AI for the public sector: Readiness, adoption, and the public value promises

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Abstract

This study investigates organisational readiness for Artificial Intelligence (AI) adoption in the Kenyan public sector, examining its role in public value creation and how readiness factors vary across contexts. Utilising the Technology–Organisation–Environment (TOE) framework, augmented by Dynamic Capability theory, qualitative interviews with public sector experts reveal that technological infrastructure, data quality, leadership support, staff competencies, organisational culture, regulatory frameworks, public trust, and external partnerships are key readiness factors. These factors enhance efficiency, service delivery, and data-driven policymaking. The findings indicate significant variations in readiness across central ministries, county governments, and regulatory bodies, necessitating tailored AI strategies. The study contributes an empirically grounded, comparative analysis of AI readiness, linking it to public value outcomes. The results also offer practical guidance for policymakers on differentiated strategies, human capital development, and ethical AI implementation.

Keywords

AI adoption, AI readiness, public sector, public value

1. Introduction

Artificial Intelligence (AI) has emerged as a pivotal force reshaping global governance and public service delivery, acting as both an enabler and disruptor across governmental tiers and agencies. Its promise lies in its ability to facilitate data-driven policy-making, optimise public service efficiency, and foster greater citizen engagement and public value [1, 2]. In recent years, AI technologies have evolved from experimental, isolated applications into mission-critical, enterprise-wide implementations within public sector organisations [3]. Yet despite AI's significant potential, its successful adoption within public organisations remains a challenging endeavour, often marked by high rates of implementation failures, resource constraints, and misaligned expectations, particularly concerning data readiness and trust [4, 5].

Organisational readiness, defined as a public entity's ability and preparedness to implement AI technologies effectively [6], is central to AI adoption in the public sector. Organisational readiness is multidimensional, encompassing technical infrastructure, workforce capabilities, managerial and political support, and external environmental factors such as regulatory landscapes, citizen expectations, and inter-agency collaboration [4, 7]. The interplay of these elements determines a public organisation's capacity to adopt AI successfully and leverage it for generating public value [8]. The promise of AI is its ability to enable profound benefits — from enhanced citizen experiences and improved monitoring to cost efficiencies and strengthened security. However, achieving these benefits depends critically on

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understanding and aligning the various dimensions of organisational readiness for AI adoption [3, 9]. Studies such as Tangi et al. [10] have articulated AI readiness frameworks, focusing primarily on large firms and sectors with significant digital resources. Nevertheless, such frameworks often fail to capture the unique constraints and dynamics within smaller governmental departments or local authorities. This is significant because public sector entities, regardless of their size, form the backbone of national service delivery, yet often struggle with legacy IT systems, poor data quality, limited access to AI talent, and constrained financial budgets [7].

On the other hand, the existing literature lacks a nuanced examination of how AI readiness operates across diverse public organisational environments and scales. Understanding AI readiness as a contextual phenomenon is vital for crafting actionable, sector-specific recommendations that resonate with the realities of public administration. Without such an understanding, AI implementation will remain an endeavour where public benefits are unrealised or disproportionately distributed [6]. Although prior work has identified critical readiness factors such as top management support, data quality, and technical infrastructure [3], their interplay across varied public organisational settings, including the crucial aspect of public trust and algorithmic accountability, remains largely unexplored. Similarly, few studies have explicitly linked readiness with generating distinct public value across differing public organisational environments, making it challenging for decision-makers to prioritise efforts and investments effectively [8].

1.1. Research aim

This study investigates how organisational readiness influences AI adoption and its ability to create public value across public organisations of differing sizes and environments. By employing a multi-case study approach within the public sector, it will identify and evaluate key AI readiness factors across the Technological–Organisational–Environmental (TOE) dimensions, compare and contrast these factors across various public sector entities, and propose actionable recommendations for AI adoption strategies tailored to specific public organisational contexts. Through this approach, the study will deepen theoretical understanding while providing practical guidance for policymakers, public sector leaders, and AI adopters within government. The following research questions guide our study:
1. *What are the key organisational readiness factors for AI adoption, and how do they enable public value creation within public organisations?* and
2. *How do these readiness factors vary across public organisations of differing sizes and environments, and what are their implications for AI implementation outcomes and the delivery of public services?*

The remainder of this paper is structured as follows. The next section reviews related literature, outlining the theoretical foundations that underpin our study. It also examines the adoption of AI and highlights the importance of contextual variation across organisations within the public sector, particularly about how AI adoption contributes to public value creation. The subsequent section details the research methodology, describing the research strategy employed alongside the data collection and analysis techniques. This is followed by the presentation of findings, where we report the results of our thematic analysis of the qualitative data. The final section revisits the two research questions, offering answers and discussing the study's contributions and implications for both academic research and professional practice. We also reflect on the limitations of the study and propose directions for future research.

2. Related works

2.1. Theoretical foundation

This study's theoretical foundation is primarily anchored in the Technology–Organisation–Environment (TOE) framework [4], which is complemented by Dynamic Capability theory [11, 12]. These integrated frameworks are particularly pertinent to the public sector context, offering a comprehensive and robust lens to examine the multifaceted nature of AI adoption and its subsequent impact on public value creation within governmental settings. The aim of this theoretical framework is to elucidate why the TOE framework, enriched by Dynamic Capability theory, is instrumental in investigating the organisational readiness for AI adoption in the public sector to create public value.

We argue that the TOE model, developed initially by Tornatzky and Fleischer [13] for technology adoption in private firms, provides a versatile and comprehensive lens for understanding AI readiness across three distinct dimensions, directly applicable to public organisations. Its utility lies in its capacity to provide a holistic view of the interconnected factors influencing technology adoption in complex public environments, making it a powerful tool for this study [14].

The ***technological context*** dimension encompasses the internal and external technologies relevant to the organisation [13]. In the context of AI adoption in the public sector, this specifically refers to the foundational infrastructure, suitable platforms, diverse AI tools, and the critical quality and accessibility of data necessary for effective AI implementation within government agencies. Public sector organisations frequently encounter significant challenges in this regard, grappling with pervasive issues such as outdated legacy IT systems and deeply entrenched data silos, which can severely impede the successful deployment and scaling of AI initiatives [15]. The technological context also considers the perceived relative advantage of AI over existing methods, its compatibility with current systems, and its complexity for integration [16, 14]. Empirical evidence suggests that relative advantage and compatibility positively influence AI adoption, while complexity can be a hindering factor [16].

The ***organisational context*** addresses the internal characteristics of the organisation that influence its capacity to adopt and utilise technology [13]. This dimension is particularly crucial for public sector entities encompassing various internal aspects. These include the prevailing public sector culture, which often exhibits a strong aversion to risk and change, potentially hindering innovation [17]. Furthermore, the availability and quality of staff competencies, particularly digital and AI-specific skills, are paramount [4]. The crucial role of senior management and sustained political support for AI initiatives cannot be overstated, as their commitment is vital for resource allocation and overcoming internal resistance [4, 14]. Finally, the organisation's absorptive capacity – its ability to recognise the value of new information, assimilate it, and apply it to commercial ends [18] – is critical for integrating new digital capabilities and translating AI investments into tangible benefits [17]. Leadership vision, strong internal communication, and change management strategies are all vital components of organisational readiness.

The ***environmental context*** dimension encompasses the external setting in which the organisation operates, influencing its decisions regarding technology adoption [13]. Key environmental factors for public sector AI adoption include evolving national and international regulatory frameworks, such as the comprehensive EU AI Act, which imposes strict guidelines on ethical AI use, data governance, and accountability. The imperative to maintain and build public trust in AI systems is another significant external pressure, as public resistance can undermine adoption efforts if systems are perceived as opaque, biased, or unfair [19]. Additionally, competitive pressure from other service delivery models (e.g., from private sector innovators or neighbouring public organisations) can incentivise AI adoption. Lastly, the availability of external collaborations with academia, research institutions, or the private sector, which can provide expertise, funding, and innovative solutions, plays a vital role in shaping the environment for AI adoption [4].

This study adopts the TOE framework as its foundational model due to its proven versatility across varying organisational settings and its empirically supported ability to provide a holistic view of the factors influencing technology adoption in complex public environments [16, 14]. It directly assists in answering Research Question 1 by identifying key readiness factors across these three domains.

While the TOE framework provides a robust static snapshot of readiness factors, Dynamic Capability theory ([12] offers a crucial temporal and adaptive lens, essential for understanding how organisations sustain AI adoption and translate it into public value in a constantly evolving technological and societal landscape. This theory posits that organisations must continuously evolve, sense new opportunities, seize them, and reconfigure their internal and external competencies to adapt effectively to rapidly advancing technological and environmental changes, particularly pertinent in the fluid AI landscape [11, 12].

The interplay between AI readiness factors, as outlined by the TOE framework, and a public organisation's ability to reconfigure its capabilities provides a crucial lens to understand how AI readiness translates into tangible public value generation. The Dynamic Capability theory highlights the importance of a public organisation's capacity to integrate, build, and reconfigure internal and external competencies. These include critical areas such as developing advanced digital skills within the workforce, establishing robust data governance frameworks, and implementing stringent ethical oversight mechanisms to address rapidly changing public demands and policy environments [15]. It underscores the adaptive capacity required to move beyond static resources towards dynamic competencies that enable sustained innovation in public service delivery and the continuous creation of public value [12].

By incorporating Dynamic Capability theory, this study can explore how public organisations not only achieve initial readiness for AI (as per TOE) but also how they sustain and leverage this readiness to continuously adapt, innovate, and thereby maximise public value creation over time. This dynamic perspective is particularly vital for addressing Research Question 2, which delves into how readiness factors vary and impact implementation outcomes across organisations of different sizes and environments, necessitating an adaptive approach to AI strategy and execution. Larger, more complex organisations, for instance, may require more sophisticated dynamic capabilities to manage AI integration across diverse departments and overcome entrenched legacy issues [19]. Conversely, smaller organisations might need to leverage external dynamic capabilities through partnerships to compensate for internal resource limitations.

We argue that the combined application of the TOE framework and Dynamic Capability theory provides a comprehensive and nuanced theoretical grounding for examining the multifaceted dimensions of AI adoption in the public sector, from foundational readiness to the dynamic processes required for sustained public value creation.

2.2. AI adoption in the public sector

The rise of AI has been one of the most significant technological developments in recent decades, profoundly reshaping public administration and service delivery across governmental sectors [2]. From predictive analytics in public safety to personalised citizen services, AI delivers benefits that extend across operational efficiency, strategic policy-making, and innovative public service offerings [3, 8]. However, its adoption is often uneven across public organisations, influenced by constraints related to legacy IT systems, talent shortages, and institutional complexities unique to the public sphere [4].

The benefits of AI adoption are well-documented across the public organisational value chain. It enhances operational efficiency by automating routine tasks and predictive maintenance for public infrastructure, leading to reduced costs and waste [20]. Furthermore, AI supports strategic decision-making by enabling public bodies to glean actionable insights from vast datasets, informing policy development and resource allocation [2]. Public entities employing AI can also rapidly develop and launch new services, fostering innovative public service offerings such as 24/7 citizen support via chatbots. Despite these advantages, AI adoption in the public sector is fraught with unique challenges. These include technical constraints, such as issues with data quality, infrastructural deficiencies, and cybersecurity concerns, particularly given the sensitive nature of public data ([3, 8]. Organisational dynamics, including resistance to change among public servants, misaligned incentives across departments, and the inherent complexities of bureaucratic structures, also pose significant hurdles [4]. Finally, environmental constraints, such as stringent regulatory restrictions (e.g., GDPR, EU AI Act), public scrutiny, competitive pressure from other service providers, and external resource limitations, further complicate AI adoption and trust-building in the public sphere [6].

2.3. Organisational readiness for AI adoption in the public sector

Organisational readiness for AI adoption in public organisations is a public entity's ability and preparedness across three primary domains. Firstly, technological readiness pertains to the availability and quality of AI infrastructure, platforms, and data, a critical challenge given the prevalence of legacy systems in government [3]. Secondly, organisational readiness encompasses the public sector culture, staff competencies, senior management and political support, and the absorptive capacity to integrate new technologies [4]. Lastly, environmental readiness considers competitive dynamics (e.g., expectations from private sector services), institutional policies (both national and international), citizen demands, and the broader vendor ecosystems [7, 6].

The Technology–Organisation–Environment (TOE) framework has become a dominant lens for assessing AI readiness due to its comprehensive consideration of internal and external factors [4, 9]. Applied to the public sector, the TOE model effectively captures the technological context, including AI infrastructure, data quality (often fragmented or inconsistent), scalability, and integrability with existing government systems [5]. It also addresses the organisational context, covering public sector culture, bureaucratic structures, top management and political support, staff skills (including a significant digital skills gap), and internal collaboration across agencies [4]. Finally, it accounts for the environmental context, which includes evolving regulations (such as the EU AI Act), public trust considerations, citizen expectations, inter-agency cooperation, and external vendor support.

2.4. AI readiness and contextualisation within the public sector

Research suggests that larger public agencies and national governments generally benefit from scale economies in AI adoption, enabling significant investments in AI infrastructure, staff training, and data governance frameworks [2, 5]. However, their typically hierarchical structures can sometimes impede agility, making AI implementation cumbersome and requiring comprehensive change management. For smaller public entities, such as local councils or specific departmental units, AI adoption presents unique opportunities. For instance, enabling operational efficiency and improving localised service delivery. Conversely, these smaller entities often face significant constraints, including limited access to capital, skilled staff, and robust external support, which frequently hamper AI adoption and scalability [7]. Furthermore, studies have observed that AI adoption dynamics vary across different public sector industries and functions. In highly regulated sectors such as defence or healthcare within the public domain, institutional and ethical constraints, alongside stringent data privacy requirements, often dominate the implementation landscape [4]. In contrast, in citizen-facing sectors like social services or public transport, competitive dynamics (e.g., from private service providers) and evolving citizen demands play a more significant role in shaping AI adoption strategies, with a strong emphasis on transparency and explainability to maintain public trust [6].

2.5. AI adoption and public value creation

The adoption of AI within the public sector offers far more than just enhancements to operational metrics; it contributes profoundly to the creation of public value. This extends beyond efficiency gains, encompassing improvements in public service delivery, resource optimisation, and enhanced citizen engagement.

AI is demonstrably linked to significant advancements in the efficiency and effectiveness of public service provision and the optimisation of resource allocation [8]. For instance, AI-driven analytics can help identify bottlenecks in service delivery, predict demand, and optimise staffing levels, leading to more responsive and effective public services. Furthermore, AI-enhanced citizen experiences foster greater public engagement, bolstering trust and increasing satisfaction by providing more accessible and personalised services [11, 8]. Examples include AI-powered chatbots for instant query resolution and personalised public health information dissemination, improving citizen interaction with public bodies [1].

Beyond service delivery, AI empowers public organisations to optimise resource utilisation critically, bolster efforts to combat fraud, and facilitate the adoption of more sustainable practices, particularly in crucial areas such as urban planning and environmental management. AI models can analyse vast datasets to identify fraudulent activities in real-time, leading to substantial savings for the public purse [21]. In environmental management, AI can predict pollution patterns, optimise waste collection routes, and model the impact of climate change policies, contributing to a more sustainable future [22].

The essence of public value, encompassing principles of fairness, trust, legitimacy, and equal treatment, is paramount when considering the societal impacts of AI. This holistic perspective ensures that AI implementation serves the broader public good, rather than merely narrow operational objectives [23]. Challenges in Capturing and Measuring Public Value from AI Despite the considerable potential of AI to deliver substantial public benefits, public organisations frequently encounter difficulties in effectively measuring and capturing this value. This persistent challenge stems from a confluence of interconnected factors. One significant hurdle is the presence of misaligned objectives across different government departments, which can hinder the development of coherent AI strategies and make it challenging to aggregate value across silos [4]. This is often compounded by inherent resistance to change within the public workforce, where established practices and a lack of familiarity with new technologies can impede AI adoption and the realisation of its benefits [17]. Furthermore, a pervasive lack of trust in algorithmic decision-making, prevalent among both public sector employees and citizens alike, poses a significant barrier to the widespread acceptance and successful integration of AI systems [4]. Concerns about data privacy, algorithmic bias, and the potential for job displacement contribute to this mistrust [24].

Additionally, the failure to seamlessly integrate AI into existing public process ecosystems can significantly impede value realisation, particularly in environments characterised by legacy IT systems [20]. These outdated systems often lack the interoperability and computational power required to support advanced AI applications, leading to fragmented implementation and limited impact [21]. Therefore, ensuring transparency, accountability, and the proactive mitigation of algorithmic bias are not merely desirable but absolutely crucial for maintaining public trust and unequivocally demonstrating ethical AI use [16]. Without these foundational elements, the full spectrum of public value from AI adoption remains elusive.

3. Research methodology

This study adopts a qualitative case study approach, deemed appropriate for investigating complex phenomena in real-world settings involving multiple institutional actors [25]. A single-country case study focused on Kenya allows for an in-depth exploration of the public sector's readiness for AI adoption and the implications for public value creation. The interpretivist perspective enables examining stakeholder experiences, perceptions, and interpretations, providing rich insights into the sociotechnical and organisational dimensions of AI readiness. Given the interdependence of policy, infrastructure, institutional capacity, and public outcomes, this approach facilitates a holistic understanding of how AI adoption is conceptualised and operationalised within the Kenyan public sector.

3.1. Data collection and analysis methods

Semi-structured interviews served as the primary data collection method, allowing for flexibility and depth in exploring the experiences and perspectives of key actors. A purposive sampling strategy was employed to identify participants with expertise and strategic involvement in AI policy, digital governance, and service delivery. A total of 17 participants were interviewed, comprising officials from national government ministries and agencies (7), county governments (4), public sector research and training institutions (3), and international and academic policy organisations (3). Supplementary data from official websites, policy documents, and strategic frameworks supported and triangulated the interview findings. All interviews, conducted in person, lasted between 35 and 50 minutes and followed a guided protocol addressing dimensions of technological, organisational, and institutional readiness, as well as perceived impacts on public value. Ethical considerations were observed, including informed consent and the anonymisation of responses.

Thematic data analysis was performed following the six-step process outlined by Braun and Clarke (2006). The researchers first familiarised themselves with the transcripts through repeated reading, then generated initial codes aligned with the research aims. These codes were clustered into candidate themes, which were iteratively refined and validated for consistency and relevance. Themes were defined and named to reflect distinct patterns across the dataset, culminating in a coherent narrative that linked AI adoption readiness to core elements of public value—efficiency, transparency, inclusion, and responsiveness. The analysis combined inductive insights with deductive framing drawn from existing literature on digital transformation and public sector innovation.

4. Results

This section presents the findings from the qualitative interviews with Kenyan public sector experts, addressing the two primary research questions. The analysis is structured first to identify key organisational readiness factors for AI adoption and their role in public value creation, followed by examining how these factors vary across different public organisational contexts and their implications for AI implementation.

4.1. Key organisational readiness factors for AI adoption and public value creation

The interview responses consistently highlighted several interconnected factors crucial for organisational readiness in AI adoption within the public sector, aligning broadly with the Technology–Organisation–Environment (TOE) framework. These factors directly contribute to creating public value by enhancing efficiency, improving service delivery, fostering transparency, and enabling data-driven decision-making.

4.1.1. Technological readiness

Technological readiness emerges as a foundational factor, encompassing the availability and quality of AI infrastructure, data, and the ability to integrate new and legacy systems.

AI infrastructure and resources: Respondents across all organisations indicated the presence of varying levels of AI infrastructure. The Ministry of Information, Communications and the Digital Economy reported a "*Government Cloud Infrastructure with GPU-enabled servers, Microsoft Azure AI services integration, and partnerships with local universities for research computing resources*". Similarly, Nairobi County Government has "*cloud-based platforms, dedicated servers, and integrated sensor networks for Smart City applications*". At the same time, Mombasa County noted "*robust AI infrastructure including cloud-based analytics platforms, integrated sensor networks for environmental and traffic monitoring*". However, limitations persist, including "limited high-performance computing resources," "*inconsistent internet connectivity in remote areas*," and "*insufficient specialised hardware*".

Data quality and availability: Data is universally acknowledged as critical, yet its quality and availability present ongoing challenges. The Ministry noted that "*approximately 60 per cent of our data requires* cleaning and preprocessing before AI implementation," with efforts underway to establish data governance standards. While Nairobi County has seen improvements with "*about 70 per cent of our operational data is now digital and suitable for AI applications*," historical data integration remains difficult. The Office of the Data Protection Commissioner (ODPC) reported generally good data quality for structured compliance data, but challenges in accessing comprehensive data across all government agencies.

Legacy systems integration: A pervasive technological barrier is integrating AI solutions with existing legacy systems. This challenge is particularly pronounced for larger, more established ministries and county governments with diverse, entrenched IT infrastructures.

Our analysis of technological readiness, in sum, indicates that it profoundly enhances public value by delivering tangible improvements in service delivery and operational efficiency. This is exemplified by the dramatic reduction in response times; for instance, chatbots significantly cut query response times from 48 hours to under 10 minutes, thereby boosting citizen satisfaction and trust through increased accessibility. Furthermore, AI-driven automation, a direct outcome of technological preparedness, has led to a notable "*35 per cent increase in departments using automated document processing*," freeing up human resources for more strategic tasks and optimising public expenditure. This foundational readiness also empowers data-driven policy development by leveraging improved data quality and analytical capabilities to provide deeper insights, leading to more effective and proactive public services. Thus, technological advancement is a critical enabler for creating a more responsive, efficient, and evidence-based public sector.

4.1.2. Organisational readiness

Organisational factors were consistently highlighted as pivotal, encompassing leadership support, staff competencies, organisational culture, and internal governance structures.

Senior management and political support: Strong senior management and political leadership support is critical for successful AI adoption. The Director of ICT Services at the Ministry reported "*strong, with direct backing from the Cabinet Secretary and inclusion of AI initiatives in our strategic plan*," backed by a "*KES 2 billion allocation*". Similarly, Nairobi County reported "*very strong*" support from the Governor and County Assembly, who "*approved significant budget allocations for AI and technology initiatives*". The ODPC highlighted the Commissioner's "strong" support and "*significant investments in AI for regulatory capabilities*".

Staff competencies and training: A notable challenge across all organisations is the mixed level of AI competencies among staff. The Ministry indicated that only "*10 per cent have advanced skills*", with ongoing training initiatives. The ODPC reported "*20 per cent have advanced capabilities in privacy-preserving AI techniques*". Continuous investment in training, partnerships with universities, and international programs are seen as essential for addressing these skill gaps.

Organisational culture: While generally progressive and supportive of innovation, particularly among younger staff, there is "*some resistance from employees concerned about job displacement*". Change management programmes are implemented to address these concerns by emphasising AI as an empowerment tool. The ODPC's culture is described as "*cautiously progressive*," prioritising privacy protection and ethical consideration in AI adoption.

Internal governance and structure: Establishing dedicated AI governance committees, specialised technical teams, comprehensive policy frameworks, and clear approval procedures is a crucial enabling structure. These structures include "*risk assessment processes, quality assurance protocols specifically for AI applications, and advisory groups with external expertise*".

4.1.3. Environmental readiness

The responses from our interviewees indicate that external factors significantly influence AI adoption, including the prevailing regulatory frameworks, public expectations, competitive pressures, and the availability of external partnerships. These elements collectively shape the opportunities and constraints for public organisations integrating AI.

Regulatory environment and governance: Evolving regulatory frameworks, such as "*international regulatory trends and best practices*," are significant in guiding AI adoption. Legislative frameworks provide essential guidelines on data protection, consumer rights, and accountability. The Office of the Data Protection Commissioner (ODPC) specifically highlights "*The Data Protection Act*" as their primary framework, emphasising "*privacy by design and algorithmic accountability*" in all AI considerations. There is also a recognised desire for "*harmonised international AI governance frameworks*" to enable more consistent and effective adoption across borders and sectors. In one of the participants' own words, "*the Data Protection Act, which guides all our considerations, emphasises privacy by design and algorithmic accountability.*"

Public expectations and trust: Public and industry expectations for "*efficient, responsive regulation*" and "*strong privacy protection*" create considerable pressure and directly influence AI adoption strategies within the public sector. Maintaining public trust through "*transparent AI operations*" and demonstrable ethical use is vital for widespread acceptance and successful implementation. Any perceived lack of transparency or potential for bias can significantly erode public confidence. According to our respondent from Nairobi County Government, "*public trust is paramount. We continuously engage stakeholders to ensure our AI applications are transparent and accountable, thereby building confidence among citizens.*"

Competitive pressure: Regional competition among "*regulatory authorities,*" "*other counties,*" or even "*other tourism destinations and ports*" drives innovation and accelerates AI adoption. Public organisations are increasingly aware that leveraging AI can provide a competitive edge in service delivery, attract investment, or improve regulatory effectiveness. This competitive landscape fosters a dynamic environment where organisations strive to enhance their offerings through technological advancement. A participant from Mombasa County Government says, "*We face regional competition from other counties and even other tourism destinations and ports that are adopting advanced technologies. This pushes us to innovate with AI continuously.*"

External partnerships: Collaborations with "*international regulatory bodies,*" "*telecommunications companies,*" "*academic institutions,*" local startups, and civil society organisations are identified as "*crucial partners.*" These partnerships are vital for accessing specialised AI expertise, leveraging advanced cloud infrastructure, fostering joint research and development initiatives, and ensuring comprehensive consumer protection considerations are embedded in AI solutions. Such collaborations are essential for complementing internal capabilities and accelerating AI maturity within the public sector. According to a respondent from the MOI, "*Partnerships with academic institutions and local startups are crucial for us to access specialised AI expertise and collaborate on pilot projects.*"

The above responses suggest that environmental readiness ultimately contributes to public value by ensuring AI systems align with citizen rights, promote market fairness through enhanced capabilities like "*improved fraud detection,*" and enable proactive service delivery by anticipating needs and preventing issues.

4.2. Variation of readiness factors across public organisations and implications

The interview data reveal discernible variations in AI readiness factors across public organisations, influenced by their size, mandate, and specific operating environments. These differences have direct implications for AI implementation outcomes and the delivery of public services.

4.2.1. Central government ministry vs. county governments

A closer look at the Technological Context, the ***Central Ministries*** (e.g., Ministry of Information, Communications and Digital Economy) possesses established "*Cloud Infrastructure with GPU-enabled servers*" and "high-speed fibre connectivity", indicative of national-level strategic investment. On the other hand, the interviewees argue that the country as a whole still struggles with "*limited high-performance computing resources*" and "*inconsistent internet connectivity in remote areas*".

Another interesting finding was the differences in focus and priorities of various ***County Governments***. For instance, Nairobi County has "*cloud-based platforms*" and "*integrated sensor networks*" for Smart City applications, indicating urban-specific infrastructure. Mombasa County, on the other hand, focuses on specialised infrastructure for "*tourism and port management*". This implies that while central ministries focus on national backbone infrastructure, counties develop AI infrastructure tailored to their specific economic drivers and geographical constraints.

A further analysis of organisational contexts reveals both universal and specific factors. For instance, when it comes to ***staff Competencies***, ministries reported "*only 10 per cent to have advanced AI skills*" among technical staff. Nairobi County also reported a similar proportion of employees possessing advanced AI capabilities. This suggests a universal challenge in advanced AI skills, requiring continuous training across all levels of government.

Regarding ***organisational culture and change management***, while all reported generally progressive cultures, ministries and larger counties (Nairobi, Mombasa) explicitly mentioned addressing "*resistance from employees concerned about job displacement*", necessitating change management programmes. Smaller or more specialised agencies like the ODPC emphasised a "*cautiously progressive*" culture, focusing on ethical considerations.

Analysis of the environmental context indicates that ***regulatory influence*** and ***partnerships*** seem to differ among the public organisations. For instance, central ministries and regulatory bodies like the ODPC are heavily influenced by "*international regulatory trends and best practices*". County governments, while mindful of national regulations, are driven more by "*citizen expectations for efficient county services*" and "*competitive pressure from other counties*". In regard to partnerships, our results suggest that all organisations leverage external vendors. However, ministries and larger counties engage with "*international technology companies for advanced AI platforms*", while county governments often prioritise vendors who "*understand development contexts*" and "*support local capacity building*", reflecting different scales of operation and local development priorities.

4.2.2. Regulatory/oversight bodies vs. service delivery entities

The roles and responsibilities of the various public sector institutions were found to have implications for the way AI is adopted.

Technological constraints: The ODPC, as a regulatory body, faces unique technological constraints due to "*stringent security and privacy requirements that limit AI system design options*" and the need for "*explainable AI systems that can justify compliance decisions*". Service delivery entities (e.g., Nairobi County) primarily face "*integration challenges with legacy systems*" and "*scalability issues for county-wide deployment*".

Organisational culture: The ODPC's culture is shaped by its mandate, with a "*strong culture of risk assessment and ethical consideration*" influencing AI adoption. Service delivery entities are often driven by "*efficiency gains*" and "*improving citizen satisfaction*", leading to a more direct embrace of technologies that yield immediate service benefits.

Public value focus: While organisations in the public sector are expected to aim for public value, the responses from our interviewees indicate that specific contributions of the technology adoption differ. For instance, the ODPC focuses on "*strengthening data protection compliance*" and "*enhancing citizen trust in government data handling*". Service delivery entities like Nairobi County emphasise "*improving service delivery efficiency*," "*better resource allocation*," and "*enhancing transparency in county operations*". This highlights how the intrinsic mission of an organisation shapes its AI objectives and perceived public value.

4.2.3. Implications for AI implementation and public service delivery

The variations observed in AI readiness across different public organisations have significant implications for the effective implementation of AI solutions and the eventual delivery of public services. These disparities call for a nuanced and flexible approach to the development and execution of AI strategies.

Tailored strategies: A 'one-size-fits-all' AI adoption strategy is unequivocally unsuitable. Large ministries, with their national mandate, tend to focus on overarching national policy development and the establishment of foundational infrastructure. In contrast, county governments require highly context-specific solutions that directly address their local demographics, unique infrastructure challenges, and specific service needs. For example, according to the participant from Nairobi county government, "*Our strategy in Nairobi focuses on Smart City solutions tailored to urban challenges, unlike some rural counties that need AI for agricultural support or remote service delivery*". This contrasts with Mombasa County's focus on "*integration of AI across maritime, tourism, and municipal services*" and Kisumu County's "*priority on inclusive development and rural service delivery*," highlighting the need for tailored approaches.

Resource allocation: Organisations with greater budgetary flexibility and national mandates, such as the Ministry of Information, Communications and the Digital Economy, are better positioned to invest in "*high-performance computing*" and broad, national-level infrastructure. Conversely, smaller or more rural-focused entities, facing inherent resource constraints, must rely more heavily on "*partnerships with technology providers and shared resources*" to bridge their technological and capacity gaps. This underscores the need for creative funding models and collaborative initiatives to support AI adoption across the public sector spectrum. The respondent from Kisumu County Government says, "*Given our budget limitations, we largely rely on partnerships with technology providers and sharing resources with other counties to implement AI initiatives.*"

Data governance prioritisation: While the emphasis on data quality and standardisation is universally acknowledged as critical, its specific application and prioritisation vary significantly across organisations depending on their core mandate. Regulatory bodies like the ODPC inherently prioritise "*data privacy and explainability,*" ensuring that AI systems comply with stringent regulations and can justify their decisions transparently. In contrast, service delivery entities primarily focus on leveraging data to achieve efficiency gains and optimise resource allocation to improve immediate public services. As one of our participants puts it, "*...explainable AI and privacy-preserving techniques are paramount due to our mandate. It's not just about efficiency but compliance and public trust.*"

Human capital development: The pervasive skill gap identified across all interviewees implies that while national strategies for AI capacity building are crucial, they must be meticulously complemented by targeted training programmes. These programmes need to address the specific AI applications and skill sets relevant to different public sector roles and the unique local needs of various governmental entities. A generalised approach to upskilling will be insufficient; customisation is key to ensuring workforce can effectively interact with and leverage AI tools. According to a respondent from one county, "*we need national-level training programs, but also very specific modules for our staff in areas like agricultural AI or water management, which differ from urban planning needs.*"

Ethical and trust considerations: While all respondents acknowledge the inherent risks associated with AI, regulatory bodies like the ODPC are inherently tasked with proactively addressing "*potential algorithmic bias" and "privacy violations,*" making "*privacy by design*" a core tenet of their AI implementation strategy. Service delivery entities also recognise these ethical considerations, but their primary focus remains on delivering tangible improvements in public services, often integrating ethical safeguards to ensure user adoption and trust in new services. A respondent from Nairobi County Government puts it "*Our main focus is service improvement, but we also run regular audits to ensure our AI systems are fair and don't introduce bias, as public trust is essential for adoption.*"

In sum, the findings demonstrate that although the fundamental factors underpinning AI readiness are widely acknowledged, their specific expressions, associated challenges, and routes to generating public value are markedly shaped by the distinctive characteristics and operational settings of individual public organisations. Effective implementation of AI thus requires a nuanced appreciation of these differences, alongside adaptive strategies tailored to each organisation's unique technological landscape, internal capabilities, and external environment.

5. Discussion and conclusion

5.1. Discussions

This study explored organisational readiness for AI adoption in the public sector, examining its role in public value creation and how readiness factors vary across contexts. The findings validate the utility of the Technology–Organisation–Environment (TOE) framework [13], augmented by Dynamic Capability theory [12], for understanding AI readiness and its impact on public value.

Technological readiness is foundational, with advanced infrastructure, quality data, and system interoperability being prerequisites for successful AI integration [15]. Organisations with superior cloud infrastructure and data management were better positioned to automate services and enable data-driven policymaking, enhancing efficiency, responsiveness, and innovation. This aligns with research showing strong correlations between data infrastructure, AI maturity, and government effectiveness [21, 8].

Organisational readiness proved decisive, encompassing leadership, employee capabilities, culture, and absorptive capacity. Strong top management support emerged as a key enabler for mobilising resources [3]. However, persistent skill shortages and cultural resistance, particularly around job displacement, mirrored broader public sector challenges [17]. As articulated by Cohen and Levinthal [18], the importance of absorptive capacity was evident as organisations learned from external partnerships to develop tailored AI solutions, supporting findings on dynamic learning in digital governance [14].

Environmental readiness critically influenced AI adoption. Evolving regulations, such as "The Data Protection Act," played a dual role, guiding responsible adoption while imposing compliance challenges [8, 5]. Citizen expectations for fairness and privacy were significant drivers, reflecting the centrality of trust in public value theory [23]. Collaborative ecosystems with academia and startups also emerged as key enablers, compensating for internal capability gaps [11].

Regarding the second research question, readiness factors varied significantly across public organisations. Larger, central government ministries benefited from substantial infrastructure but faced constraints from legacy systems and bureaucracy, supporting findings that scale can impede agility [2]. Conversely, smaller, local government entities, like county governments, showed greater flexibility but were limited by resources, often relying on external partnerships and modular solutions [7]. AI strategies were tailored to local needs, such as "Smart City solutions for urban challenges" or "tourism and port management," reinforcing the context-sensitive nature of public value creation.

Furthermore, regulatory bodies differed from service delivery organisations. Regulators, like the ODPC, prioritised "data privacy and explainability," aligning with normative governance priorities [24]. Service delivery entities focused more on AI's operational benefits like "efficiency gains" and "improving citizen satisfaction." These variations strongly support the need for differentiated AI adoption strategies, rather than universal frameworks, as organisational environments demand tailored dynamic capabilities [4]. AI readiness is not static but a dynamic, contextually evolving capability, underscoring the value of blending the TOE framework with a Dynamic Capability perspective. For public sector organisations to fully realise AI's promise, strategies must be adaptive, inclusive, and grounded in their specific operational realities.

5.2. Contributions to research and practice

This study makes several significant contributions to the burgeoning field of AI in public sector research and offers practical guidance for policymakers.

This study attempts to further our understanding by providing an empirically grounded, multi-dimensional analysis of organisational AI readiness through an integrated Technology–Organisation–Environment (TOE) and Dynamic Capability lens. This hybrid framework not only identifies crucial readiness factors but also captures the dynamic, adaptive processes essential for sustained public value creation, thereby extending more static models of technology adoption. Secondly, the study introduces a comparative perspective on AI readiness. It illuminates how organisational size, functional mandate (e.g., regulatory vs. service delivery), and specific environmental contexts mediate the expression and impact of readiness factors. This comparative approach addresses a notable gap in existing literature, which often overlooks contextual variation within the public sector, assuming a more uniform adoption model. Thirdly, the research establishes a clear empirical link between AI readiness and tangible public value outcomes. It demonstrates precisely how foundational capabilities—such as robust infrastructure, sound data governance, and proactive ethical oversight—translate into improved service delivery, enhanced citizen trust, and bolstered institutional legitimacy.

For practitioners and policymakers, the study offers actionable insights for fostering successful AI adoption and maximising public value. It strongly advocates for developing differentiated AI adoption strategies that are acutely sensitive to the unique organisational context of each public entity. This implies moving away from a 'one-size-fits-all' approach towards bespoke solutions that align with specific mandates and environments. Furthermore, the findings necessitate rethinking public sector training programmes to address domain-specific AI skills, moving beyond general AI literacy to cultivate competencies relevant to particular public service areas. The study also underscores the strategic imperative of fostering partnerships with academia and private providers to offset internal resource and capability constraints. It also highlights the imperative of embedding ethical safeguards and transparency mechanisms within all AI systems to maintain public trust and ensure robust accountability, reinforcing the public's confidence in AI-driven government services.

5.3. Limitations and future research directions

Despite offering valuable insights, this study is subject to some limitations, which present avenues for future research.

Firstly, the case study design, explicitly focused on Kenyan public organisations, may limit the direct generalisability of the findings to other national contexts. While the insights are analytically transferable, future research could conduct cross-country comparative studies to explore how diverse political, economic, and cultural variables influence AI readiness and its impact on public value. Secondly, the qualitative nature of this study, while providing rich depth and nuance, inherently restricts statistical generalisation. Subsequent studies could adopt mixed-methods or large-scale survey designs to validate the identified readiness factors and assess their predictive influence on AI adoption outcomes across broader populations. Thirdly, whilst the study integrates the TOE and Dynamic Capability frameworks, it does not exhaustively explore the interdependencies and causal pathways between readiness factors and public value creation over extended periods. Longitudinal studies would be highly beneficial to illuminate how AI readiness evolves, particularly in response to shifting political landscapes, budget cycles, and changing citizen expectations. Finally, future research should investigate the role of emerging readiness dimensions, such as algorithmic literacy, specialised AI ethics training, and inclusive design principles, in shaping equitable and sustainable AI adoption. Furthermore, exploring how marginalised groups are affected by, or potentially excluded from, AI-driven public services would significantly deepen the normative foundations for responsible AI implementation within the public sector.

Declaration on Generative AI

Generative AI tools were employed to assist with grammatical corrections and stylistic improvements of the manuscript. All scientific content and argumentation remain the sole responsibility of the authors.

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