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Assessing artificial intelligence and advanced analytics adoption: A technological, organizational, and environmental perspective

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Abstract: This study examines the organizational capabilities necessary for the effective adoption of Artificial Intelligence (AI) and advanced analytics across key industries. Employing an integrated approach, the research combines thematic analysis with an AI Maturity Model (AIMM) within the Technological-Organizational-Environmental (TOE) framework to assess AI readiness. The framework evaluates critical factors such as technology readiness, leadership support, organizational culture, and compliance. Findings reveal that successful AI adoption is strongly influenced by core organizational competencies, including data management, IT infrastructure, and cross-functional integration. Sector-specific examples from healthcare and finance demonstrate how AI enhances operational efficiency, customer experience, and decision-making processes. The study also benchmarks AI adoption trends in healthcare, finance, manufacturing, and retail, uncovering varying levels of readiness and capability. The results underscore the importance of aligning technological infrastructure with strategic leadership and a supportive organizational environment. By offering practical recommendations tailored to Saudi Arabia's Vision 2030, the study provides actionable insights for organizations seeking to improve their digital maturity. Overall, this research delivers a comprehensive understanding of AI adoption prerequisites and offers a roadmap for leveraging analytics to gain a competitive edge in the digital economy.
Keywords: *AI adoption, Predictive analytics, Technological organizational environment (TOE).*

1. Introduction

Artificial intelligence (AI) and analytics are revolutionizing industries by equipping organizations with the ability to make informed decisions, automate processes, and create innovative business models. AI-supportive technologies such as machine learning, natural language understanding, and predictive analytics are revolutionizing industries from the banking sector and the medical sector through manufacturing and the retail sector. Organizations using AI can realize the potential for business expansion, automate the consumption of resources, and allow for enhanced customer experience. However, the adoption of AI-supportive solutions is not only dependent upon technology; it is also a complex process involving the alignment of the organization, the culture, and the adaptation towards the forces from the environment.

The question of whether and how AI technologies can be adopted by organizations has been hotly debated. While AI promises greater efficiency, personalization, and the delivery of services, concerns about overreliance on automation, privacy risk, ethical concerns, and the potential for AI-driven decision-making being biased [1] also need consideration. Besides these concerns, concerns about AI-led organizations being excessively technocratic also prevail [2] resulting in potential dangers like decreased transparency, unequal access to services, and the challenge of governing them. In the wake of all these concerns, AI presents transformational opportunities like superior decision-making, real-time

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predictive analytics, superior fraud prevention, and the ability to automate administrative processes seamlessly [3].

Organizations, both private and public, realize the importance of investment in AI capability now. Enhanced access to large data sets, transaction data, and high-compute infrastructure enables organizations to have the capacity for applying AI for greater business value [4]. AI is being applied for functions including knowledge management, conversation agents, predictive models, threat analysis, and optimizing resources. Adoption is not even, however, even though AI has potential. While some organizations are adopting AI sooner, others face adoption stumbling blocks, resistance, and the need for strategic direction [5]. TOE is a theoretical structure for measuring AI adoption capability. This theoretical structure assists organizations in assessing the tech environment's readiness, the internal support structures' strength, and the impact of the environment. TOE structures the adoption variables into three dimensions:

- Technological Factors – Evaluates the infrastructure of the firm, data handling capacity, AI tool suites, and overall level of tech maturity. AI will only work effectively for the firm when the infrastructure is robust.
- Organizational Factors – Evaluates commitment from the leader, culture readiness, resources deployed, and the ability for the firm to transform towards AI-driven changes. Organizational agility and worker engagement are the prerequisites for AI adoption sustainably.
- Environmental Factors – Explains regulatory frameworks, market forces, competitive forces, and stakeholder expectations. Organizations must deal with complex external forces informing AI adoption agendas and ethical considerations.

Given the complexity involved in adopting AI, the determinants for the adoption of AI by organizations are far from being known conclusively [6]. Empirical work for AI adoption is scant, especially for sector-specific enablers and inhibitors for adoption levels [7, 8]. AI adoption is best seen not as a one-time-event implementation, but rather as a continuous, ongoing process, for its lasting achievement is only possible by understanding this process correctly [9, 10].

This paper will provide a formal analysis of AI adoption by organizations through the TOE framework, acknowledging the enablers and inhibitors for the successful implementation of AI technologies. Based on real-life applications and case studies, the study presents the best practice for the mitigation of adoption barriers. Apart from this, this study highlights the strategic value of workforce up-skilling, strategic alignment, and ethical AI governance for the formation of data-driven, AI-enabled business culture [11, 12]. Based on this study, the objective is to enable organizations to gain deeper insights into AI adoption forces and provide concrete advice for the formation of innovative and competitive advantages for the digital economy. Organizations can enhance efficiency, generate business growth, and form their presence as market leaders for the rapidly evolving tech environment by incorporating AI and high analytics strategically.

1.1. Research Contribution

The key Contribution of this research is summarized as follows:

- The integration of AIMM within the TOE framework provides a structured AI adoption assessment, covering technological readiness, leadership support, and regulatory compliance.
- The study pursues a two-fold approach, embracing Thematic Analysis for qualitative analysis and AI Maturity Assessment for quantitative analysis, which allows organizations to measure AI adoption success.
- Through analysis of AI adoption trends in finance, healthcare, manufacturing, and retail, the report offers industry-specific benchmarking and strategic recommendations in support of Saudi Arabia's Vision 2030 AI strategy.

2. Literature Review

The integration of advanced technologies such as artificial intelligence (AI) and big data analytics (BDA) has been observed and increasingly recognized as a transformative force across various industries [11]. A growing body of research emphasizes how generative AI platforms, like ChatGPT, can serve as an enabler of both operational efficiency and environmental stewardship. Evidence from recent investigations suggests that multiple organizational dimensions—including technology infrastructure, internal capabilities, and external influences—play a vital role in shaping the extent to which these tools are adopted within professional settings. These enabling conditions collectively determine the influence of AI-enabled analytics on business outcomes. Another study focusing on professionals in Taiwan highlights the substantial connection between AI usage and improved environmental and operational outcomes. The findings suggest that when organizations possess the necessary resources and skills, and operate within conducive environmental and institutional frameworks, AI tools like ChatGPT can support sustainable and efficient operations. Furthermore, the ability to embed environmental considerations into business processes was shown to enhance ecological performance, reinforcing the synergy between digital transformation and environmental integration.

Another stream of research, centered on firms of varying sizes, reveals the differential impact of AI depending on company scale [13]. By comparing small and medium-sized enterprises (SMEs), it was observed that medium-sized firms tend to gain more from AI adoption, especially when technological benefits are evident and aligned with market needs. This comparative analysis also underlines the moderating role of firm size in the relationship between adoption drivers and performance outcomes, suggesting that tailored strategies may be required for different organizational contexts. Within the broader framework of Industry 4.0, intelligent data systems and predictive capabilities are reshaping how managers make decisions and respond to evolving economic pressures [14]. Research conducted in China, involving both qualitative interviews and quantitative surveys, points to AI-powered analytics, smart sensors, and related technologies as the most impactful tools for promoting both economic gains and environmental responsibility. However, the study also uncovers barriers such as limited understanding of AI tools and concerns around e-waste and sustainability, signaling the need for enhanced awareness and responsible innovation.

Another, emerging research based on conversational data and organizational feedback identifies a range of human-centered and experiential factors—such as adaptability, innovation potential, emotional response, and fear of failure—that affect the pace and quality of AI integration within teams [15]. These insights help form a practical guide for practitioners looking to navigate the opportunities and obstacles of AI implementation, further enriching the strategic discourse on digital transformation. Together, these studies underscore the multifaceted nature of AI and BDA adoption, demonstrating that their influence is not only technological but also organizational, environmental, and psychological. The literature establishes a solid foundation for exploring how generative AI platforms can serve as catalysts for both operational success and environmental accountability.

3. Proposed Methodology

This study adopts a qualitative research design to explore AI and advanced analytics adoption within organizations using the Technological-Organizational-Environmental (TOE) framework. This research design is suitable as it allows for an in-depth understanding of how organizations assess, implement, and integrate AI-driven solutions, considering internal and external factors that influence adoption.

3.1. Data Collection

A case study approach is employed to collect data from multiple organizations across various industries, enabling a comparative analysis of AI readiness and adoption challenges. The study uses semi-structured interviews, document analysis, and secondary data sources to gather insights from key stakeholders, including technology executives, data scientists, policymakers, and industry experts. This study is based on three primary sources within Saudi Arabia, ensuring publicly available and accessible data depicted in Table 1.

Table 1.
Primary Collection Organization.

Organization Name	**Description**	**Web Address**
Saudi Data and Artificial Intelligence Authority (SDAIA)	Oversees AI adoption frameworks, government-led AI initiatives, and national AI strategies in Saudi Arabia.	https://sdaia.gov.sa/en/default.aspx
UNESCO's Global AI Ethics and Governance Observatory	Provides AI-related policies, governance insights, and ethical AI considerations at a global level.	https://www.unesco.org/ethics-ai/en
Ministry of Communications and Information Technology (MCIT) – Saudi Arabia	Publishes official reports on AI readiness, national AI adoption strategies, and digital transformation policies in Saudi Arabia.	https://www.mcit.gov.sa

Primary data is collected through semi-structured interviews as designed in Figure 1, with key stakeholders, including AI policymakers, business executives, and data scientists. The interview structure follows the TOE framework, capturing insights on technological readiness, organizational AI culture, and external influences. Thematic analysis is applied to transcribe and categorize responses.

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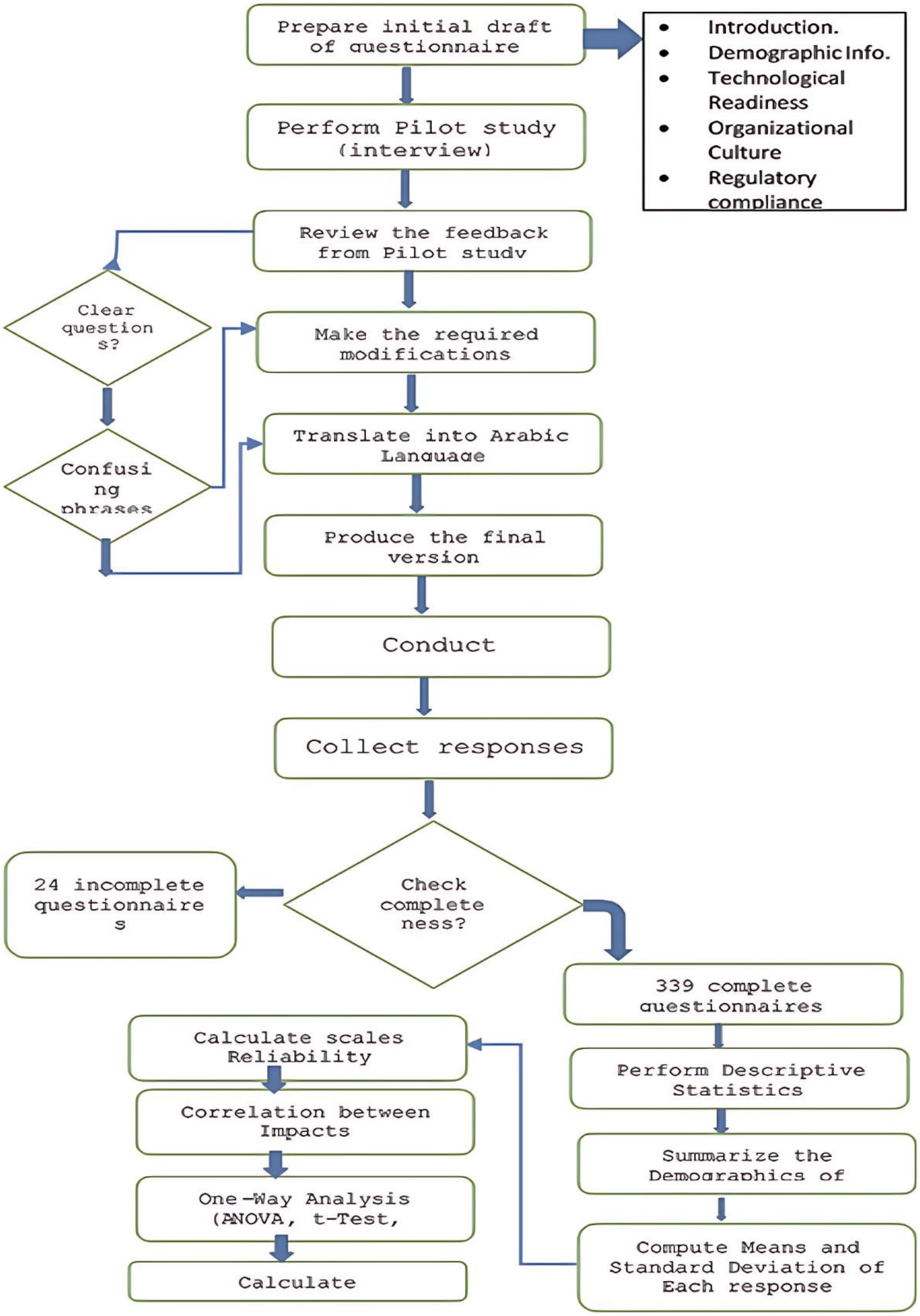

Figure 1.
The Data Collection Workflow

Whereas, secondary data is gathered from government reports, industry white papers, and research publications, providing insights into AI governance, infrastructure readiness, and market competitiveness.

Table 2.
Data Description.

Variable	Description	Min.	Max.	Mean
AI Adoption Score	Overall success measure of AI adoption	0	100	75
Tech Readiness	AI infrastructure readiness index	1	10	7.5
Org Culture	Employee AI adaptability and leadership support	1	10	6.8
Market Influence	Effect of competition and regulations	1	10	8.0

Table 2 shows an overview of the key variables assessed in the study, highlighting their minimum, maximum, and average values. The AI Adoption Score represents the overall success measure of AI implementation across various organizations, with a mean value of 75, indicating a relatively high adoption level [16, 17]. Technological Readiness, which evaluates the availability of AI infrastructure, ranges from 1 to 10, with an average score of 7.5, suggesting that most organizations possess a moderate to high level of AI capability. Organizational Culture, capturing leadership support and employee adaptability to AI, has a mean score of 6.8, reflecting variability in how organizations integrate AI into their work environments. Lastly, Market Influence, representing external factors such as regulatory compliance and competitive pressures, averages 8.0, demonstrating that external forces play a significant role in AI adoption. These indicators provide a structured assessment of AI readiness, allowing for comparative analysis of AI adoption trends across organizations in Saudi Arabia [18, 19].

3.2. Selection of Organizations and Participants

This study applies the comparative analysis technique for the industries' choice and the stratified sample technique for the study participants. Comparative analysis helps the study leverage multiple industries with various levels of AI adoption, enabling greater knowledge about the enablers and the challenges encountered by industries [20]. Finance, manufacturing, the healthcare sector, and the retail sector were selected for the study, each possessing distinctive AI adoption patterns and being pertinent to the Saudi Arabian Vision 2030 agenda for transformation through the digital space. A stratified sample is applied for the representative distribution of the stakeholders, preventing the impact of one stakeholder type on the conclusions drawn by the study. Stratifying the study participants into data by scientists, tech leaders, policymakers, and executives helps the study obtain the overall viewpoints about the adoption of AI.

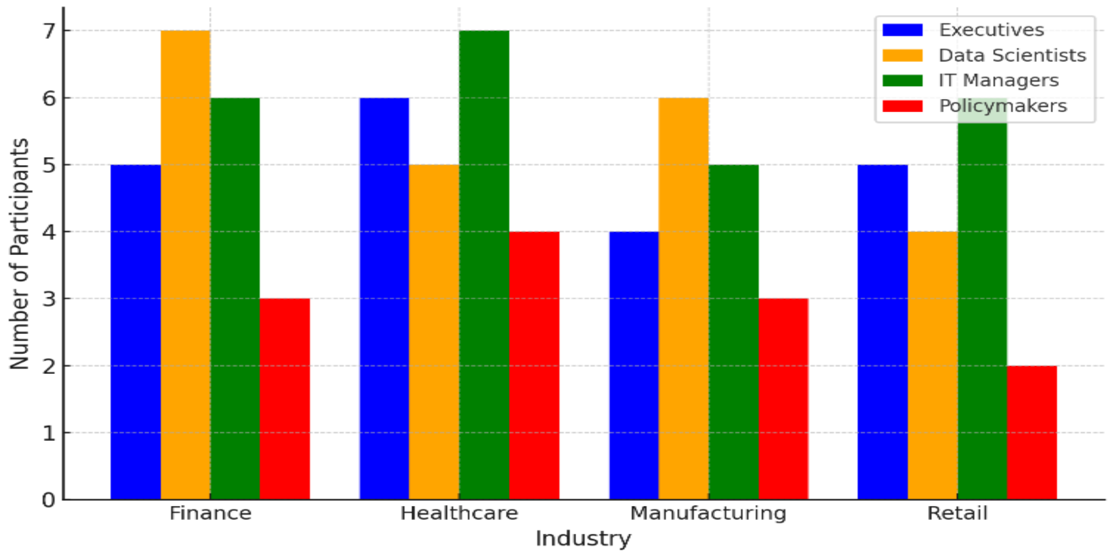

Figure 2.
Stakeholder Distribution Across Industries.

The comparative analysis technique used here helps the evaluation of AI adoption by categorizing organizations by their AI levels of maturity, AI applications by sector, and regulatory forces from the exterior. Based on the use of government reports, sector benchmarks, and market reports, the study captures industries where AI adoption is high (healthcare, finance) and where AI adoption is weak (manufacturing, retail). Stratified sampling ensures the stakeholders identified are proportionate to their contribution towards AI adoption. Balanced selections from the study incorporate the appropriate proportion of executives, data scientists, IT managers, and policymakers for strategic, operating, and regulatory opinions [21, 22].

Figure 2 illustrates the formal distribution breakdown of the participants by their job type and industry. Overall, participants total 78, and the distribution is balanced by the finance, manufacturing, healthcare, and retail industries. Finance and Healthcare industries hold the largest proportion of AI professionals (IT managers and data scientists) due to their high levels of AI adoption and reliance upon predictive analytics and automations. Manufacturing and the Retail industries hold less AI-intensive jobs, given the industries' adoption levels for AI technologies earlier. Even the distribution is split by the executives and the policymakers, providing balanced strategic and regulatory inputs. This distribution ensures the evaluation of AI infrastructure readiness, levels for workforce skills, commitment by the leadership, and regulatory influence is thoroughly evaluated. The selection of the organizations and the stakeholders ensures AI adoption insights from multiple industries and stakeholders [23, 24]. The comparative analysis method ensures the analysis of high AI adoption industries and the industries with the lowest AI adoption, providing balanced AI readiness analysis. Stratified sampling methodology ensures the extraction of insights from the decision-makers, the AI technical specialists, and the policymakers, including all levels of AI strategy execution.

3.3. TOE Framework

AI adoption is not one-size-fits-all, multi-phase, and varies from one sector to the next, subject to their tech infrastructure, their readiness for the organization, and regulatory forces from the environment [25]. To measure AI readiness and adoption variables, organizations require a tool that measures the dimensions extensively. In this research, the AI Maturity Model (AIMM) under the TOE structure is a formal methodology for classifying organizations by their AI level of maturity, reviewing their readiness, adoption effectiveness, and AI longevity over the long term. TOE is a general structure for reviewing AI adoption, from the ability of the tech through the readiness for the organization and the environment [26]. However, organizations vary by their AI adoption level, from experimentation phases through the mass adoption of AI. If the AIMM methodology is applied under the TOE structure, organizations can be assigned multiple levels of maturity and establish the variables causing them to progress. The AIMM model defines four AI maturity levels based on technological, organizational, and environmental factors, as shown in Table 3 below. This classification helps organizations assess their current AI maturity level and determine the steps needed for progression.

Table 3.
AI maturity levels.

Maturity Level	Technological Readiness	Organizational Support	Environmental Influences
Level 1: Initial	Limited AI infrastructure, experimental use of AI tools	Minimal leadership support, lack of AI literacy	Low external pressure, weak regulatory enforcement
Level 2: Developing	Basic AI tools in use, limited data analytics capability	Some AI training programs, partial leadership involvement	Increasing market competition, growing regulatory influence
Level 3: Established	Well-integrated AI systems, predictive analytics in decision-making	AI governance policies in place, dedicated AI teams	Strong regulatory frameworks, industry-driven AI transformation
Level 4: Advanced	AI-driven automation, deep learning, and large-scale AI deployment	Full AI integration into corporate strategy, AI-centric culture	Strict compliance with AI ethics, data protection laws, and competitive AI adoption

4. Results

The study assessed the degree of AI adoption across various organizations in Saudi Arabia, considering technological readiness, organizational culture, and external market influences. The findings reveal significant variations in AI adoption maturity, industry-specific challenges, and enablers shaping AI implementation.

4.1. AI Adoption Levels Across Industries

Organizations were categorized into different AI maturity levels based on their adoption progress and strategic implementation. Table 4 presents an overview of the AI adoption levels observed across the selected industries.

Table 4.
AI Adoption Levels in Organizations.

Organization	Al Projects Initiated Year	Number of AI Projects	AI Maturity Level
Case A	2012, 2017	~50	Managed
Case B	2017, 2019	~100	Managed
Case C	2018	1	Assessing
Case D	2019	~10	Determined
Case E	2018	2	Determined
Case F	2017, 2019	1	Assessing
Case G	2019	1	Assessing

The organizations in the managed level (Cases A & B) showed robust AI processes and widespread AI adoption for various business functions. These organizations invested resources into AI-facilitated optimization tools, predictive analytics, and automated support for making decisions. The determined level organizations (Cases D & E) have implemented one high-complexity AI initiative and infrastructure for scalability for AI adoption. These organizations focus on embedding AI for some functions, including operational efficiency improvement and customer service automation. The assessing level organizations (Cases C, F, G, & H) are starting their AI adoption process, where the majority were in the pilot stage or were for one business function only, such as the use of conversational AI agents.

These organizations face concerns over commitment from the leadership, AI workforce literacy, and regulatory uncertainty.

4.2. Influence of Organizational and Market Factors

Findings indicate that AI adoption maturity correlates with organizational structure, industry sector, and regulatory influences.

- Large state-owned enterprises (Cases A & B) exhibit higher AI maturity due to strong leadership support, investment in AI infrastructure, and defined AI governance frameworks.
- Government ministries and agencies (Cases D & E) align with the determined level, demonstrating strategic AI adoption but facing bureaucratic challenges in implementation.
- Local administrations and private sector firms (Cases C, F, G, & H) are in the early adoption phase, experimenting with AI but constrained by limited resources and regulatory uncertainties.

Additionally, market competition and regulatory compliance serve as external pressures accelerating AI adoption. Organizations in highly competitive industries such as finance and healthcare report higher AI readiness compared to sectors like manufacturing and retail, where adoption remains slow due to cost barriers and workforce resistance.

4.3. AI Adoption Success and Challenges

Despite advancements in AI integration, some organizations struggle to achieve their AI project objectives. Among the cases studied:

- Two organizations (Cases A & B) successfully implemented AI initiatives, reaching full-scale deployment.
- Two organizations (Cases D & E) have made progress toward their goals, with plans for future expansion.
- Five organizations (Cases C, F, G, & H) remain uncertain about achieving AI implementation success, mainly due to a lack of technical expertise, leadership commitment, and unclear ROI.

These insights emphasize the need for structured AI roadmaps, continuous AI training programs, and regulatory clarity to facilitate AI adoption across industries in Saudi Arabia. The comparative analysis confirms that industry-specific challenges, leadership support, and external pressures significantly influence AI adoption success.

4.3.1. Technological Factors

Following the TOE framework, the technological factors influencing AI adoption across different cases were analyzed. A key finding was that AI adoption was driven primarily by technological necessity rather than strategic intent. Most organizations went for AI bottom-up when traditional technologies were unable to address complex problems. In others, AI was only added after the realization that traditional solutions were not scalable. For example, the use of deep learning in Case A was guided by its scalability advantages, while AI was added during the execution of the project when traditional technologies were not good enough.

Another critical element was the impact of AI on business processes. Results were variable because some organizations avoided the alteration of internal processes, whereas others adopted AI proactively into their processes. Successful cases for adopting AI underlined the importance of high-quality data, appropriate infrastructure, and APIs for easier adoption. Others were frustrated by the lack of these prerequisites, which tended to undermine the business feasibility for AI projects. Others also adopted AI reactively, using the top-down approach by hiring specialists and mapping data infrastructure prior. These organizations were observed to use a formal AI adoption process compared to those adopting AI reactively.

4.3.2. Organizational Factors

Organizational factors also played their part in the adoption of AI. Leadership support topped the list of the highest influences. In all cases, support from the leader helped secure financing, resolve the resistance, and make AI adoption possible. Organizations where the transition was approached proactively by solving the concerns of the employees towards AI adoption were able to make the transition less complicated. Resistance towards AI tended to come from the inability to explain and fear of job loss, and thus, transparent communication and education were required.

Innovative culture also played the deciding role. Organizations using the adaptive style of management and the capability for experimentation were likely to succeed in AI adoption. However, risk-averse organizations were held back by the risk associated with AI adoption, particularly for publicly funded bodies where risk mitigation is the culture. AI strategy also varied by case. Formal strategic papers were present for AI adoption for some organizations, while for others, ad-hoc adoption rested upon the need for technology. In the absence of a specified AI strategy, adoption turned patchy, and the attempts for its integration were also uneven.

Other organizational dimensions, such as resources, size, and collaboration, also played their roles in AI adoption. Smaller organizations lagged behind larger organizations when it came to AI initiative progress, although the size did not determine AI maturity. Availability of resources such as financing, talent, and high-quality data was the deciding point. Budget-constrained organizations turned towards partners and financing from the outside to supplement the shortfall. Collaboration also played its role. Most organizations collaborated with the outside world, including universities, private providers, and the public sector. Academic collaborations were non-formal, while collaborations with private organizations were formal contracts. Expertise from the outside contributed, but internal knowledge about the technology by the employees contributed towards bringing AI adoption through the door. Better AI integration took place when organizations encouraged knowledge-sharing through internal activities and functional collaborations.

Lastly, organizational communication and internal motivation from the members contributed extensively towards the adoption of AI. AI solution adoption varied by proximity to the business units being affected. In some cases, AI enjoyed good support from the side of the management but faced rejection from the operating units, stressing the need for inclusive decision-making and communication towards AI adoption by the organizations.

4.3.3. Environmental Factors

To assess the influence of the environment on the adoption of AI, competitive pressure, regulatory barriers, the presence of resources, the processes for project management, and customer readiness were analyzed. Unlike private sector corporations, the public sector organizations were not immediately under the influence of competition. However, some organizations were concerned about increased pressure in the future. For instance, Case E planned for potential competitive scenarios even when not under the influence of immediate competition. In contrast, some organizations reported that their AI projects were unique, and similar projects were available, but did not bring much competitive pressure. Data protection regulations were the pervasive challenge in most cases. Compliance worries continually deferred or hindered AI adoption, particularly from the uncertainty arising from the vagueness in the interpretation of federal and cantonal digital policies. Uncertainty caused by the vague regulatory environment made the organizations find it difficult to comply with AI projects.

Public organizations also faced common challenges in acquiring financial and human resources for AI projects. Budget processes were also rigid, limiting spontaneous and innovative projects from being funded, and IT professionals were typically assigned to long-term projects for digitalization rather than AI innovation. AI talent also became difficult to find owing to the perception that the public sector is less innovative compared to private business. The adoption of AI in public organizations was often constrained by adherence to traditional project management approaches. Many digital projects benefit from agile methodologies that facilitate iterative improvements, but public organizations were often required to follow rigid, linear project management structures. Case D, for example, encountered resistance when proposing an agile methodology, with federal authorities insisting on traditional project workflows. Customer readiness was not perceived as a major obstacle in the adoption of AI. While some organizations lacked sufficient customer feedback to assess readiness, interviewees emphasized that customer acceptance was generally favorable, particularly for AI-driven solutions aimed at improving public services.

4.4. AI Maturity Level Aggregation

A comparative analysis of AI adoption factors across different maturity levels revealed distinct priorities among organizations at the assessing, determining, and managing levels (see Table 5).

- Assessing Level: Organizations in this category focused primarily on technological feasibility, project structure, collaboration, and intrinsic motivation. Business processes played a minimal role in AI adoption at this stage, as organizations were still exploring the potential of AI solutions.
- Determined Level: Organizations at this stage placed significant emphasis on top management support, change management strategies, strategic alignment with broader organizational goals, budget allocation, employee engagement, and collaboration with external partners. Customer readiness was also considered a moderate influencing factor.
- Managed Level: Organizations at this maturity level exhibited well-defined AI processes and infrastructure. The most critical factors influencing AI adoption included top management support, collaboration strategies, and the organizational affiliation of AI initiatives. Technological factors remained relevant but were integrated seamlessly into existing operational frameworks.

Overall, environmental factors were not identified as highly influential in AI adoption. While regulatory challenges and resource constraints posed barriers, they did not decisively impact adoption trajectories. Instead, AI maturity level determined the relative importance of technological and organizational factors, with increasing emphasis on structured AI processes as organizations progressed from assessing to managed levels.

5. Discussion

The findings of this study provide new insights into AI adoption in public institutions, applying the TOE framework to examine the drivers of AI adoption. The results point to AI adoption in divergent directions, namely strategic, top-down, or technological, bottom-up. The latter was more dominant, in that institutions tended to turn to AI after other technologies failed to deliver. This underscores the role of necessity-based innovation in AI adoption. Further, while some institutions planned to support AI using specialists and infrastructure readiness of data, others integrated AI solutions organically in response to evolving projects. This underscores divergent organizational readiness and strategic vision in AI undertakings in the public sector [26-28].

The study also underscores organizational factors in AI adoption. Top management support was a crucial enabler that provided required resources, ensured support from within, and overcame resistance. Change management was also a crucial enabler in overcoming resistance to AI, largely in terms of AI's transparency and potential interference in existing work processes. Institutions that also possessed a culture of innovation and agile project management were better positioned to support AI, pointing to flexibility and adaptability in AI implementation success. Risk-averse organizational culture, a universality in public institutions owing to their political and financial constraints, was a principal challenge, though [29]. This conforms with existing studies pointing to risk mitigation as a principal dimension of public sector technological innovation. Resource readiness in terms of finances and human capital was also a determining factor in AI adoption. Greater institutions, predominantly state-owned, possessed higher AI maturity, owing to planned funding, specialist staff, and strategic planning. In contrast, smaller institutions suffered from budget constraints and a lack of specialist knowledge, resorting to external cooperation with universities and service providers in most instances. Partnerships facilitated exposure to specialist knowledge, yet such cooperation was contingent on open project frameworks and reciprocal understanding between in-house groups and partners. Such outcomes attest to resource allocation strategies and cooperation strategies as decisive to AI adoption success. Environmental forces impacted AI adoption to a smaller extent compared to organizational and technical forces. Competitive pressures were not a primary driver in view of the non-market nature of government institutions, yet a small number of institutions anticipated looming pressures and took a proactive stance towards AI adoption in expectation of such pressures in the future. Regulatory challenges, such as the protection of information and vagueness in legislative frameworks, were dominant challenges.

The inelasticity of government budgeting and project management practices also impeded AI adoption, in view of established methods lacking iterative trial-and-error flexibility that is a prerequisite to AI projects [30, 31]. Surprisingly, customer readiness was not perceived as a primary challenge, though higher AI maturity institutions perceived it as more relevant, attesting that when AI adoption is more developed, end-user adoption is more relevant. Overall, the studies indicate that AI adoption in government is driven by a complex interaction of organizational, contextual, and technological factors. Organizations in different AI maturity levels face different challenges and priorities, with those in the assessing phase having trouble dealing with project arrangements and cooperation, while those in the determined and managed phases work on strategic alignment, organizational change, and resource allocation. The findings have practical implications for policymakers and government leaders in that they indicate that there is a need for targeted strategies to enable AI adoption, such as explicit regulation frameworks, flexible funding mechanisms, and capacity development programs. Further studies can continue to explore the long-term consequences of AI adoption in government, particularly its impact on organizational efficiency, decision-making processes, and citizen engagement.

6. Conclusion

This study applied the TOE framework to analyze the determinants of AI adoption by public organizations, finding the salient technological, organizational, and environmental considerations. Results identified AI adoption is frequently necessity-led, where AI is adopted by public organizations when traditional technologies fail to resolve complex problems. While some organizations planned for AI adoption through strategic top-down processes, many adopted AI through bottom-up processes, incorporating intelligence into projects over their lifespan. Organization-specific considerations, including the support of top management, the process of change, and the availability of resources, were the prime enablers for AI adoption. Organizations with innovative culture and adaptive structures for projects showed greater potential for AI adoption, while bureaucratic structures and risk culture were the main inhibitors. Future research is needed to study the long-term implications of AI adoption by the public sector, including its impact on the delivery of services, efficiency, and stakeholder interaction. If these concerns can be met, the public sector can harness AI for informed decision-making, optimizing operations, and enhancing public service delivery.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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