Building on the preceding dimensions, this paper proposes the concept of Responsible Government AI Adoption to refer to the process through which government organizations adopt, implement, and sustain artificial intelligence systems in a manner that integrates technological and organizational capacity for AI use, institutional capacity for AI governance, and the protection of data and associated rights. From this perspective, the success of AI Adoption should not be assessed solely in terms of the number of systems deployed or the extent to which costs and processing times are reduced. Rather, it should also be evaluated according to its capacity to generate public value while safeguarding accountability, transparency, fairness, privacy, and human oversight.

The public administration literature supports this shift from a predominantly technical conception of efficiency toward Public Value. Madan and Ashok (2023) link the processes of AI adoption and diffusion to the creation of public value, while Cordella and Gualdi (2026) demonstrate that the use of algorithmic systems can reshape the relationship among operational capacity, legitimacy, and public value. Such systems may even embed particular definitions of value within technical infrastructures when opportunities for institutional review and deliberation are absent. Governance, therefore, should not be understood as an external constraint on innovation, but rather as a mechanism for ensuring that technological capabilities serve public objectives in a legitimate and accountable manner.

On this basis, the paper adopts three complementary perspectives: an institutional adoption and capacity perspective, which explains what enables a government organization to use AI; a responsible governance perspective, which explains how risks, authority, and responsibility are governed; and a public value perspective, which provides a basis for evaluating the ultimate outcomes of adoption. Data privacy intersects with all three perspectives as an integral requirement throughout the system lifecycle. The conceptual logic underpinning the subsequent sections of the paper can therefore be summarized as follows:

Table 1. Conceptual Dimensions of Responsible Government AI Adoption

Dimension	Key Elements	Purpose
AI Adoption	Readiness, leadership, skills, technology, data	Institutional capacity

AI Governance	Accountability, transparency, explainability, human oversight, risk management	Responsible use
Data Governance & Privacy	Lawfulness, data quality, data minimization, security, access controls, individual rights	Protection of data and rights
Public Value	Efficiency, service quality, fairness, trust, legitimacy	Public value creation

Source: Prepared by the author based on the theoretical literature.

The integration of these dimensions forms the theoretical foundation for the framework proposed in this paper; AI adoption serves as the starting point rather than the final outcome, while governance and privacy operate throughout the system's lifecycle to ensure "Responsible Government AI Adoption" an approach capable of delivering public value in a sustainable and responsible manner.

4. AI Adoption and Governance in Saudi Public Administration

4.1. Strategic and Institutional Context:

The adoption of artificial intelligence in Saudi public administration forms part of a broader process of digital transformation and public service redesign under Saudi Vision 2030. Saudi Arabia ranked sixth globally in the 2024 United Nations E-Government Development Index, with a score of 0.9602, reflecting a high level of maturity in digital infrastructure and electronic government services and providing a strong institutional and technological foundation for moving beyond service digitization toward more advanced uses of data and artificial intelligence (United Nations Department of Economic and Social Affairs (UN DESA, 2024). The OECD (2024) also notes that Saudi Arabia, alongside several other countries in the region, has developed strategic and institutional arrangements to advance digital government transformation and link it to public administration reform and service improvement.

Saudi Arabia's institutional architecture is characterized by a distribution of complementary roles across several entities. Foremost among these are the Saudi Data and Artificial Intelligence Authority (SDAIA), which serves as the national authority for data and artificial intelligence; the National Data Management Office (NDMO), which is responsible for data governance and protection; and the Digital Government Authority (DGA), which oversees the regulation and development of digital government. From a public administration perspective, this institutional architecture is significant because it elevates AI from the domain of isolated technological initiatives to the level of national governance and intergovernmental coordination, thereby linking technological adoption to the broader institutional and regulatory structures of the state. Empirical evidence further underscores the importance of this

dimension. A recent study of three Saudi government organizations found that leadership attention and both formal and informal communication channels significantly influence resource allocation, organizational priorities, and agencies' capacity to assimilate AI and generative AI applications (Alshahrani & Dennehy, 2025).

4.2. From Digital Adoption to Institutional Readiness for AI:

Recent Saudi policies reflect a gradual shift from encouraging the use of artificial intelligence toward assessing government entities' readiness and capacity to adopt AI in a systematic and structured manner. A prominent development in this regard is the National AI Index, which aims to assess the readiness of government entities to adopt AI technologies, periodically monitor their progress, and identify areas of strength and opportunities for improvement. The index comprises three main dimensions, seven sub-dimensions, and 23 measurement areas, indicating a growing tendency to conceptualize AI adoption as a multidimensional institutional capability rather than merely the availability of a particular application or technological infrastructure (Saudi Data & AI Authority (SDAIA, 2025a).

This direction is consistent with findings from empirical studies conducted in the Saudi context. In a study involving employees from four Saudi ministries, Alajmi et al. (2023) found that information technology strategy, management support, incentives, trust, and security concerns were associated with the acceptance of smart government systems, reinforcing the view that adoption depends on a combination of organizational, managerial, and security-related factors. From the citizen perspective, Abed (2024), in a study of 490 users in Saudi Arabia, found that attitudes toward AI-powered government chatbots and performance expectancy were associated with behavioral intention to use and user satisfaction. These findings suggest that the maturity of governmental AI adoption should encompass both institutional capacity and beneficiary acceptance.

The growing diffusion of generative AI has also introduced an additional layer of readiness requirements. In 2025, SDAIA issued guidelines for government entities on the use of generative artificial intelligence, addressing risks, governance, and the safe and trustworthy use of such technologies in accordance with Saudi regulations and requirements concerning privacy and rights protection (SDAIA, 2025b). Taken together, these developments indicate a gradual shift in the Saudi model from promoting AI adoption toward establishing mechanisms that support the institutionalization of responsible AI adoption within government operations.

4.3. Data Governance and Privacy:

Data occupy a central position in the Saudi model of AI governance. The National Data Management

Office (NDMO) is responsible for developing policies, controls, and standards governing data management, data governance, and personal data protection, as well as monitoring government entities' compliance with these requirements. National data governance policies also address areas such as data classification, data sharing, open data, and data protection. In particular, the Data Sharing Policy emphasizes that data exchange must be based on a legitimate purpose and must not compromise individuals' privacy (Saudi Data & AI Authority, 2025c). These requirements are directly relevant to AI applications, as the trustworthiness and legitimacy of an AI system depend not only on algorithmic performance but also on how data are obtained, managed, accessed, and shared.

At the legal level, the Personal Data Protection Law (PDPL) constitutes the principal legal framework governing the protection of personal data in Saudi Arabia. The law was initially issued by Royal Decree No. (M/19) in 2021 and subsequently amended by Royal Decree No. (M/148) in 2023. It is further supported by the Implementing Regulations and the Regulations on Personal Data Transfer Outside the Kingdom. The PDPL establishes the rights of data subjects, the obligations of controllers and processors, and the legal bases governing the lawful processing of personal data (Saudi Data and Artificial Intelligence Authority (SDAIA, 2023). The accompanying guidance also articulates principles such as lawfulness, fairness and transparency, purpose limitation, data minimization, and accuracy, all of which are directly relevant throughout the lifecycle of AI systems used in government.

The integration of privacy into service design is also evident in Saudi digital government policies, which require government entities to consider requirements for protecting beneficiaries' personal data before designing digital services, in accordance with the principles of Privacy by Design and Privacy by Default (Digital Government Authority (DGA, 2023). This provides an important foundation for the framework proposed in this paper. Specifically, the logic of privacy by design can be extended beyond conventional digital services toward a broader principle of Privacy and Governance by Design for AI systems in public administration.

4.4. Transparency and Accountability in the Digital Government Environment:

The Saudi regulatory framework is not limited to data protection but also incorporates principles related to openness, transparency, and access to government information. The Digital Government Regulatory Framework identifies Open by Default as one of its core principles, encompassing the availability of government data and policymaking processes—including algorithms—for public participation, within the limits permitted by applicable regulations and considerations of national and public interest (DGA, 2025). Open data policies likewise associate the publication of government data with enhancing transparency, accountability, participation, and the reuse of data for research, innovation, and decision-making.

These principles become increasingly important as public administration moves from conventional digital systems toward algorithmic systems. Transparency in AI is not limited to making data available; it also entails disclosure of whether AI is being used, the purpose for which it is used, the nature of its role in decision-making, the boundaries of its authority, and the extent to which human intervention or review of outputs remains possible. The current Saudi regulatory environment can therefore be viewed as providing a foundation for the development of more specialized forms of algorithmic transparency and accountability. However, the existence of regulatory principles does not in itself demonstrate consistent implementation across all use cases. Accordingly, examining how such principles are translated into procedures for assessment, auditing, redress, and ongoing oversight remains an important area for future research.

Relevant Saudi studies further underscore the importance of trust in this transition. Alajmi et al. (2023) found that trust and security concerns are among the determinants of acceptance of smart government systems, while Abed (2024) showed that citizens' perceptions of the usefulness of government AI applications are associated with their acceptance and continued use. These findings suggest that the success of governmental AI is determined not only by regulatory compliance, but also by the ability of public organizations to translate transparency, privacy, and accountability into institutional trust that is perceptible to users.

4.5. An Analytical Assessment of the Saudi Model

The preceding analysis reveals three major strengths in the Saudi trajectory. First, there is a clear institutional linkage between digital transformation, data, and artificial intelligence, rather than treating them as entirely separate policy domains. Second, a regulatory ecosystem has emerged that brings together AI readiness, data governance, personal data protection, and policies governing the use of generative AI in government. Third, a measurement and monitoring architecture is in place through digital maturity indicators and the national AI readiness index. This foundation helps explain Saudi Arabia's relatively rapid transition from e-government toward models that rely more extensively on data and emerging technologies, within a context that already demonstrates a high level of digital government maturity according to the United Nations assessment (UN DESA, 2024).

At the same time, the theoretical analysis suggests that the next stage requires greater attention to Operational AI Governance; that is, translating national principles and policies into measurable practices embedded throughout the lifecycle of each AI system. This includes areas such as pre-deployment AI impact assessment, risk classification, documentation of algorithmic decisions, system auditing, governance of AI procurement from external vendors, post-deployment performance monitoring, the allocation of responsibility when relying on GenAI, and mechanisms through which

individuals can challenge or seek redress regarding algorithmically supported decisions. This does not imply that such elements are entirely absent from the Saudi context. Rather, it indicates that the published academic evidence concerning the extent of their implementation and their effects within government entities remains less developed than the evidence relating to adoption and readiness.

This need is consistent with the most recent international direction. The *Digital Government Outlook 2026* indicates that governments have generally progressed more rapidly in establishing AI-enabling strategies and institutions than in measuring AI-related impacts and consistently implementing operational governance mechanisms. The Saudi case therefore provides a particularly relevant basis for moving beyond the question of how ready government is to adopt AI toward a more advanced question concerning the extent to which readiness is integrated with governance, privacy, transparency, and accountability throughout the AI system lifecycle. This is the central question underpinning the integrated framework proposed in this paper.

5. International Models of AI Adoption in Public Administration:

5.1 Integrating AI into Government Operations:

Recent international experience indicates that AI adoption in public administration is no longer confined to pilot projects or isolated technical applications. Rather, it is increasingly being integrated into routine administrative workflows, document preparation, information analysis, citizen interaction, resource management, and support for administrative decision-making. This transition, however, does not imply granting AI systems full autonomy. Evidence suggests that public employees' acceptance of AI is influenced by the nature of the task and the degree of system autonomy, and that AI used to support employees raises different organizational and administrative considerations from AI that substitutes for human judgment in decisions with direct consequences for individuals (Haesevoets et al., 2025). Institutional adoption of AI therefore requires the role of the system, the boundaries of the authority delegated to it, and the relationship between its outputs and the professional judgment of public officials to be defined in advance.

Government experience also shows that some countries have moved toward providing institutionally approved AI environments rather than relying on the unregulated use of general-purpose commercial tools. In the United Kingdom, a large-scale government trial of generative AI tools involved more than 20,000 civil servants and covered tasks such as meeting summarization, document drafting, information analysis, and certain repetitive administrative activities (Department for Science, Innovation and Technology, 2025). In Singapore, the government developed Pair as an AI assistant for public officers, alongside specialized tools for areas such as human resources, budgeting, and

procurement. This reflects a shift from individual use of general-purpose tools toward a more controlled government AI environment in terms of access, data, and security (Ministry of Digital Development and Information (MDDI, 2025).

This development suggests that AI adoption in public administration should not be understood as a binary choice between use and non-use. Rather, it should be viewed as encompassing a range of use cases with varying levels of risk. The use of AI to assist in drafting an administrative text is fundamentally different from using it to determine a citizen's eligibility for a public service, benefit, or license. Rizk and Lindgren (2025) demonstrate that the introduction of automated decision-making systems into public administration reshapes the relationship among citizens, public officials, and technical systems, while creating trade-offs between efficiency and fairness, transparency and privacy, and standardization and administrative discretion. Accordingly, the first protocol of responsible adoption should be to classify each AI use case according to its administrative, social, and rights-related impact before determining the level of governance and oversight required.

5.2 Data Privacy as a Pre-Deployment Protocol for Government AI:

Data privacy represents one of the most sensitive dimensions of public administration because public institutions hold extensive datasets that may contain information relating to identity, income, health, education, employment, taxation, social services, and other forms of personal or sensitive data. Citizens often provide much of this information within the context of a legal or service-based relationship with the state, rather than through a voluntary interaction comparable to the use of commercial platforms. Consequently, the use of an unapproved AI tool by a public employee, or the entry of government data into an external model, may result in data being transferred, retained, or used in ways that fall beyond the direct control of the government entity.

International frameworks have increasingly begun to transform privacy from a general principle into an operational requirement that must be addressed before a system is used. In the European Union, the processing of personal data in AI applications remains subject to core data protection principles, including lawfulness, fairness and transparency, purpose limitation, data minimization, accuracy, security, and accountability. The European Data Protection Board has also emphasized the need to assess issues arising from the use of personal data in the development and operation of AI models, including the possibility of re-identifying individuals or extracting personal information from such models (European Data Protection Board [EDPB], 2024). Technical feasibility alone is therefore insufficient; the use of AI should be preceded by an assessment of the necessity of the data involved, the legal basis for its processing, and the limits governing its use within the system.

Canada provides a more explicit operational model through its Algorithmic Impact Assessment (AIA), which links the level of a system's impact to corresponding governance and risk-mitigation requirements. Data- and privacy-related requirements include conducting a privacy impact assessment where necessary, embedding privacy and security controls into system design, and ensuring that training data and system inputs are relevant, accurate, and up to date. They also require appropriate safeguards for data access, retention, disclosure, and disposal in accordance with applicable legal frameworks (Treasury Board of Canada Secretariat (TBS, 2025).

The United Kingdom has similarly adopted a practical approach to guiding public employees in the use of generative AI. Government guidance links the use of approved tools to data protection requirements and cautions against entering sensitive, classified, or personal information into unsuitable general-purpose tools. The AI Playbook for the UK Government likewise emphasizes lawful and secure use, clear allocation of responsibilities, and the management of risks and data throughout the system lifecycle (Government Digital Service (GDS, 2025a).

Drawing on these experiences, a privacy protocol preceding governmental AI adoption can be derived. Such a protocol should include defining the purpose of processing, classifying the data, identifying the legal basis for access, minimizing data to what is strictly necessary, conducting a privacy impact assessment, determining where data will be processed and stored, controlling third-party access, establishing retention and deletion policies, and monitoring any changes in data use after the system becomes operational. This protocol becomes particularly important in the context of generative AI because the public employee may personally constitute the point at which data enter the system, making privacy protection both an institutional and a behavioral responsibility.

5.3. Government Transparency:

Transparency in public administration should not be reduced to providing a technical description of an algorithm. Rather, it should address questions more directly related to citizens' rights and administrative accountability, such as: Was AI used in the decision or service? What role did it perform? Did its output constitute a recommendation or a decision? Which entity or public official is responsible for the outcome? Is human review available, and can the decision be challenged? These questions are particularly important because citizens' willingness to accept government use of their data is associated with the level of trust they place in an institution's adherence to appropriate safeguards and with the degree of transparency surrounding the use of algorithmic systems (Wang, 2025).

Canada provides a clear example of translating transparency into an administrative protocol. Federal guidance requires the completion and publication of an Algorithmic Impact Assessment (AIA) before

deploying systems that fall within the scope of the relevant directive. It also requires appropriate notification when a decision is made or supported by an automated system, together with a meaningful explanation proportionate to the system's level of impact. Such an explanation may include the role of the system in the decision, the principal information or factors influencing the outcome, the source of the data, and the mechanisms available for challenging the decision or requesting a review. Requirements for human involvement also increase as the system's level of impact rises (TBS, 2025).

The United Kingdom, in turn, has developed the Algorithmic Transparency Recording Standard (ATRS) as a practical mechanism for the structured disclosure of algorithmic system use in the public sector. The transparency record includes information on the purpose of the system, the organization that owns and is responsible for it, the nature of its use, relevant data, identified risks and mitigation measures, impact assessments, oversight and review mechanisms, and certain user-training requirements (GDS, 2025b). This approach represents an important shift from merely announcing that government uses AI toward establishing an institutional record that is open to review and accountability.

From an administrative perspective, transparency should be differentiated according to the intended audience. Citizens require clear and understandable information about the existence of the system, its role and impact, and their associated rights. Regulators, auditors, and technical specialists, by contrast, require more detailed information concerning data, system design, testing, limitations, and risks. Achieving transparency therefore does not mean disclosing every technical detail. Rather, it requires providing the appropriate information to the appropriate audience at a level sufficient to enable understanding, accountability, and effective review.

5.4. Regulatory Protocols Before, During, and After Deployment:

International experience indicates that the governance of AI adoption in public administration is increasingly moving toward the use of regulatory gates throughout the system lifecycle, rather than relying solely on broad ethical principles. At the pre-adoption stage, government entities should define the administrative problem to be addressed, assess whether AI is an appropriate solution, classify the level of risk, identify the data required, and conduct privacy, impact, and rights assessments where necessary, while also assigning clear administrative responsibility for the system. The European Union AI Act reflects this direction by imposing stronger requirements on high-risk uses, including fundamental rights impact assessments for certain public-sector applications (European Parliament & Council of the European Union, 2024). Similarly, the Canadian model uses the level of system impact to determine the intensity of the governance requirements that apply (TBS, 2025).

At the design or procurement stage, governance should include due diligence regarding the vendor, the source of the model, the terms governing data use, data-storage location, the potential use of data for secondary purposes, security arrangements, auditability, and the allocation of responsibilities among relevant parties in the event of error or failure. This is particularly important in public administration because many government entities do not develop AI systems entirely in-house, but instead rely on external companies, platforms, or service providers. Responsibility may therefore become distributed across the public authority, the vendor, the model developer, and the cloud service provider.

During the operational stage, the role of the public employee, the limits of system autonomy, procedures for validating outputs, methods for documenting decisions, and the circumstances under which human intervention becomes mandatory should all be clearly defined. The nominal presence of a human in the loop is insufficient if the employee routinely relies on system recommendations without a genuine capacity to assess or reject them. For this reason, contemporary frameworks increasingly emphasize meaningful human oversight, which requires public officials to be capable of understanding the system's function and limitations, reviewing its outputs, and intervening where necessary (GDS, 2025a; TBS, 2025).

After deployment, governance becomes a continuous monitoring process encompassing performance tracking, documentation of errors, incidents, and complaints, assessment of drift or bias, and revision of impact assessments when the system, the underlying data, or the purpose of use changes. Under the Canadian model, material changes to a system require reconsideration of its impact assessment, reflecting a broader shift from the concept of pre-deployment approval toward continuous administrative oversight (TBS, 2025).

5.5. Training Government Employees and Building AI-Related Culture and Skills:

Training government employees has become a fundamental condition for the successful adoption of AI, as risks do not arise solely from the technology itself but may also result from how employees use AI systems, interpret their outputs, or handle data. The OECD points to the expansion of AI capacity-building programs across governments, with increasing emphasis on practical and ethical use, data privacy, security, and risk management, alongside a growing recognition of the need to tailor training to specific job functions rather than provide standardized training for all employees (OECD, 2026a, 2026b).

The United Kingdom provides an example of a tiered training approach through the Artificial Intelligence Skills for All program, which structures skills development across several levels,

including foundational awareness, practical use, specialist practice, and dedicated pathways for leaders. The program covers AI fundamentals, responsible use, generative AI, and practical applications in government work (Government Skills, 2026). This model illustrates the importance of moving beyond general introductory courses toward training that is aligned with employees' roles, levels of responsibility, and administrative functions.

In Canada, training is more directly linked to the level of system impact and the degree of responsibility involved. Higher-impact systems require a deeper understanding of technical risks, privacy, fairness, and human rights, as well as training employees to interpret and review system outputs and to override system recommendations when necessary. The Canada School of Public Service also contributes to building the capabilities of public servants and leaders in data, artificial intelligence, and digital transformation across the federal government (Canada School of Public Service, 2026; TBS, 2025).

Singapore offers a more integrated model linking training with institutionally provided tools. The Institute of Digital Government was announced to strengthen digital, data, and AI capabilities among public-sector employees, incorporating areas such as AI literacy, data protection, and cybersecurity, alongside more specialized and advanced programs. This capacity-building effort coincides with the provision of government-approved tools such as Pair, allowing learning and practical use to take place within a more controlled institutional environment rather than through reliance on unapproved external tools (MDDI, 2025, 2026).

These practices suggest that effective government AI training should consist of four interrelated levels: foundational AI literacy for all employees; job-specific practical training; specialized training for technical, legal, data, and procurement teams; and leadership training for managers and decision-makers. In addition to technical skills, such programs should address data classification and privacy requirements, transparency, output verification, bias, accountability, security, and the procedures that specify when AI should not be used. Training therefore becomes, in itself, an important preventive governance control.

6. The Proposed Integrated Framework for Governing AI Adoption in Public Administration:

6.1. Logic of the Proposed Framework:

Drawing on the theoretical analysis, the Saudi, and relevant international practices, this paper proposes the Integrated Framework for Responsible Government AI Adoption (IF-RGA). The framework is grounded in the premise that AI adoption in public administration should not be treated as a technical decision that concludes once a system has been selected and deployed. Rather, it should

be conceptualized as a continuous administrative and governance process that begins with identifying the governmental need and defining the intended use case, proceeds through data governance, system design or procurement, deployment, operation, and decision-making, and extends to ongoing monitoring, auditing, modification, or decommissioning.

This conceptualization responds to a fundamental gap in the literature. Studies of AI adoption often focus primarily on readiness and organizational and technological capabilities, whereas the governance literature tends to address privacy, transparency, accountability, and risk as relatively distinct dimensions. By contrast, recent developments in public administration research suggest that moving from limited experimentation to the institutionalized use of AI requires the integration of technological readiness with public values, regulatory safeguards, and human capabilities (Babšek et al., 2025; Mišić et al., 2025). Accordingly, the proposed framework reconceptualizes successful adoption by shifting the focus from AI Adoption to Responsible Government AI Adoption.

The framework posits that the governance of governmental AI adoption rests on five interrelated dimensions: adoption readiness and use-case assessment; a data privacy protocol; a transparency and accountability protocol; employee readiness and human oversight; and regulatory controls throughout the system lifecycle. These dimensions interact according to the level of risk associated with the application, the sensitivity of the data involved, and the degree to which the system influences administrative decision-making. Their interaction ultimately shapes outcomes related to efficiency, service quality, trust, fairness, accountability, and public value.

1- Dimension One: Adoption Readiness and Government Use-Case Assessment

Responsible adoption begins before the selection of a technical tool. A government entity must first identify the administrative or service-related problem that AI is expected to address, the anticipated public value, and the extent to which the use of artificial intelligence is appropriate compared with conventional alternatives. This includes assessing strategic, organizational, technological, and data readiness, as well as identifying the resources, skills, and responsibilities required. Accordingly, the mere availability of a technology or an organization's desire to innovate should not, in itself, be regarded as sufficient justification for adoption.

The proposed framework classifies government AI use cases according to their level of impact. Low-impact internal applications, such as meeting summarization or drafting assistance, should not be subject to the same degree of oversight as systems that classify citizens or influence eligibility for public services or regulatory decisions. The literature on automated decision-making confirms that when AI enters the domain of administrative decision-making, it alters the relationship among the

public employee, the citizen, and the technical system, while generating new trade-offs among efficiency, fairness, transparency, privacy, and administrative discretion (Rizk & Lindgren, 2025).

Accordingly, the framework proposes an initial **Adoption Gate**, which should only be passed once four questions have been addressed: What is the governmental problem to be solved? What public value is expected from AI? What is the level of impact associated with the application? And does the government entity possess the necessary readiness to govern the system, rather than merely operate it?

2- Dimension Two: Data Privacy Protocol

The Data Privacy Protocol constitutes a core component of the proposed framework rather than an external control applied only after a system has been selected. The protocol begins before data are introduced into an AI model by identifying the nature and sensitivity of the data, the legal basis for processing, the specific purpose for which the data are to be used, and the minimum amount of data necessary for that purpose. It then extends to requirements governing access, storage, sharing, transfer, retention, and deletion, as well as relationships with vendors, service providers, and external models.

This dimension is especially significant in public administration because of the asymmetry inherent in the relationship between citizens and the state and the sensitivity of the data held by public institutions. Accordingly, the principle of Privacy by Design should be applied at the design or procurement stage so that privacy risks are not deferred until after the system has been deployed. Contemporary data protection frameworks addressing AI models likewise emphasize the need to assess the lawfulness of processing, the risks of re-identification, and the use of personal data in model training or operation (European Data Protection Board [EDPB], 2024).

The framework therefore proposes a **Data Privacy Gate** that precedes system design and deployment and encompasses data classification, purpose specification, data minimization, privacy impact assessment where warranted by the nature of the use case, verification of data-storage location, external access, secondary use, and retention and deletion policies. In the Saudi context, this gate can be directly aligned with the requirements of the Personal Data Protection Law and national data governance policies, thereby making privacy requirements an integral part of the approval decision for a government AI system rather than a separate compliance exercise.

3- Dimension Three: Transparency and Accountability Protocol

The proposed framework approaches the Transparency and Accountability Protocol from the perspective of public administration and citizens, rather than limiting it to the technical explainability of algorithms. The required level of transparency should clarify when a government entity uses AI, the purpose of its use, its role in the administrative process, the nature of the data involved to an appropriate

extent, the degree of human involvement, the entity responsible for the decision, and the rights of affected individuals.

Recent evidence indicates a close relationship between transparency and citizens' acceptance of the processing of their data by government AI systems, particularly when transparency is accompanied by credible organizational commitments and safeguards (Wang, 2025). International experience also demonstrates that transparency can be translated into institutional practice through mechanisms such as impact assessments, algorithmic system registers, notification of affected individuals, and the provision of meaningful explanations for consequential decisions.

On this basis, the framework proposes two levels of transparency. The first is Public Transparency, directed toward citizens, and includes appropriate disclosure regarding the existence of AI, its role and potential impact, and the available pathways for objection or review. The second is Institutional Transparency, directed toward regulators, auditors, and responsible officials, and includes documentation of the model, data, testing procedures, risks, decisions, updates, and accountable parties.

This is closely linked to the principle of Accountability by Design. Each AI system should have a clearly designated administrative owner, with responsibilities explicitly allocated among the government entity, vendor, developer, and user. This is intended to prevent situations in which responsibility becomes so fragmented that it is difficult to determine who is accountable when an error occurs. Accordingly, the framework proposes a **Transparency and Accountability Gate** for systems that have a direct impact on citizens, encompassing disclosure, documentation, responsibility assignment, explanation, review, and redress.

4- Dimension Four: Employee Readiness and Human Oversight

The framework assumes that the government employee is not merely an end user of an AI system, but rather a key governance actor, because the employee's ability to understand the system, assess its outputs, and protect data substantially influences the level of actual risk. Studies have shown that managers' and employees' attitudes toward AI adoption vary according to the nature of the work and the role assigned to the system, reinforcing the view that integrating AI into public organizations requires a redesign of the relationship between humans and technology rather than merely the introduction of a new tool (Haesevoets et al., 2025).

Accordingly, the framework proposes four levels of capacity building. The first is AI Literacy for all employees, covering AI capabilities and limitations, data protection, output verification, and fundamental risks. The second is Role-Based AI Training, tailored to the nature of the tasks for which

employees use AI systems. The third consists of specialized training for technical, data, legal, cybersecurity, procurement, and auditing functions. The fourth targets government leaders, who require a strategic understanding of AI's benefits, risks, and the institutional responsibilities arising from its use. The OECD (2026) emphasizes that governments require differentiated levels of AI literacy according to employees' roles rather than a one-size-fits-all training model.

Training is closely linked to human oversight. Human-in-the-Loop cannot be regarded as a sufficient safeguard if the employee lacks the competence to review or challenge the system's decisions. The framework therefore adopts the concept of Meaningful Human Oversight, referring to the presence of a public official who possesses the knowledge, authority, and sufficient time to understand the system's limitations, review its outputs, intervene when necessary, and override its recommendations where circumstances require.

5- Dimension Five: Regulatory Controls Across the System Lifecycle

The fifth dimension integrates the preceding components within a Lifecycle Regulatory Protocol extending from the initial conception of the system through to its decommissioning. The purpose is to avoid treating governance as a one-time approval prior to deployment. AI-related risks may change as a result of model updates, changes in data, users, vendors, or the scope of use, while drift, errors, or other problems may emerge that were not detectable during initial testing.

The framework proposes seven governance stages: needs identification; assessment and risk classification; design or procurement; testing and validation; deployment and operation; monitoring and auditing; and review, modification, or decommissioning. Each stage is associated with a clearly defined governance decision, while higher-risk systems are subject to more stringent requirements relating to privacy, testing, transparency, and human intervention.

Within this framework, Risk Level functions as a governing variable that determines the intensity of the applicable protocols rather than as an independent dimension. As data sensitivity, system autonomy, or the system's impact on rights, public services, or administrative decisions increases, so too should the requirements for impact assessment, documentation, transparency, human review, and auditing.

6.2 Framework Outcomes:

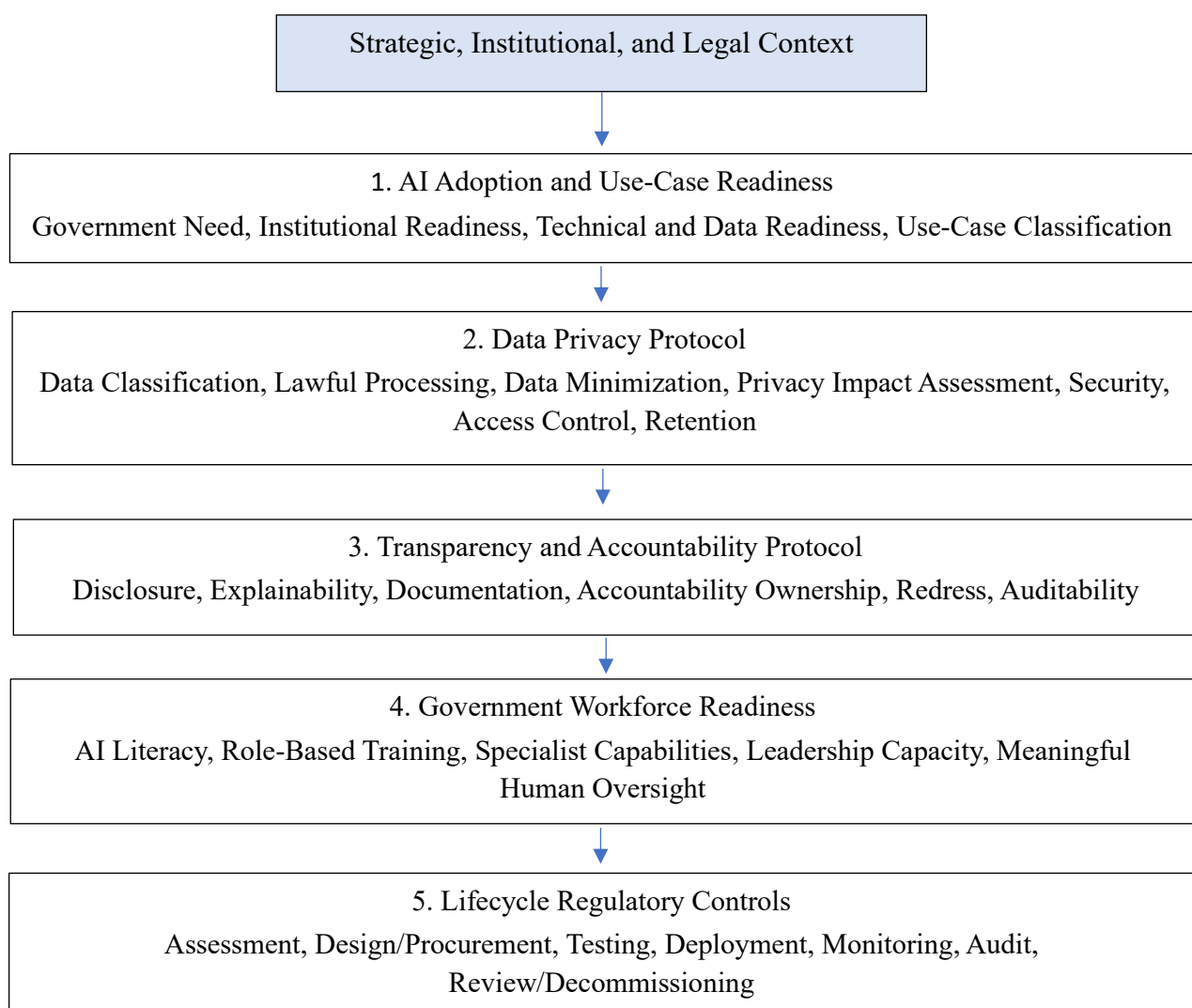
The framework does not regard system deployment as the final outcome of the process. Rather, the intended outcome is Responsible Government AI Adoption, defined as the capacity of a government organization to use AI in an effective, sustainable, lawful, and accountable manner while protecting data and rights and preserving an appropriate human role in decisions that require human judgment.

This form of adoption produces two broad categories of outcomes. The first comprises Administrative Performance Outcomes, including efficiency, reductions in time and cost, improved service quality, enhanced analytical capacity, and innovation. The second comprises Public Governance Outcomes, including trust, fairness, transparency, accountability, privacy protection, legitimacy, and public value. Distinguishing between these two categories is important because an AI system may generate improvements in speed or efficiency while still failing to constitute successful governmental adoption if it simultaneously reduces trust, undermines fairness, or compromises privacy. This is consistent with the perspective that links AI governance in the public sector to the simultaneous achievement of the values associated with good administration and a just society (Mišić et al., 2025).

6.3. Proposed Representation of the Theoretical Framework:

The framework can be represented in the paper as follows:

Figure 1. Proposed Theoretical Framework



Responsible Government AI Adoption



Administrative Performance and Public Value Outcomes

Efficiency, Service Quality, Innovation, Privacy Protection, Fairness, Transparency, Accountability
· Public Trust

Source: Prepared by the author based on the theoretical literature.

All stages of the framework are encompassed by a Risk-Based Governance Layer, whereby the intensity of governance and regulatory requirements is proportionate to data sensitivity, the system's level of impact, and its degree of autonomy.

Table 2. Key Dimensions and Components of the Proposed Integrated Framework

Dimension	Core Elements	Guiding Question
Adoption Readiness and Use-Case Assessment	Objective, expected value, readiness, use-case classification	Should AI be used in this case?
Data Privacy	Lawfulness, classification, minimization, security, access, retention	Can these data be used, and under what conditions?
Transparency and Accountability	Disclosure, explainability, documentation, responsibility, redress	Can the use of AI be understood and those responsible be held accountable?
Workforce Readiness	AI literacy, role-based training, specialist training, human oversight	Can employees use and oversee the system responsibly?
Lifecycle Governance	Assessment, testing, deployment, monitoring, auditing, decommissioning	Does governance continue throughout the system lifecycle?
Risk Level	Data sensitivity, decision impact, AI autonomy, user scope	What level of governance is required?
Outcomes	Efficiency, service quality, privacy, fairness, trust, public value	Does adoption generate responsible governmental and public value?

Source: Prepared by the author based on the theoretical literature.

The table 2. illustrates that the responsible government adoption of artificial intelligence relies not on a single dimension, but on an interconnected ecosystem. This process begins with assessing the suitability of the use case and the readiness of the government entity, followed by ensuring the legitimacy and protection of data usage. It then entails guaranteeing transparency and accountability through disclosure, explanation, documentation, and the clear assignment of responsibility. The table also highlights the importance of workforce readiness specifically the ability of employees to use and oversee AI systems consciously and responsibly alongside the necessity of continuous governance throughout the system's lifecycle, spanning assessment and testing to deployment, monitoring, auditing, and decommissioning. Risk levels serve as a governing factor that dictates the stringency of these requirements. Consequently, adoption success is measured not merely by technical efficiency, but by the ability to deliver high-quality services, trust, fairness, privacy, accountability, and public value in a balanced and sustainable manner.

6.4. Added Value of the Proposed Framework:

The principal contribution of the IF-RGA lies in shifting the focus from governing artificial intelligence as a technology to governing the process of its adoption within public administration. The framework also integrates dimensions that are frequently addressed separately in the literature, particularly AI Adoption, Data Privacy, Transparency and Accountability, Workforce Readiness, and Lifecycle Governance.

Second, the framework places government employees, data, and administrative decision-making at the center of the adoption process, rather than focusing solely on the organization and the technical system. Third, it distinguishes between technological success and successful governmental adoption; the latter requires the simultaneous achievement of administrative performance and public value.

Finally, the framework has been designed to be adaptable to the Saudi context. The existence of national data and AI institutions, a personal data protection regime, and established frameworks for readiness and adoption provides an institutional foundation upon which more integrated protocols for use-case classification, privacy and impact assessment, algorithmic transparency, role-based training, and continuous oversight can be built. At the same time, the framework remains sufficiently general to allow for its future application and empirical testing in other governmental contexts.

7. Conclusion, Summary of Findings, and Recommendations:

7.1. Summary of Findings:

This paper aimed to develop a more integrated understanding of artificial intelligence adoption in public administration by linking AI Adoption, AI Governance, and Data Privacy, with particular

emphasis on data privacy, transparency, accountability, workforce readiness, and the regulatory protocols associated with the system lifecycle. The analysis showed that AI adoption in government is no longer merely a technical matter concerned with the availability of tools or digital infrastructure. Rather, it has become an institutional process requiring alignment among governmental objectives, organizational capabilities, data, legal and regulatory safeguards, and public values.

The findings indicate that data privacy constitutes a foundational condition for responsible governmental AI adoption rather than a downstream compliance requirement. As the sensitivity of government data and the extent of its use in training or operating AI systems increase, so too does the need to define the purpose of processing, minimize data use, control access, establish retention and deletion policies, and conduct *ex ante* assessments of privacy risks. The analysis also shows that recent international approaches increasingly seek to integrate data protection into the design, procurement, testing, and operation of AI systems rather than treating it as a separate requirement outside the adoption process.

The paper further demonstrates that government transparency in the age of AI must move beyond general disclosure toward operational transparency that is reviewable and auditable. Citizens do not necessarily need access to complex technical details; rather, they need to know whether AI was used in a decision, what role it played, who is responsible for the outcome, and whether mechanisms for review or appeal are available. From this perspective, mechanisms such as algorithmic impact assessments, government registers of algorithmic systems, and continuous documentation provide practical means of transforming transparency into an instrument of administrative accountability.

The analysis also finds that government workforce readiness forms part of the governance architecture rather than merely a training concern. Human oversight cannot serve its intended purpose unless employees are able to understand the system's limitations, verify its outputs, protect data, and identify circumstances in which an AI recommendation should be rejected or escalated to a higher level of human decision-making. More advanced governments are therefore increasingly adopting role-based training approaches in which the learning needs of general public employees differ from those of technical and legal specialists and senior leaders (OECD, 2026).

In the Saudi context, the analysis identifies a strong institutional and regulatory foundation upon which further development can be built. This foundation includes the national data and AI institutional architecture, AI adoption frameworks, data governance policies, the Personal Data Protection Law, and the growing emphasis on measuring government AI readiness. However, the next stage requires strengthening the transition from policy-level governance to Operational AI Governance; that is,

translating national principles into measurable and implementable protocols at the level of each governmental AI use case.

7.2. Conclusion:

The paper concludes that the central question facing public administration is no longer whether governments will adopt artificial intelligence, but rather how they will adopt it in a responsible and accountable manner while protecting privacy and sustaining public trust. Accordingly, measuring the success of AI Adoption solely through the number of applications deployed, the extent of automation, or cost reductions provides an incomplete picture of governmental success, particularly when AI systems affect citizens, their rights, and their access to public services.

Against this background, the paper proposed the Integrated Framework for Responsible Government AI Adoption (IF-RGA), which connects five principal dimensions: adoption readiness and use-case assessment, data privacy, transparency and accountability, workforce readiness and human oversight, and governance across the system lifecycle. Risk Level operates as a governing factor that determines the stringency of these requirements.

The framework's principal theoretical contribution lies in shifting the discussion from AI Governance in general toward Governing AI Adoption in Public Administration. The unit of analysis is therefore not the technology itself, but the administrative process through which a need is identified, a system is selected, data are handled, roles and responsibilities are assigned, employees are trained, the system is deployed and operated, and its performance is monitored, reviewed, modified, or discontinued. In this way, the framework integrates administrative performance, on the one hand, with public value, privacy, fairness, and trust, on the other.

This approach is particularly relevant to Saudi Arabia given the rapid expansion of digital transformation and governmental AI. The presence of an advanced national institutional and regulatory architecture provides a strong foundation for moving toward a more mature governance model that embeds Privacy by Design, Transparency by Design, Accountability by Design, and Human Oversight by Design directly into the AI adoption process rather than introducing them only after systems have been deployed.

7.3. Recommendations:

Based on the findings of the paper and the proposed framework, the following recommendations can be advanced for public administration, with particular emphasis on the Saudi context:

1. Classify government AI use cases according to their level of risk, distinguishing between low-impact internal applications and systems that directly affect citizens' rights, access to public services, or regulatory and administrative decisions.

2. Integrate data privacy assessment into the pre-adoption stage, linking the approval of sensitive AI systems to the identification of the types of data involved, the purpose of their use, the legal basis for processing, data-storage location, and the parties authorized to access them.
3. Develop a government registry of high-impact AI systems containing information on system ownership, purpose of use, types of data involved, risk level, and oversight and review mechanisms, thereby strengthening institutional transparency and auditability.
4. Adopt ex ante AI impact assessments for medium- and high-impact use cases, covering privacy, fairness, security, transparency, rights, and operational risks before deployment is authorized.
5. Establish a clear protocol for disclosure to citizens when AI plays a material role in a decision or service affecting them, accompanied by an appropriate explanation and access to human review or redress mechanisms in high-impact cases.
6. Assign clear administrative accountability for each AI system and avoid situations in which accountability becomes fragmented among the government entity, vendor, developer, and user. Procurement contracts for AI systems and services should also incorporate requirements relating to transparency, auditability, and data protection.
7. Develop a national, multi-level AI training program for government employees, beginning with foundational AI literacy for all employees, followed by role-based training, specialized programs for technical, data, legal, procurement, and audit functions, and leadership programs for senior management.
8. Adopt the principle of Meaningful Human Oversight for high-impact systems, ensuring that public officials are genuinely capable of understanding the system, reviewing its recommendations, and rejecting or modifying them when necessary.
9. Shift from initial approval toward continuous monitoring, through periodic reviews of system performance, documentation of errors, incidents, and complaints, and updates to risk and privacy assessments whenever the data, model, or scope of use changes.
10. Evaluate the success of government AI through dual sets of indicators that combine efficiency and service quality, on the one hand, with privacy, transparency, fairness, accountability, and public trust, on the other.

7.4. Future Research Directions:

The proposed framework opens several avenues for future research. Among the most important are the empirical testing of the IF-RGA within Saudi government entities, comparative assessment of governance maturity across public organizations, examination of the effects of algorithmic

transparency on citizen trust, analysis of the relationship between AI literacy and employee behavior when handling sensitive data, and evaluation of the effectiveness of human oversight in AI-supported administrative decision-making.

Government AI procurement and vendor governance also constitute important areas for future research, particularly as governments increasingly rely on models and platforms developed by external providers. Other promising directions include the development of measures for Government AI Governance Maturity, the study of algorithmic impact assessments and public registries of AI systems, and the governance of generative AI within government workplace environments.

Finally, the relationship between Responsible Government AI Adoption and Public Value represents a particularly important agenda for future research. Public administration requires models that move beyond the question of whether a technology functions efficiently toward a more consequential question: Does its use contribute simultaneously to a government that is more efficient, transparent, fair, and trusted?

8. Declaration:

The author declares that this research received no funding or financial support from any public, private, or non-profit entity, and that there are no financial, personal, or professional interests that could be construed as a conflict of interest regarding this research. Given that the study is theoretical in nature—relying on a literature review and the analysis of publicly available documents and policies—it did not involve human participants or the collection of personal data; consequently, it did not require research ethics committee approval or informed consent. Furthermore, no independent original dataset was generated or collected for this study; the analysis was based on the scholarly sources and official documents cited in the references.

AI-based tools were used to assist during certain stages of manuscript preparation, including proofreading, spelling and stylistic corrections, and assistance in searching for, gathering, and verifying bibliographic details of references. These tools were not used as a substitute for the author's scholarly judgment or to independently formulate conclusions. The author reviewed all outputs to verify their accuracy and sources, and bears full responsibility for the research content, the validity of citations and references, the analysis, the interpretations, and the conclusions presented therein.

9. References:

- Abed, S. S. S. (2024). Understanding the determinants of using government AI-chatbots by citizens in Saudi Arabia. *International Journal of Electronic Government Research*, 20(1), 1–20.
<https://doi.org/10.4018/IJEGR.349733>

- Agbabiaka, O., Ojo, A., & Connolly, N. (2025). Requirements for trustworthy AI-enabled automated decision-making in the public sector: A systematic review. *Technological Forecasting and Social Change*, 215, 124076. <https://doi.org/10.1016/j.techfore.2025.124076>
- Akhourshieda, M. S., Ku Khalif, K. M. N., & Awang, S. (2024). Artificial intelligence in the United Arab Emirates public sector: A systematic literature review. *IAES International Journal of Artificial Intelligence*, 13(3), 2472–2481. <https://doi.org/10.11591/ijai.v13.i3.pp2472-2481>
- Alajmi, M., Mohammadian, M., & Talukder, M. (2023). The determinants of smart government systems adoption by public sector organizations in Saudi Arabia. *Heliyon*, 9(10), e20394. <https://doi.org/10.1016/j.heliyon.2023.e20394>
- Alshahrani, A., & Dennehy, D. (2025). The role of leadership and communication in AI assimilation: Case studies from Saudi Arabia's public sector organizations. *Transforming Government: People, Process and Policy*, 19(4), 875–894. <https://doi.org/10.1108/TG-06-2025-0187>
- Alshahrani, A., Dennehy, D., & Mäntymäki, M. (2022). An attention-based view of AI assimilation in public sector organizations: The case of Saudi Arabia. *Government Information Quarterly*, 39(4), 101617. <https://doi.org/10.1016/j.giq.2021.101617>
- Altammar, S. (2026). Governing artificial intelligence risks for effective public administration: The case of Kuwait. *Journal of Policy Studies*, 41(1), 41–57. <https://doi.org/10.52372/jps.250358>
- Alyileili, M., & Opoku, A. (2025). Ethical AI integration in municipal self-service technologies: A case study from UAE public sector transformation. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(4), 100648. <https://doi.org/10.1016/j.joitmc.2025.100648>
- Aoki, N., Tatsumi, T., Naruse, G., & Maeda, K. (2024). Explainable AI for government: Does the type of explanation matter to the accuracy, fairness, and trustworthiness of an algorithmic decision as perceived by those who are affected? *Government Information Quarterly*, 41(4), 101965. <https://doi.org/10.1016/j.giq.2024.101965>
- Babšek, M., Ravšelj, D., Umek, L., & Aristovnik, A. (2025). Artificial intelligence adoption in public administration: An overview of top-cited articles and practical applications. *AI*, 6(3), 44. <https://doi.org/10.3390/ai6030044>
- Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: A systematic literature review. *AI and Ethics*, 5, 3265–3279. <https://doi.org/10.1007/s43681-024-00653-w>
- Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal*, 9(2), 27–40. <https://doi.org/10.3316/QRJ0902027>

- Canada School of Public Service. (2026). *2026–27 departmental plan*. Government of Canada.
- Chen, T., Gasco-Hernandez, M., & Gil-Garcia, J. R. (2026). Understanding accountability in AI use within the public sector: Insights from state governments in the United States. *Public Administration*, 1–19. <https://doi.org/10.1111/padm.70051>
- Cordella, A., & Gualdi, F. (2026). AI public value creation: Data encoding, aggregation, and algorithmic computation. *Public Administration*. Advance online publication. <https://doi.org/10.1111/padm.70071>
- Department for Science, Innovation and Technology. (2025). *Landmark government trial shows AI could save civil servants nearly two weeks a year*. UK Government.
- Digital Government Authority. (2023). *Digital government policies* (Version 2.0).
- Digital Government Authority. (2025). *Digital government regulatory framework*.
- Diljoor, Z., & Coulon, T. (2026). A framework for AI readiness and strategic adoption: Developing a public sector AI maturity model through systematic review and synthesis. *Transforming Government: People, Process and Policy*, 1–24. <https://doi.org/10.1108/TG-01-2026-0019>
- European Data Protection Board. (2024). *Opinion 28/2024 on certain data protection aspects related to the processing of personal data in the context of AI models*.
- European Parliament & Council of the European Union. (2024). *Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. *Official Journal of the European Union*.
- Government Digital Service. (2025a). *Algorithmic transparency recording standard: Guidance for public sector bodies*. UK Government.
- Government Digital Service. (2025b). *Artificial intelligence playbook for the UK Government*. UK Government.
- Government Skills. (2026). *Artificial intelligence skills for all*. UK Government.
- Haesevoets, T., Verschuere, B., & Roets, A. (2025). AI adoption in public administration: Perspectives of public sector managers and public sector non-managerial employees. *Government Information Quarterly*, 42(2), 102029. <https://doi.org/10.1016/j.giq.2025.102029>
- Kim, E. (2026). Generative AI in public administration: A quasi-experimental analysis of bureaucratic productivity. *Government Information Quarterly*, 43(1), 102108. <https://doi.org/10.1016/j.giq.2026.102108>

- Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly*, 40(1), 101774. <https://doi.org/10.1016/j.giq.2022.101774>
- Ministry of Communications and Information Technology. (2025). *Principles and guidelines for ethical development and deployment of artificial intelligence*. State of Qatar.
- Ministry of Digital Development and Information. (2025). *Progress of adopting AI tools within the public service*. Government of Singapore.
- Ministry of Digital Development and Information. (2026). *Launch of Institute of Digital Government*. Government of Singapore.
- Mišić, J., van Est, R., & Kool, L. (2025). Good governance of public sector AI: A combined value framework for good order and a good society. *AI and Ethics*, 5, 4875–4889. <https://doi.org/10.1007/s43681-025-00751-3>
- Neumann, O., Guirguis, K., & Steiner, R. (2024). Exploring artificial intelligence adoption in public organizations: A comparative case study. *Public Management Review*, 26(1), 114–141. <https://doi.org/10.1080/14719037.2022.2048685>
- OECD. (2024a). *AI, data governance and privacy: Synergies and areas of international co-operation* (OECD Artificial Intelligence Papers No. 22). OECD Publishing. <https://doi.org/10.1787/2476b1a4-en>
- OECD. (2024b). *Governing for sustainable prosperity in the Middle East and North Africa*. OECD Publishing. <https://doi.org/10.1787/d0da1d30-en>
- OECD. (2026a). *Building an AI-ready public workforce*. OECD Publishing.
- OECD. (2026b). *Digital Government Outlook 2026*. OECD Publishing.
- Rizk, A., & Lindgren, I. (2025). Automated decision-making in public administration: Changing the decision space between public officials and citizens. *Government Information Quarterly*, 42(3), 102061. <https://doi.org/10.1016/j.giq.2025.102061>
- Røhl, U. B. U., & Hansen, M. B. (2024). Automated, administrative decision-making and good governance: Synergies, trade-offs, and limits. *Public Administration Review*, 84(6), 1184–1199. <https://doi.org/10.1111/puar.13799>
- Saqib, H. M., & Amin, H. (2026). Comparative analysis of AI regulation for fintech cybersecurity and privacy in the European Union and Qatar. *Discover Artificial Intelligence*, 6, Article 59. <https://doi.org/10.1007/s44163-025-00736-5>

- Saudi Data & AI Authority. (n.d.). *National strategy for data and AI*.
- Saudi Data & AI Authority. (2023). *Personal Data Protection Law and its implementing regulations*.
- Saudi Data & AI Authority. (2024a). *AI adoption framework*.
- Saudi Data & AI Authority. (2024b). *AI ethics principles and controls*.
- Saudi Data & AI Authority. (2025a). *Generative artificial intelligence for government*.
- Saudi Data & AI Authority. (2025b). *National Artificial Intelligence Index*.
- Saudi Data & AI Authority. (2025c). *National data governance policies*. National Data Management Office.
- Selten, F., & Klievink, B. (2024). Organizing public sector AI adoption: Navigating between separation and integration. *Government Information Quarterly*, 41(1), 101885. <https://doi.org/10.1016/j.giq.2023.101885>
- Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
- Tangi, L., Rodriguez Müller, A. P., & Janssen, M. (2025). AI-augmented government transformation: Organisational transformation and the sociotechnical implications of artificial intelligence in public administrations. *Government Information Quarterly*, 42(3), 102055. <https://doi.org/10.1016/j.giq.2025.102055>
- Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, 4(3), 356–367. <https://doi.org/10.1177/1534484305278283>
- Treasury Board of Canada Secretariat. (2025). *Directive on automated decision-making*. Government of Canada.
- UAE Government. (2024). *The UAE charter for the development and use of artificial intelligence*. The Official Platform of the UAE Government.
- United Nations Department of Economic and Social Affairs. (2024). *UN e-government survey 2024: Accelerating digital transformation for sustainable development*. United Nations.
- van Noordt, C., & Tangi, L. (2023). The dynamics of AI capability and its influence on public value creation of AI within public administration. *Government Information Quarterly*, 40(4), 101860. <https://doi.org/10.1016/j.giq.2023.101860>
- Wang, C., Yin, Y., & Hu, H. (2026). The rise of algorithmic governance and the dual revolution: Applications, challenges, and governance of artificial intelligence in public administration. *Technology in Society*, 86, 103264. <https://doi.org/10.1016/j.techsoc.2026.103264>

- Wang, Y. (2025). Is the public willing to provide personal information for processing by government AI? An experimental study based on regulatory commitment and algorithmic transparency. *Journal of Asian Public Policy*. Advance online publication. <https://doi.org/10.1080/17516234.2025.2544139>
- Whittemore, R., & Knafl, K. (2005). The integrative review: Updated methodology. *Journal of Advanced Nursing*, 52(5), 546–553. <https://doi.org/10.1111/j.1365-2648.2005.03621.x>
- World Governments Summit, & Arab Administrative Development Organization. (2026). *State of Arab public administration report: Practical models for AI adoption*.

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