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AI Adoption in the Public Sector: Organizational Readiness and the Pursuit of Public Value

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Abstract. Artificial Intelligence (AI) has attracted significant attention among researchers and practitioners as it emerges as a strategic asset for organizations across sectors and industries. Within the public sector, the deployment of AI is anticipated to enhance the responsiveness of public organizations in delivering appropriate services and addressing complex societal challenges. This study examines the readiness of public organizations for AI adoption within Kenya's public sector and explores its implications for public value creation. Anchored in the Technology-Organization-Environment framework and informed by Dynamic Capabilities theory, the article analyzes how structural conditions within organizations interact with adaptive capabilities to shape trajectories of AI readiness. Drawing on qualitative interviews with seventeen public sector experts, the study identifies a set and dynamic interdependence of critical readiness factors, including technological infrastructure, data quality, leadership commitment, staff competencies, organizational culture, regulatory frameworks, public trust, and external partnerships. By offering an empirically grounded and comparative perspective, the study aims to enhance our understanding of the relationship between AI readiness and public value creation, drawing on Kenya's example. The results may also provide valuable inputs for policymakers in formulating actionable plans concerning differentiated implementation pathways, capacity development, and the ethical governance of AI in the public sector.
Keywords: Artificial Intelligence (AI), AI Readiness, Public Value Creation, Dynamic Capability Theory, Technology–Organization–Environment (TOE) Framework.

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1 Introduction

Artificial Intelligence (AI) has emerged as a transformative force reshaping global governance and public service delivery, functioning both as an enabler and a disruptor across governmental tiers and agencies [1]. Historically, the public sector has been slow to adopt emerging technologies due to institutional inertia, regulatory rigidity, and risk-averse administrative cultures [2], [3]. However, this trend is shifting as governments worldwide increasingly recognize the strategic potential of AI to strengthen public governance, enhance transparency, and foster closer engagement with citizens [4]. AI's promise lies in its capacity to facilitate data-informed policymaking, optimize public service efficiency, and generate greater public value through more responsive and anticipatory governance models [5], [6]. In recent years, AI technologies have evolved from experimental and isolated applications to mission-critical, enterprise-level implementations within public sector organizations [7]. Nevertheless, despite AI's considerable promise, its effective adoption across public organizations remains a complex undertaking that is frequently characterized by high implementation failure rates, resource constraints, and misaligned expectations, particularly concerning data preparedness and trust [8], [9].

Organizational readiness, which can be defined as a public entity's capacity and preparedness to implement AI technologies effectively [10], is a critical determinant of successful AI adoption in the public sector. It is inherently multidimensional, encompassing not only technical infrastructure and workforce capabilities but also managerial and political commitment, as well as external factors such as regulatory frameworks, citizen expectations, and inter-agency collaboration [8], [11]. The dynamic interplay of these elements shapes a public organization's ability to adopt AI and harness it to generate public value [12].

The transformative potential of AI lies in its ability to deliver far-reaching benefits, including enhanced citizen experiences, improved monitoring and decision-making, cost efficiencies, and strengthened public security. Yet, realizing these benefits depends fundamentally on how effectively public organizations understand and align the interrelated dimensions of readiness for AI adoption [7], [13]. While studies such as Tangi et al. [14] have advanced conceptual frameworks for assessing AI readiness, these are predominantly oriented towards large private firms or resource-rich sectors. Such frameworks often fail to capture the unique institutional constraints and operational dynamics faced by smaller governmental departments and local authorities. This omission is consequential, as public sector entities (irrespective of size) constitute the backbone of national service delivery, yet frequently contend with legacy IT infrastructures, poor data quality, limited AI expertise, and restricted financial capacity [11].

Despite growing scholarly attention, existing research offers limited insight into how AI readiness manifests across diverse public organizational contexts and administrative scales. Recognizing AI readiness as a contextual and relational phenomenon is essential for formulating actionable, sector-specific strategies that reflect the complex realities of public administration. In the absence of such understanding, AI implementation risks becoming an endeavor in which anticipated public benefits remain unrealized or unevenly distributed [10]. Although prior studies have identified critical readiness factors such as top management support, data quality, and technical infrastructure [7], their dynamic interdependencies across different organizational settings remain insufficiently explored. Moreover, few studies have explicitly examined how varying levels of readiness translate into distinct forms of public value creation, thereby limiting the capacity of policymakers and practitioners to target investments and interventions effectively [12].

In this study, we conceptualize organizational readiness for AI within the context of a public sector body. This readiness refers to the technical, organizational, and environmental preparedness of the institution to successfully implement and sustain changes enabled by AI. This comprehensive view incorporates elements such as infrastructure, necessary competencies, effective governance structures, and supportive enabling institutional conditions. Public value, conversely, is defined as the tangible enhancement of core attributes that benefit the public.

Specifically, it encompasses the augmentation of efficiency, transparency, responsiveness, and citizen trust. These enhancements are generated through mechanisms including improved public service delivery, strengthened accountability mechanisms, and the establishment of inclusive governance processes [15].

This study aims to explore how organizational readiness shapes the adoption of AI and its impact in generating public value across public organizations of varying sizes and contexts in Kenya. It seeks to identify and assess key AI readiness factors across the Technological-Organizational-Environmental (TOE) dimensions, compare their manifestations across diverse organizational settings, and suggest actionable recommendations for context-sensitive AI adoption strategies within the public sector of Kenya. Through this analytical approach, the study aims to contribute to the existing literature, furthering the theoretical understanding of AI readiness while offering practical insights for policymakers, public sector leaders, and practitioners seeking to foster responsible and effective AI implementation in government.

This is an extended version of the study presented in [16], which addresses the gap in the scientific literature and explores AI readiness in the public sector and how it is related to public value creation. The study is guided by the following research questions:

RQ1: What are the key organizational readiness factors for AI adoption, and how do they enable public value creation within public organizations?
RQ2: How do these readiness factors vary across public organizations of differing sizes and environments, and what are their implications for AI implementation outcomes and the delivery of public services?

The remainder of this article is structured as follows. Section 2 presents and discusses the extant literature outlining the theoretical foundations that underpin the study. It also examines patterns of AI adoption and underscores the importance of contextual variation across public sector organizations, particularly in relation to how AI contributes to public value creation. Section 3 presents the research methodology, detailing the research strategy, data collection procedures, and analysis techniques employed. This is followed by the presentation of findings, where the results of the thematic analysis of the qualitative data are discussed in depth. Section 4 revisits the research questions, synthesizing the key findings and elaborating on their theoretical and practical implications for both research and public sector practice. The article concludes by acknowledging the study's limitations and suggesting directions for future research (Section 5).

2 Related Work

2.1 Theoretical Foundation

This study is theoretically grounded in the Technology-Organization-Environment (TOE) framework [8], complemented by the Dynamic Capabilities theory [17], [18]. The frameworks are used together to provide a comprehensive and integrative lens through which to examine the complex processes shaping AI adoption in the public sector. The TOE framework offers a systematic means of analyzing how *technological*, *organizational*, and *environmental* factors interact to influence adoption decisions and implementation outcomes. In contrast, the Dynamic Capabilities perspective highlights the adaptive, learning-oriented capacities that enable public organizations to sense, seize, and reconfigure resources in response to technological change. Integrating these perspectives allows for a more nuanced understanding of how structural conditions and managerial capacities jointly determine organizational readiness for AI adoption and its contribution to public value creation.

The TOE framework, originally developed by Tornatzky and Fleischer [19] to explain patterns of technological innovation in private-sector firms, provides a versatile and comprehensive analytical lens for examining AI readiness also within public organizations. Its relevance lies in its capacity to capture the systemic interplay among technological infrastructure, organizational capability, and environmental context, which are factors that collectively shape the adoption and institutionalization of emerging technologies. When applied to the public sector, the TOE model may enable a nuanced understanding of how structural, institutional, and contextual forces interact to influence readiness for AI deployment in this domain. Unlike more narrowly focused frameworks, it accommodates the multidimensional complexity of public sector environments, where technological change is inseparable from governance structures, regulatory pressures, and citizen expectations. Consequently, it provides a holistic and integrative foundation for investigating the diverse determinants of AI readiness in governmental settings [20].

To enhance analytical clarity and ensure consistency across TOE dimensions, Table 1 synthesizes the key technological, organizational, and environmental factors that have an influence on AI readiness in the public sector, as identified in the extant literature.

Table 1. The TOE Dimensions, along with key factors and corresponding descriptions in the AI context within the public sector.

TOE Dimension	Key Factors	Description in AI Context
Technological	Infrastructure and systems	Availability of digital infrastructure, AI platforms, tools, and data architectures; constraints posed by legacy systems and data silos [19], [21], [22]
	Data quality and accessibility	Reliability, interoperability, and accessibility of data required for AI development and deployment [21]
	Relative advantage	Perceived benefits of AI compared to existing methods [20], [23]
	Compatibility	Alignment of AI solutions with existing systems and processes [20], [23]
	Complexity	Perceived difficulty of AI integration and use [23]
Organizational	Leadership and political support	Senior management and political backing enabling resources, legitimacy, and strategic prioritization [19], [20]
	Staff competencies	Availability of digital and AI-related skills within the organization [8]
	Organizational culture	Risk aversion and resistance to change within public sector organizations [12]
	Absorptive capacity	Ability to recognize, assimilate, and apply new knowledge and technologies [24], [25]
	Change management	Internal communication, vision, and strategies supporting organizational adaptation [25]
Environmental	Regulatory frameworks	National and supranational regulations governing ethical AI, data governance, and accountability (e.g., EU AI Act) [26]
	Public trust and legitimacy	External societal expectations regarding transparency, fairness, and accountability in AI use [27]
	Competitive pressure	Influence of alternative service delivery models and peer organizations [19]
	External collaboration	Partnerships with academia, research institutions, and private sector actors [8]

As summarized in Table 1, the technological dimension of the TOE framework describes the infrastructure and tools required for AI adoption. This includes all factors necessary to ensure data quality, accessibility, and interoperability, serving as the critical foundations. Although the adoption of AI is expected to bring benefits, significant friction is created by legacy IT systems and persistent data silos, which make the anticipated benefits difficult to realize [22]. These constraints, alongside high technical complexity, often limit the scalability of AI solutions within resource-constrained public sector environments. The organizational dimension reflects the internal conditions necessary to mobilize the technological capabilities. The existing literature suggests that leadership and sustained political support are crucial for securing the resources and legitimacy necessary that are necessary for strategic AI initiatives [19], [20]. However, AI adoption suffers when organizations have a risk-averse culture and lack the necessary staff competencies [8], [25]. Therefore, AI adoption requires robust change management (i.e., addressing the necessary cultural shift and reskilling) that can support the technical investments to turn it into an operational reality. The environmental dimension helps us position AI adoption within a broader institutional and regulatory context. For instance, national and supranational frameworks establish the ethical and legal boundaries for the use of AI [19]. This may take the form of stringent requirements for accountability and data governance. In addition to regulations, public trust in AI adoption remains a crucial external factor [27], stemming from concerns about algorithmic bias or opacity. On the other hand, competitive pressures and cross-sector partnerships also determine how public organizations develop their AI capabilities.

In sum, Table 1 shows that the three dimensions of the TOE framework are interdependent rather than isolated silos. Technological capabilities provide the functional means for AI deployment; organizational factors determine the effectiveness of implementation, while the environmental dimension describes the scope of what organizations are allowed to pursue. This integrated view is fundamental, ensuring that AI readiness is robust enough to generate meaningful public value in the context in which public organizations operate.

This study adopts the TOE framework as its model due to its proven versatility across varying organizational settings and its empirically supported ability to provide a holistic view of the factors influencing technology adoption in complex public environments [20], [23]. It directly assists in answering *RQ1* by identifying key readiness factors across these three domains, i.e., technological, organizational, and environmental. While the TOE framework provides a robust static snapshot of readiness factors, Dynamic Capability theory [18] offers a temporal and adaptive lens, essential for understanding how organizations sustain AI adoption and translate it into public value in a constantly evolving technological and societal landscape. This theory posits that organizations 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 [17], [18]. The Dynamic Capability theory highlights the importance of a public organization'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 [22]. 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 [18].

By incorporating Dynamic Capability theory, this study can explore how public organizations not only achieve initial readiness for AI (as per the TOE framework) but also how they sustain and leverage this readiness to continuously adapt, innovate, and thereby maximize public value creation over time. This dynamic perspective is particularly vital for addressing *RQ2*, which delves into how readiness factors vary and impact implementation outcomes across organizations of different sizes and environments, necessitating an adaptive approach to AI strategy and execution. Larger, more complex organizations, for instance, may require more sophisticated dynamic capabilities to manage AI integration across diverse departments and overcome entrenched legacy issues [27]. Conversely, smaller organizations might need to leverage external dynamic capabilities through partnerships to compensate for internal resource limitations. Combined application of the TOE framework and Dynamic Capability theory may provide a comprehensive and nuanced theoretical basis 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. The term "foundational readiness" has surfaced in the existing literature to describe the prerequisite technological, organizational, and environmental conditions that enable public sector organizations to engage meaningfully with AI adoption [28]. Drawing on the TOE framework and informed by empirical findings, foundational readiness in this study refers to the presence of essential infrastructure, data quality, governance arrangements, leadership support, and regulatory conditions that constitute the bare minimum conditions for AI adoption. This study, therefore, utilizes the foundational readiness concept to identify the primary conditions essential for enabling dynamic capability processes through which AI adoption is turned into public value outcomes.

To strengthen the conceptual synthesis, this study interprets the TOE framework as the structural foundations that condition the emergence and evolution of dynamic capabilities. As explained above, the TOE framework defines the contextual scaffolding (technological, organizational, and environmental) within which organizations operate. These dimensions constitute the infrastructural and institutional prerequisites that enable organizations to sense emerging opportunities, seize critical resources, and reconfigure internal routines in response to technological and societal shifts. Dynamic capabilities, in turn, influence how these structural conditions are leveraged and transformed through cycles of learning, adaptation, and reorientation. This reciprocal interaction creates a co-evolutionary mechanism in which structural readiness both enables and is reshaped by dynamic processes. Readiness, therefore, transcends a static measure of preparedness; it represents a continuous and iterative trajectory of capability renewal, institutional adaptation, and value creation that, in the context of the public organizations of Kenya addressed by this research, sustains the responsible and strategic adoption of AI in the public sector.

In summary, this study employs an integrated use of the TOE framework and the Dynamic Capabilities theory as analytical lenses to examine AI adoption in the public sector. While the TOE framework informed the identification of the factors shaping AI readiness, the dynamic capability theory was instrumental in explaining how public organizations adapt, learn, and reconfigure their resources to appropriately adopt AI. Specifically, RQ1 is addressed through the systematic identification of AI readiness factors that are rigorously mapped across the three scaffolds of the TOE framework. Furthermore, RQ2 is examined by investigating the mechanisms through which adaptive capabilities, such as organizational learning and reconfiguration, actively influence and account for the observed variations in AI readiness when contextualized across diverse public sector organizations.

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 [6]. From predictive analytics in public safety to personalized citizen services, AI delivers benefits that extend across operational efficiency, strategic policy-making, and innovative public service offerings [7], [12]. However, its adoption is often uneven across public organizations, influenced by constraints related to legacy IT systems, talent shortages, and institutional complexities unique to the public sphere [8].

The benefits of AI adoption are well-documented across the public organizational value chain. It enhances operational efficiency by automating routine tasks and predictive maintenance for public infrastructure, leading to reduced costs and waste [29]. Furthermore, AI supports strategic decision-making by enabling public bodies to glean actionable insights from vast datasets, informing policy development and resource allocation [6]. 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 [4], [22]. These include technical constraints, such as issues with data quality, infrastructural deficiencies, and cybersecurity concerns, particularly given the sensitive nature of public data [7], [12]. Organizational dynamics, including resistance to change among public servants, misaligned incentives across departments, and the inherent complexities of bureaucratic structures, also pose significant problems [8]. Finally, environmental constraints, such as stringent regulatory restrictions (e.g., GDPR, EU AI Act) [26], public scrutiny, competitive pressure from other service providers, and external resource limitations, further complicate AI adoption and trust-building in the public sphere [10].

2.3 Operationalizing AI Readiness in the Public Sector Through the TOE Lens

Organizational readiness for AI adoption in public organizations 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 [7]. Secondly, *organizational readiness* encompasses the public sector culture, staff competencies, senior management and political support, and the absorptive capacity to integrate new technologies [8]. 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 [10], [11].

The TOE framework has emerged as a leading analytical lens for evaluating organizational readiness for AI adoption, owing to its holistic treatment of both internal and external determinants [8], [13]. When applied to the public sector, the TOE model captures the multifaceted nature of readiness across three interrelated groups of factors. The technological factors encompass the quality and availability of AI infrastructure, data integrity (which is often fragmented or inconsistent in government settings), scalability of digital systems, and interoperability with legacy platforms [9]. The organizational factors include the influence of administrative culture, hierarchical structures, top management and political support, workforce competencies, and the capacity for interdepartmental collaboration, areas where a persistent digital skills gap remains a critical constraint [8]. The environmental factors extend beyond institutional boundaries to include the broader regulatory landscape (e.g., the EU AI Act), evolving public trust dynamics, citizen expectations, inter-agency cooperation, and the ecosystem of private vendors and technology partners [26]. Collectively, these groups of factors provide a comprehensive framework for understanding the systemic and contextual factors that shape AI readiness in public organizations [30]–[32].

2.4 Contextual Differences in Public Sector AI Adoption

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 [6], [9]. However, their typically hierarchical structures can sometimes impede agility, making AI implementation difficult to handle 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 localized 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 [11]. Furthermore, studies have observed that AI adoption dynamics vary across different public sector industries and functions. In highly regulated sectors such as defense or healthcare within the public domain, institutional and ethical constraints, alongside stringent data privacy requirements, often dominate the implementation landscape [8]. In contrast, in citizen-facing sectors such as 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 [10].

2.5 AI-Driven Public Value Creation

The deployment of AI within the public sector extends well beyond the pursuit of operational efficiency; it also represents a transformative avenue for generating public value [4], which aligns with three strategic pillars of public value, i.e., public value proposition, legitimacy and support, and operational capacity [15] (see also Table 2).

Beyond improving performance indicators, AI has the potential to redefine how governments design, deliver, and evaluate public services. It enhances not only efficiency and resource optimization but also inclusivity, responsiveness, and citizen engagement, which are core dimensions of public value in contemporary governance.

Empirical studies and reports from consultancy firms have shown that AI is associated with significant advancements in the efficiency and effectiveness of public service provision and optimization of resource allocation [12]. For instance, AI-driven analytics can help identify bottlenecks in service delivery, predict demand, and optimize 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 personalized services [12], [17]. Examples include AI-powered chatbots for instant query resolution and personalized public health information dissemination, improving citizen interaction with public bodies [5]. Beyond service delivery, AI empowers public organizations to optimize resource utilization critically, bolster efforts to combat fraud, and facilitate the adoption of more sustainable practices, particularly in such areas as urban planning and environmental management. AI models can analyze vast datasets to identify fraudulent activities in real-time, leading to substantial savings for the public purse [33]. In environmental management, AI can predict pollution patterns, optimize waste collection routes, and model the impact of climate change policies, contributing to a more sustainable future [21].

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 [15]. Challenges in Capturing and Measuring Public Value from AI Despite the considerable potential of AI to deliver substantial public benefits, public organizations frequently encounter difficulties in effectively measuring and capturing this value. This persistent challenge stems from a confluence of interconnected factors. One significant problem 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 [8]. 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 realization of its benefits [25]. 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 [8]. Concerns about data privacy, algorithmic bias, and the potential for job displacement contribute to this mistrust [34].

Additionally, the failure to seamlessly integrate AI into existing public process ecosystems can significantly impede value realization, particularly in environments characterized by legacy IT systems [29]. These outdated systems often lack the interoperability and computational power required to support advanced AI applications, leading to fragmented implementations and limited impact [33]. Therefore, ensuring transparency, accountability, and the proactive mitigation of algorithmic bias are not merely desirable but essential for maintaining public trust and unequivocally demonstrating ethical AI use [23]. Without these foundational elements, the full spectrum of public value from AI adoption remains elusive.

Finally, ethical readiness forms an indispensable dimension of AI adoption within the public sector. Responsible AI frameworks, such as the OECD AI Principles [35] and the EU Ethics Guidelines for Trustworthy AI [36], emphasize fairness, transparency, and accountability, principles equally relevant in African, in general, and Kenyan, in particular, public administrations. Integrating these guidelines within national digital policies can help Kenyan institutions embed “ethics-by-design” mechanisms into procurement, system design, and public oversight. Doing so aligns technological advancement with the broader normative goal of ensuring that AI enhances, rather than undermines, public trust and social equity. In practical terms, Kenyan public agencies operationalize ethical safeguards through several mandated measures. These include the requirement for mandatory privacy-impact assessments (PIAs), the imposition of model explainability requirements specifically for decisions that have regulatory implications, and the execution of periodic algorithmic fairness audits, which are often conducted in collaborative partnerships with academic institutions.

Table 2. Potential Contribution of AI in Public Value Creation

Strategic Pillars	Public value dimensions	Contributions of AI
Public value proposition	Efficiency and Effectiveness Responsiveness Sustainability Fairness and Inclusivity	AI improves service delivery through predictive analytics, automation, and optimization, enabling more timely, equitable, and sustainable public outcomes [12], [15], [17]. In areas such as healthcare, taxation, urban planning, and environmental management, AI supports outcome-oriented governance by improving decision quality and resource allocation [12], [21], [33].
Legitimacy and support	Citizen trust Transparency Accountability Ethical governance	Explainable and transparent AI systems, combined with accountability mechanisms (e.g., audits, PIAs, fairness checks), help maintain legitimacy among citizens, public servants, and political actors [23], [34]. Ethical AI frameworks and inclusive governance processes reinforce public confidence and social acceptance of AI-enabled decisions [15], [35], [36].
Operational capacity	Institutional capacity Data quality and accessibility Digital infrastructure Organizational alignment and skills	AI adoption strengthens the operational capacity of public organizations when supported by robust infrastructure, interoperable data systems, skilled personnel, and aligned organizational objectives [29], [33].

As mapped in Table 2 and discussed above, AI-enabled public value creation benefits citizens in multiple ways. However, the realization of the anticipated success depends on the simultaneous alignment of all three pillars of Moore's strategic triangle [15] (i.e., public value proposition, legitimacy and support, and operational capacity). The argument is that while AI can enhance public value outcomes through efficiency, responsiveness, and sustainability, fairness, and inclusivity, these benefits cannot be realized without the legitimacy and support founded in transparency, ethics, accountability, and citizen trust. It is also worth noting that public organizations lacking adequate operational capacity (those with weak data infrastructures, misaligned objectives, or limited employee skills) struggle to tap into the potential of AI and create tangible public value. Therefore, viewed through Moore's [15] public value conceptualization, AI in the public sector emerges not merely as a technological innovation, but as a strategic capability that must be institutionally embedded to generate enduring public value.

3 Research Methodology

This study is a part of a qualitative case study, deemed appropriate for investigating complex phenomena in real-world settings involving multiple institutional actors [26]. A single-country case study focused on Kenya allowed for an in-depth exploration of the public sector's readiness for AI adoption and the implications for public value creation. The interpretivist perspective taken enabled examining stakeholder experiences, perceptions, and interpretations, providing rich insights into the technological, organizational, and environmental factors 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 conceptualized and operationalized within the Kenyan public sector.

Semi-structured interviews were used as the primary method of data collection, offering both flexibility and depth in examining the experiences and perspectives of key stakeholders. All interview questions are available in Appendix A. A purposive sampling strategy was employed to recruit participants with recognized expertise and strategic involvement in AI policy, digital governance, and public service delivery. In total, seventeen participants were interviewed: seven from national government ministries and agencies, four from county governments, three from public sector research and training institutions, and three from international and academic policy organizations (see the details in Table 3).

Data collection was executed over five months, commencing in March 2025 and concluding in July 2025. This timeframe was strategically significant as it coincided with Kenya's intensified national digital transformation initiatives, which included the phased roll-out of national digital identity systems, accelerated public-sector cloud migration, and critical early-stage AI policy consultations. All interviews were conducted in person and lasted between 35 and 50 minutes, guided by a protocol structured around the technological, organizational, and institutional factors of the TOE framework, as well as the dynamic capability theory, and the perceived implications for public value creation. Ethical standards were rigorously observed, including obtaining informed consent, ensuring voluntary participation, and maintaining the anonymity of all responses. The complete list of interview questions is attached in Appendix A (Table A1).

Organizations in this study were categorized into two primary groups based on their functional mandates. Those under the category of regulatory include federal ministries, regulators, policy bodies, and intergovernmental organizations—including hybrid entities such as universities and UN agencies. These organizations are primarily involved in rulemaking, oversight, strategic direction, and policy formulation. On the other hand, those under the service delivery category are county governments, revenue authorities, utilities, and ICT authorities, which take the lion's share of responsibilities for the implementation and operation of AI-driven digital services. Table 3 provides an overview of our study participants, including their roles within their organizations and their functional mandates (i.e., service delivery or regulatory).

Table 3. Overview of interview participants, their roles, and corresponding organizations

ID	Role	Organization	Category
P1	Director of ICT Services	Ministry	Service Delivery
P2	Head of Government Digitization Projects	Ministry	Service Delivery
P3	Director of e-Government Services	Government Agency	Service Delivery
P4	Head of Policy & Regulations	Regulatory Body	Regulatory
P5	Director of Data Protection Compliance	Regulatory Body	Regulatory
P6	Director of ICT Services	County Government	Service Delivery
P7	Chief Information Officer	County Government	Service Delivery
P8	Head of Digital Services & Innovations	County Government	Service Delivery
P9	ICT Project Manager	County Government	Service Delivery
P10	Head of AI and Emerging Technologies Unit	Regulatory Body	Regulatory
P11	Director of Policy and Regulations	Policy Research Institute	Regulatory
P12	Head of Research and Innovation	Higher Education	Service Delivery
P13	Director of Digital Services and AI Adoption	Government Agency	Service Delivery
P14	Head of ICT Infrastructure and Services	Utility / Government Agency	Service Delivery
P15	Director, AI and Public Policy Program	Higher Education	Service Delivery
P16	Director, Innovation and AI Policy Unit	UN Agency	Service Delivery
P17	Head of Technology and Innovation	International Organization	Service Delivery

The qualitative data gathered from interviewees yielded specific and concrete examples of organizational readiness across various public sector bodies, including the implementation of departmental AI pilot programs (e.g., automated document processing systems and early-stage fraud detection models), county-level smart city deployments showcasing integrated technology use, and proactive data-cleaning initiatives explicitly aimed at improving data quality and preparing datasets for subsequent machine-learning applications. Furthermore, to enhance the robustness of the analysis, we gathered supplementary data from official government websites and policy documents, including the *Kenya National Digital Masterplan (2022–2032)* and the *Data Protection Act (2019)*. These sources were informative in providing a realistic context for the study's integrated view, which is relevant to AI adoption. These include infrastructure roadmaps (technology), institutional mandates (organization), and regulatory compliance (environment), as well as the dynamic capabilities required for adaptation during the adoption of AI. During the data analysis phase, we followed the same thematic content analysis procedure as that used for the interview transcripts. This approach was deliberate, allowing us to verify interviewee accounts against official strategic mandates. The complete list of supplementary documents used in the study is presented in Appendix B.

Thematic analysis was conducted following the six-phase process outlined by Braun and Clarke [38]. The researchers began with an intensive familiarization phase, repeatedly reading and annotating the interview transcripts to develop a deep understanding of the data. Initial codes were generated in alignment with the study's research aims and theoretical framing, and these were systematically organized into provisional themes capturing recurring ideas, relationships, and patterns relevant to AI adoption readiness. To strengthen analytical consistency, all interview transcripts were coded in NVivo 12 using a hybrid approach that integrated inductive and deductive coding. The initial codebook comprised 46 first-order codes mapped onto the TOE and Dynamic Capabilities dimensions. Through iterative comparison and refinement, these codes were consolidated into 12 second-order themes and four aggregate dimensions: technological readiness, organizational readiness, environmental readiness, and adaptive capability readiness. Each theme was subsequently defined, named, and validated for internal coherence and analytical relevance. Collectively, these themes formed a coherent interpretive narrative linking organizational readiness for AI adoption to the core elements of public value: efficiency, transparency, inclusion, and responsiveness [15]. By combining data-driven insights with a deductive orientation informed by existing literature on digital transformation and public sector innovation, the analysis achieved both empirical depth and theoretical rigor.

4 Results

This section presents the key findings derived from qualitative interviews conducted with experts across Kenya's public sector, organized in response to the study's two research questions. The analysis is structured in two parts. Corresponding to the research questions RQ1 and RQ2, the first identifies and elaborates on the principal organizational readiness factors that influence AI adoption, highlighting how these factors collectively enable or constrain the creation of public value. The second examines how readiness conditions differ across various institutional settings, specifically central ministries, county governments, and regulatory agencies, and how these contextual variations shape approaches to AI implementation and capacity development. By combining these perspectives, the results demonstrate the multidimensional nature of AI readiness in the public sector and its evolving relationship with value generation, legitimacy, and organizational transformation.

4.1 Determinants of AI Readiness and Public Value in the Public Sector

The interviews consistently revealed a set of interrelated factors that are critical to readiness for AI adoption in the public sector, aligning closely with the dimensions of the TOE framework. These factors were found to underpin the creation of public value by enhancing operational efficiency, improving the quality and responsiveness of service delivery, fostering transparency and accountability, and enabling more data-informed decision-making.

As shown in Figure 1 and discussed in the next sub-sections, technological and organizational factors, such as AI infrastructure and leadership backing, act as the important antecedents that empower Dynamic Capabilities. These capabilities, for instance, the ability to "sense" technological opportunities and "reconfigure" existing resources, enable the creation of public value. This is supported by the responses from our participants who noted that the technical ability to process data, combined with organizational agility, favorably affected service responsiveness and operational efficiency. Finally, the feedback loop from created public value back to the organization (depicted by the broken line in the figure) ensures that successful outcomes will result in institutional trust and political support necessary for sustained AI adoption in public organizations.

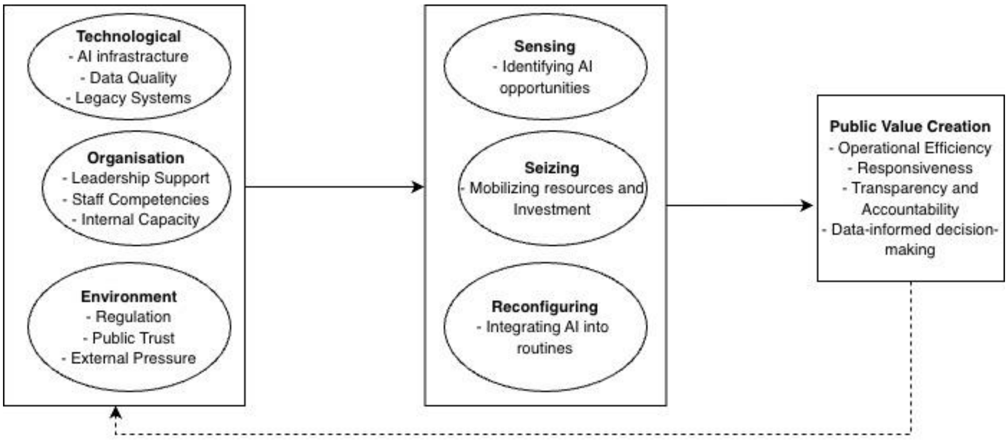

Figure 1. Graphical representation of the relationships between AI readiness factors, dynamic capabilities, and public value creation.

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 organizations 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 specialized 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 optimizing 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 Organizational Readiness

Organizational factors were consistently highlighted as pivotal, encompassing leadership support, staff competencies, organizational 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 top-level support, with direct backing from the Cabinet Secretary and inclusion of AI initiatives in our strategic plan*," backed by a "*Kenyan Shilling of 2 billion allocation* (i.e., approximately USD 12.5 million at prevailing exchange rates*)*". 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 organizations is the mixed level of AI competencies among staff. The Ministry indicated that only "*10% have advanced skills*", with ongoing training initiatives. The ODPC reported "*20% have advanced capabilities in privacy-preserving AI technique*s". Continuous investment in training, partnerships with universities, and international programs is seen as essential for addressing these skill gaps.

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

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

Our analysis indicates that organizational factors, including leadership support, staff competencies, organizational culture, and internal governance structures, play important roles in AI adoption across public organizations. Particularly, strong senior management and political backing were invaluable in supporting strategic prioritization and resource allocation. On the other hand, uneven AI capabilities among employees suggest the need for formalized training and external partnerships. Additionally, progressive organizational cultures and formalized internal governance arrangements are invaluable for managing risks, addressing resistance, and ensuring the implementation of ethically grounded AI.

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 organizations 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 its primary framework, emphasizing "*privacy by design and algorithmic accountability*" in all AI considerations. There is also a recognized desire for "*harmonized 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, emphasizes 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 organizations 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 organizations 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 organizations are identified as crucial partners. These partnerships are vital for accessing specialized 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 specialized 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 such as "*improved fraud detection*," and enable proactive service delivery by anticipating needs and preventing issues.

4.2 Variation of Readiness Factors Across Public Organizations and Implications

The interview data reveal discernible variations in AI readiness factors across public organizations, 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 Ministries versus County-Level Governments

In the technological context, the Central Ministries (e.g., Ministry of Information, Communications, and Digital Economy) possess established Cloud Infrastructure with GPU-enabled servers and high-speed fiber 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 specialized 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 organizational contexts reveals both universal and specific factors. For instance, when it comes to staff competencies, ministries reported "*only 10% 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 organizational culture and change management, while all interviewees reported generally progressive cultures, ministries and larger counties (Nairobi, Mombasa) explicitly mentioned addressing "*resistance from employees concerned about job displacement*", necessitating change management programs. Smaller or more specialized agencies, such as the ODPC, emphasized 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 organizations. For instance, central ministries and regulatory bodies, such as 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 organizations leverage external vendors. However, ministries and larger counties engage with "*international technology companies for advanced AI platforms*", while county governments often prioritize vendors who "*understand development contexts and support local capacity building*", reflecting different scales of operation and local development priorities.

4.2.2 Regulatory versus Service-Delivery Organizations

The roles and responsibilities of various public sector institutions were found to significantly shape how AI is adopted and utilized. Organizations with regulatory or oversight mandates tend to approach AI adoption with a focus on governance, compliance, and risk management, whereas service delivery entities are more inclined toward solutions that enhance operational efficiency, citizen engagement, and service quality. Consequently, institutional mandates influence not only the pace and scope of AI implementation but also the strategic priorities, resource allocation, and capacity development efforts surrounding such initiatives.

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*".

Organizational 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 organizations 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 handlin*g". Service delivery entities like Nairobi County emphasize "*improving service delivery efficiency, better resource allocation, and enhancing transparency in county operations*". This highlights how the intrinsic mission of an organization 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 organizations have significant implications for the effective implementation of AI solutions and the eventual delivery of public services. These disparities necessitate 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 instance, according to a participant from the 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: Organizations 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 prioritization: While the emphasis on data quality and standardization is universally acknowledged as critical, its specific application and prioritization vary significantly across organizations depending on their core mandate. Regulatory bodies, such as the ODPC, inherently prioritize "*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 optimize 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 pivotal, they must be meticulously complemented by targeted training programs. These programs 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 generalized approach to upskilling will be insufficient; customization is key to ensuring the 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, such as 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 recognize 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*."

4.3 The AI Readiness Trajectory Model

The study reveals that AI readiness in Kenya's public sector is a dynamic, path-dependent process rather than a fixed organizational state. Readiness is shaped by the interplay between technological, organizational, and environmental factors (consistent with the TOE framework), but also evolves through the development and recombination of capabilities over time, in line with Dynamic Capabilities theory.

Three interdependent domains underpin this evolution. Technological readiness provides the structural foundation through data infrastructure, system interoperability, and computational resources, though disparities remain across ministries, counties, and regulatory agencies. Organizational readiness, expressed through leadership commitment, governance structures, and workforce competencies, determines the extent to which technology is translated into meaningful capability. Environmental readiness, reflected in regulatory regimes, partnerships, and societal expectations, defines the enabling or constraining conditions for AI adoption.

Importantly, variations across institutional types demonstrate that AI readiness trajectories are contingent on organizational mandate and governance level. Central ministries concentrate on national coordination and infrastructure; county governments focus on context-specific service delivery; and regulatory bodies prioritize compliance, transparency, and ethical oversight. These differentiated pathways show that AI adoption and its public value outcomes depend on how institutions align their roles, resources, and learning mechanisms within their specific operational contexts.

Drawing on these insights, the AI Readiness Trajectory Model (Figure 2) conceptualizes readiness as an iterative and cumulative process comprising three overlapping phases: foundational readiness, capability development, and institutional integration. Feedback loops of learning and adaptation link these phases, illustrating that progress is non-linear and shaped by continual sense-making and capacity renewal.

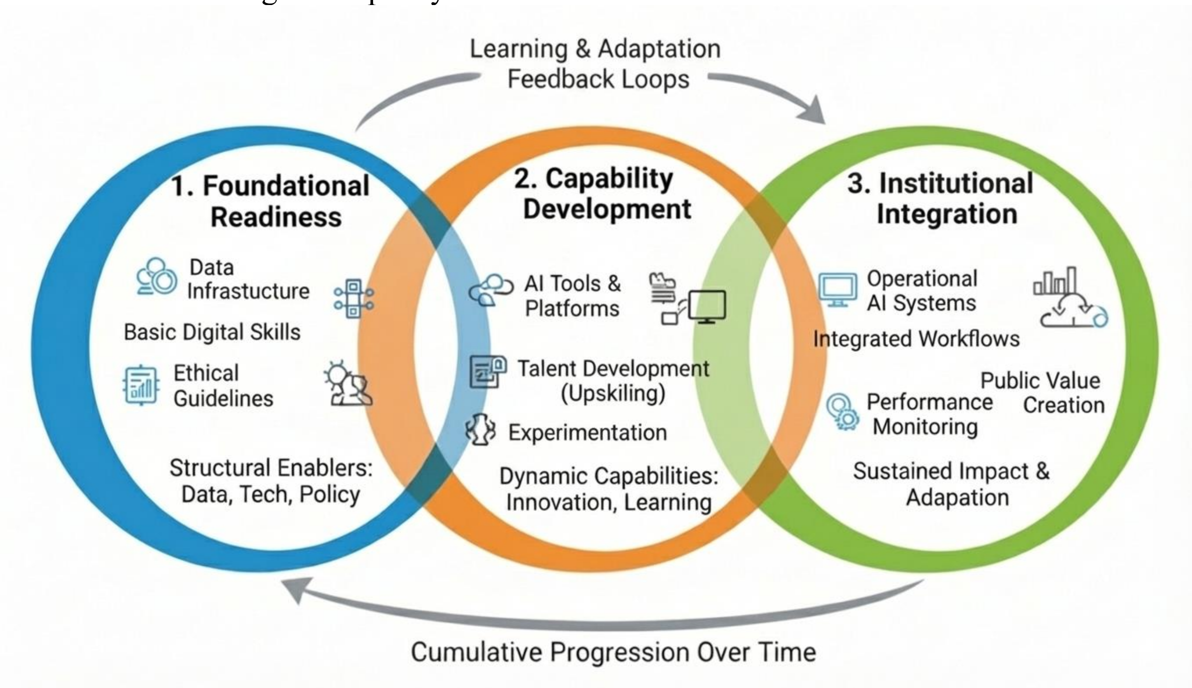

Figure 2. AI Readiness Trajectory Model

We derived the feedback loops in this framework not only from our interview responses, but also from the integrated view of TOE, Dynamic Capabilities, and Public Value Theory. For instance, a loop connects Public Value to the Environmental context, as interviews showed that "*when an AI pilot project faces public scrutiny, that feedback is used to reconfigure Ethical Guidelines*". Another loop links Institutional Integration back to the Organization, where embedding AI into routine workflows reveals human resource gaps, triggering fresh Talent Development. Finally, the Evolutionary Adaptation Loop connects Sustained Impact back to Foundational Readiness, as early successes build the legitimacy and trust needed to upgrade the Data Infrastructure for future sensing and seizing. Thus, the model visualizes how structural enablers interact with dynamic capabilities over time, demonstrating that AI readiness is not achieved through isolated interventions but through sustained organizational learning, strategic alignment, and institutional embedding. Ultimately, the model positions AI readiness as a developmental trajectory towards enduring public value creation, where digital technologies become integral to effective, legitimate, and responsive governance.

Table 4 provides descriptions of the concepts in the AI readiness and public value trajectory model (Figure 2), along with their relationships to our theoretical underpinnings, systematically mapping each concept to the TOE framework, Dynamic Capabilities theory, and Moore's [15] public value perspective. The table also shows how structural readiness conditions constitute the enabling antecedents for AI adoption and how dynamic capabilities explain organizational action and adaptation, as well as how these processes collectively result in the creation of public value. By making these relationships explicit, Table 4 ensures the transparency, coherence, and analytical validity of our proposed model.

Table 4. Theoretical grounding of concepts in the AI Readiness Trajectory Model

Concept	**Description**	**TOE Framework [19]**	**Dynamic Capabilities Theory [18]**	**Public Value Theory [15]**
Foundational Readiness	Baseline conditions enabling AI adoption	Represents core Technological, Organizational, and Environmental readiness conditions	Preconditions for capability development: sensing and mobilizing resources	Relates to the operational capacity required to create public value
Data infrastructure	Availability of data systems and architectures	Technology: data availability, interoperability	Resources enabling sensing and analytics	Relates to effective service delivery and evidence-based decision-making
Basic digital skills	Minimum workforce capabilities	Organization: human resources	Micro-foundations of learning and capability building	Supports competent and reliable public service provision
Ethical guidelines	Rules governing AI use	Environment: regulatory and normative context	Constraints shaping resizing and reconfiguring	Crucial to legitimacy, trust, and fairness
Structural enablers	Enabling conditions across systems (data, tech, policy)	Integrated TOE conditions	Resource-based for dynamic capability enactment	Institutional capacity to pursue public value
Capability Development	Organizational processes for AI experimentation and learning	Technology and Organization	Core dynamic capabilities: sensing, seizing, learning	Managerial capacity to align resources with public value goals
AI tools and platforms	Practical AI applications and systems	Technology adoption and use	Artefacts used in seizing opportunities	Instruments for improving efficiency and responsiveness
Talent development	Skill accumulation and learning (upskilling)	Organization: skills and training	Learning mechanisms underpinning capability renewal	Sustains long-term value creation capacity
Experimenta-tion	Pilots and trial initiatives	Enabled by organizational and environmental context	Crucial to sensing and seizing	Enables innovation in service design

Table 4. Continued

Concept	Description	TOE Framework [19]	Dynamic Capabilities Theory [18]	Public Value Theory [15]
Dynamic capabilities	Adaptive organizational processes (innovation, learning)	Not explicit in TOE; complements it	Core theoretical foundation	Continued strategic alignment of action with public value
Institutional Integration	Embedding AI into routine operations	Outcome of aligned TOE dimensions	Reconfiguring resources and processes	Translation of capability into sustained public value
Operational AI systems	AI embedded in daily workflows	Technology institutionalization	Result of successful reconfiguration	Delivers efficient and reliable services
Integrated workflows	Alignment of AI with organizational processes	Organization: structure and routines	Reconfiguration of organizational processes	Improves service quality and consistency
Performance monitoring	Ongoing assessment of AI impact	Organization and Environment: accountability	Learning feedback loops	Accountability and value assessment
Sustained impact	Long-term use and evolution of AI (adaptation)	Stable TOE alignment over time	Continuous renewal of capabilities	Enduring public value outcomes
Public Value Creation	Societal and organizational benefits	Result of effective TOE alignment	Outcome of successful dynamic capability enactment	Core goal: efficiency, trust, legitimacy, fairness
Learning and adaptation	Iterative refinement over time (feedback loops)	Environmental and organizational feedback	Reinforces sensing and reconfiguring	Maintains legitimacy and support
Cumulative progression	Evolutionary adoption trajectory over time	TOE conditions evolve dynamically	Path-dependent capability development	Sustainable public value creation

5 Discussion and Conclusion

5.1 Discussion

This study explored organizational readiness for AI adoption in the public sector in Kenya, examining its role in public value creation and how readiness factors vary across contexts. The findings validate the utility of the TOE framework [19], augmented by Dynamic Capability Theory [18], for understanding AI readiness and its impact on public value creation.

Technological readiness of the TOE framework emerged as a foundational dimension of AI adoption, with advanced infrastructure, high-quality data, and interoperable systems serving as indispensable prerequisites for effective integration [22]. Organizations possessing robust cloud infrastructure and mature data management systems were notably better positioned to automate services, support evidence-based policymaking, and foster innovation across administrative functions. These technological assets not only enhance operational efficiency and service responsiveness but also strengthen institutional capacity for learning and adaptation, which are core elements of digital governance maturity. This pattern resonates with prior research linking data infrastructure and interoperability to higher levels of AI maturity and government effectiveness [21], [25], underscoring that technological readiness constitutes both a structural enabler and a strategic capability in the evolution of public sector digital transformation.

Organizational readiness of the TOE framework proved decisive, encompassing leadership commitment, employee capabilities, and institutional culture. Strong top management support emerged as a critical enabler for mobilizing resources and legitimizing AI initiatives [7]. Yet, persistent skill shortages and cultural resistance (particularly concerns over job displacement) reflected enduring challenges characteristic of the public sector [25]. As emphasized in [19], absorptive capacity plays a pivotal role in enabling organizations to recognize, assimilate, and apply new knowledge. This capacity was evident as public agencies engaged in learning through external partnerships, collaborations with universities, and pilot projects to develop contextually relevant AI solutions. Such adaptive learning processes align with findings on dynamic learning and capability renewal within digital governance [20], underscoring that sustained readiness for AI depends not only on formal structures but on an organization's capacity to internalize and institutionalize innovation.

Environmental readiness of the TOE framework exerted a critical influence on AI adoption, shaping both the opportunities and constraints within which public organizations operated. Evolving regulatory frameworks, such as *The Data Protection Act*, played a dual role—establishing essential safeguards for responsible innovation while simultaneously introducing compliance-related complexities [9], [25]. Heightened citizen expectations for fairness, transparency, and privacy further reinforced the centrality of trust as a cornerstone of legitimate public value creation [15]. In this context, collaborative ecosystems involving academia, startups, and industry partners emerged as pivotal enablers, bridging internal capability gaps and fostering knowledge exchange [17]. These inter-organizational partnerships exemplify the increasingly networked nature of digital governance, where readiness is collectively constructed through shared learning, policy coordination, and cross-sector innovation.

The findings further reveal that AI readiness factors varied markedly across public organizations, reflecting differences in scale, mandate, and institutional context. Larger, central government ministries possessed substantial digital infrastructure and policy coordination capacity but were constrained by entrenched legacy systems and bureaucratic rigidity, echoing prior findings that organizational scale can impede agility and innovation [6]. In contrast, smaller, decentralized entities such as county governments demonstrated greater flexibility and adaptability, yet faced acute resource limitations, often compensating through external partnerships and modular, cost-effective solutions [11]. AI strategies were thus highly contextualized: urban counties prioritized *Smart City* initiatives to address mobility and service delivery challenges, while coastal administrations focused on *tourism and port management* applications. These patterns underscore the context-dependent and path-specific nature of public value creation, where institutional readiness and strategic priorities are shaped by local needs, developmental goals, and governance capacity.

The analysis also highlights clear distinctions between regulatory and service delivery organizations in their approaches to AI adoption. Regulatory bodies, such as ODPC, prioritized *data privacy, transparency,* and *algorithmic explainability*, reflecting their normative governance mandates and alignment with broader accountability and ethical oversight frameworks [34]. By contrast, service delivery entities emphasized the operational and performance-oriented benefits of AI, such as *efficiency gains*, *improved responsiveness*, and *enhanced citizen satisfaction*. These variations underscore the importance of differentiated AI adoption strategies, as organizational environments necessitate distinct configurations of dynamic capabilities and governance arrangements [8]. AI readiness, therefore, emerges not as a fixed condition but as a dynamic, contextually contingent capability that evolves through continuous learning and adaptation. Integrating the TOE framework with a Dynamic Capabilities perspective offers a more nuanced understanding of this evolution, emphasizing that for public sector organizations to fully realize AI's transformative potential, their strategies must remain adaptive, inclusive, and grounded in their specific institutional and operational realities.

The empirical findings delineate specific causal pathways that link AI readiness factors directly to the achievement of enhanced public value. For instance, targeted investments in staff competencies are shown to enable the necessary experimentation and iterative refinement of newly implemented AI systems, which subsequently translates into a measurable improvement in public service responsiveness. Concurrently, the establishment of enhanced data governance mechanisms directly leads to an increase in decision-making accuracy, thereby serving to strengthen and uphold citizen trust in public services.

In comparison with other AI readiness models for the public sector, our proposed model contributes by moving beyond TOE-only analysis [39]. We recognize that TOE-based studies (e.g., [20], [40] identify structural determinants of AI adoption. However, these models conceptualize AI readiness as a static configuration of technological, organizational, and environmental factors, paying limited attention to how public organizations actively mobilize these conditions over time [40], [41]. Other models [42]–[44] are developed based on specific factors of AI readiness in organizations, including human resource management, knowledge management, or the role of particular stakeholder groups in AI adoption. Moreover, AI readiness indices and maturity models operationalize AI readiness as a sum of scores or a staged progression, focusing on infrastructure, skills, and governance indicators [45]. On the other hand, these studies seem to underestimate the organizational processes through which AI is leveraged to create public value [45], [46].

In summary, we argue that our model is consistent with studies that call for integrative theorization in AI readiness studies within the public sector [45], [47]. The proposed model integrates the TOE framework with Dynamic Capabilities theory and Moore's [15] conceptualization of public value. Our approach, thus, reconceptualizes AI adoption as a dynamic, capability-driven trajectory rather than a static state of readiness. By positioning sensing, seizing, and reconfiguring capabilities [18] as the means through which public organizations navigate political discourse, policy formulation, economic instability, legitimacy demands, and competing public value demands, the model provides explanations for a process-oriented understanding of AI adoption and public value creation over time.

5.2 Contributions to Research and Practice

This study makes several contributions to the growing body of research on AI in the public sector and provides actionable insights for policymakers.

In terms of research, firstly, the study provides an empirically grounded, multi-dimensional analysis of organizational AI readiness through an integrated TOE and Dynamic Capability lens in a particular country. This integrated view not only identifies pivotal readiness factors but also captures the dynamic, adaptive processes essential for sustained public value creation, thereby extending the limitations of more static models of technology adoption. Secondly, the study introduces a comparative perspective on AI readiness. It illuminates how organizational size, functional mandate (e.g., regulatory vs. service delivery), and specific environmental contexts mediate the expression and impact of readiness factors. This comparative perspective addresses a notable gap in existing literature, which often overlooks contextual variation within the public sector, assuming a more uniform adoption model [39]. Thirdly, the proposed framework fills a critical gap in extant literature by presenting a structured, three-stage trajectory that is considered to be a departure from discussions of public administration as a regulator to an increasingly active user of AI [41], [47]. Even though there were calls for theoretical frameworks to bridge organizational capabilities with AI adoption [45], [48], this model is novel in bringing the Dynamic Capabilities theory with the aim of Public Value Creation [45]. For instance, by centering "Dynamic Capabilities: Innovation, Learning" within the second stage and "Public Value Creation" in the third, the model operationalizes Moore's [15] strategic triangle within the TOE context. Furthermore, the model highlights the "Cumulative Progression Over Time" and "Learning and Adaptation Feedback Loops," which respond to scholars' calls to integrate absorptive capacity and path dependency from previous digital transformation initiatives into AI adoption [45].

For practitioners and policymakers, this study provides actionable guidance for advancing effective AI adoption and maximizing public value in the public sector. It strongly advocates for the development of differentiated AI strategies that are acutely attuned to the unique institutional mandates, capacities, and governance environments of individual public entities. This necessitates a deliberate shift away from *one-size-fits-all* approaches towards context-specific and adaptive solutions that align with organizational objectives and operational realities. Moreover, the findings call for a reconfiguration of public sector training programs to build domain-specific AI competencies, moving beyond general literacy initiatives to cultivate specialized expertise relevant to distinct service domains. The study further highlights the strategic importance of cross-sectoral partnerships (particularly with academia and private technology providers) as a means of bridging resource and capability gaps. Finally, it underscores the critical need to embed ethical safeguards and transparency mechanisms within all AI systems to maintain public trust and ensure accountability, thereby reinforcing legitimacy and confidence in AI-enabled governance. A further contribution lies in linking AI readiness to responsible governance. By identifying ethical capacity and algorithmic accountability as integral elements of readiness, the study broadens prevailing frameworks that often overlook normative and societal considerations (e.g., [20], [40], [42], [44]). Embedding ethical reflexivity into readiness assessments ensures that technological progress in the public sector remains aligned with principles of legitimacy, fairness, and citizen trust.

Based on the empirical findings, practical guidelines for public organizations can be derived, aiming to enhance their AI readiness. These include the necessity to establish a centralized AI governance framework that clearly delineates accountability mechanisms and ethical guidelines, alongside a suggestion to invest strategically in domain-specific AI capacity-building as opposed to generic training programs. Furthermore, organizations should prioritize modular, scalable AI solutions that ensure compatibility with existing legacy systems, while simultaneously working to strengthen data governance through the implementation of standardized, sector-wide interoperability guidelines. Finally, fostering cross-county collaborations is shown to facilitate the efficient sharing of both digital infrastructure and specialized technical expertise.

5.3 Limitations and Future Research Directions

We acknowledge a few limitations of our study, which in turn open promising avenues for future research. Firstly, the study concerns Kenyan public organizations only, which constrains the direct generalizability of the findings to other national contexts. While the results are analytically transferable, comparative studies across different countries could shed light on how political, economic, and cultural conditions influence AI readiness and its relationship with public value creation.

Secondly, the qualitative approach, although instrumental in generating rich and nuanced insights, inherently limits statistical generalization. Another related limitation is that while the use of purposive sampling successfully ensured the representation of perspectives from key institutional roles within the public sector, it is acknowledged that this approach may have inadvertently excluded viewpoints from smaller, rural counties or from frontline implementers. Consequently, a critical recommendation for future research is to broaden participation to explicitly capture these currently underrepresented organizational and geographical perspectives. Future research could also adopt mixed-methods or large-scale quantitative designs to validate the identified readiness factors and test their predictive influence on AI adoption outcomes across broader populations.

Thirdly, although this study integrates the TOE and Dynamic Capabilities frameworks, it does not exhaustively examine the causal interdependencies and feedback mechanisms between readiness dimensions and public value creation over time. Longitudinal studies would therefore be highly valuable for tracing how AI readiness evolves in response to shifting political priorities, budgetary constraints, and changing citizen expectations. Furthermore, future work should explore emerging readiness dimensions, such as algorithmic literacy, specialized AI ethics training, and inclusive design principles, to understand their influence on equitable and sustainable AI adoption. Investigating how marginalized communities experience or are potentially excluded from AI-enabled public services would further strengthen the normative foundations for responsible AI governance. Finally, sector-specific studies across domains such as health, education, and urban governance could reveal variations in readiness trajectories. Employing quantitative techniques, such as structural equation modeling, would enable empirical testing of the causal pathways proposed in this study, thereby extending and validating its theoretical propositions.

Declaration on the use of AI tools

The authors declare that GenAI tools and Grammarly were used solely to support language editing, including improvements to grammar, clarity, and stylistic consistency of the manuscript and figures. All research design, data collection, data analysis, result interpretation, and conclusions were conducted independently by the authors. The authors take full responsibility for the scientific content of the manuscript.

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Appendix A – Interview Guide

Table A1. Interview questions and theoretical motivation

	Interview Questions	Motivation (Relation to Theory)
Participant background (contextualization)		
1	Could you briefly describe your role and responsibilities within the organization?	Establishing the position (expertise) and organizational perspective. This also supports the interpretation of responses
2	How long have you been working here?	Provides contextual depth and experience level, relevant for interpreting, particularly organizational learning and capability development (Dynamic Capabilities)
3	What is your experience with AI or digital transformation projects in your role?	Identifies exposure to sensing, experimentation, and learning processes (Dynamic Capabilities); also contextualizes readiness perceptions
Understanding AI adoption and impact		
4	How do you understand AI and its role within the public sector?	Captures sense-making and interpretive frames shaping AI adoption (Dynamic Capabilities: sensing; Public Value orientation)
5	What AI initiatives or projects has your department implemented or attempted?	Identifies concrete AI adoption practices and maturity (TOE: technological & organizational readiness)
6	What benefits have you observed (or expect) from AI adoption?	Links AI adoption to perceived outcomes and value creation (Public Value: efficiency, service quality, responsiveness)
7	What role do you think AI can play in creating public value within your department or the wider organization?	Operationalizes public value dimensions (efficiency, trust, accountability, inclusivity)
Technological readiness (TOE – Technology)		
8	What AI infrastructure (tools, platforms, hardware) is available within your department?	Assesses technological readiness and baseline infrastructure (TOE: Technology)
9	How would you assess the quality and availability of data required for AI implementation?	Examines data readiness, interoperability, and constraints (TOE: Technology; Public value-enabling operational capacity)
10	What are the main technological constraints or limitations your department faces when adopting AI?	Identifies barriers such as legacy systems and complexity (TOE: Technology)
11	What role do external vendors or service providers play in AI adoption within your department?	Explores dependency, sourcing strategies, and capability extension (TOE: Technology; Dynamic Capabilities: seizing)
12	How do existing IT systems integrate with newer AI solutions?	Clarifies compatibility and integration challenges (TOE: Technology; Dynamic Capabilities: reconfiguration)
Organizational readiness (TOE – Organization)		
13	What is the level of support from senior management for AI adoption?	Examines leadership support and strategic alignment (TOE: Organization; Dynamic Capabilities: seizing)
14	To what extent do staff have the knowledge, training, and competencies required for AI adoption?	Assesses skills, learning, and absorptive capacity (Dynamic Capabilities; TOE: Organization)
15	How would you describe the organizational culture when it comes to accepting new technologies like AI?	Captures cultural enablers and resistance to change (TOE: Organization)
16	What internal structures (teams, policies, governance) enable AI adoption?	Identifies internal governance and coordination mechanisms (TOE: Organization; Operational capacity)
17	What are the main internal challenges or barriers you have encountered in trying to adopt AI?	Reveals organizational inertia, silos, and change-management challenges (TOE: Organization)
18	How does your organization learn from pilot projects or failed AI initiatives?	Explicitly probes organizational learning and feedback loops (Dynamic Capabilities)

Table A1. Continued

	Interview Questions	Motivation (Relation to Theory)
Environmental readiness (TOE – Environment)		
19	What role do external factors (regulation, competitive pressure, public expectations) play in AI adoption within your department?	Examines the institutional and regulatory environment shaping adoption (TOE: Environment)
20	How do partnerships with external stakeholders (vendors, NGOs, other governmental institutions) impact AI readiness?	Explores ecosystem dynamics and resource access (TOE: Environment; Dynamic Capabilities: seizing)
21	What role do legislative or institutional constraints play in shaping AI adoption?	Assesses legal, ethical, and accountability constraints (TOE: Environment; Public Value: legitimacy)
22	What changes in the external environment would enable more effective AI adoption in your department or sector?	Identifies enabling conditions and future trajectories (TOE: Environment)
AI and public value creation		
23	In your view, how does AI contribute to creating public value?	Core public value construct (efficiency, effectiveness, trust, fairness)
24	What indicators or measures are used in your department to assess the public value generated by AI?	Examines evaluation practices and performance measurement (Public Value outcomes)
25	What do you consider the biggest benefits and risks of AI adoption in the public sector?	Balances value creation with ethical, social, and legitimacy concerns (Public Value; legitimacy and support)
26	What would enable AI to have a greater role in creating long-term public value?	Probes sustainability, institutionalization, and capability reconfiguration (Dynamic Capabilities; Public Value)
27	Do you have any further thoughts or recommendations for policymakers or managers seeking to implement AI in the public sector?	Captures reflective insights and policy implications (Public Value; TOE-organization, environment)

Appendix B

Table B1. List of supplementary documents used in the study for data triangulation

	Document Name	Source / Author	Relevance to AI Readiness
1	Computer Misuse and Cybercrimes Act Amendment (2025)	Parliament of Kenya	Relates to the “Environment” and security readiness.
2	Data Protection Act (2019)	Office of the Data Protection Commissioner	The primary regulatory framework for data quality and ethics.
3	Digital Economy Blueprint (2019)	Government of Kenya	Establishes the “pillars” for a digital government (digital government, infrastructure).
4	Emerging Technologies for Kenya	Ministry of ICT	The foundational government report recommending AI adoption pathways.
5	Kenya National Digital Masterplan (2022–2032)	Ministry of ICT	Outlines the 10-year roadmap for infrastructure and digital skills.
6	National AI Strategy (2025–2030)	Ministry of ICT	Current strategic direction for AI governance.
7	Public Service Commission (PSC) Annual Reports	PSC Kenya	Provides data on workforce competencies and organizational culture in public service.