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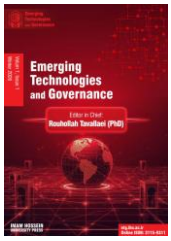

Strategic Governance of Generative AI in the Public Sector: A Grounded Theory Study

Morteza Nesari[1*] Abdul-Amir Madhi Mathkour Al-Abboudi[2]

1.Ph.D in Strategic Cultural Management, Faculty of Strategic Management, National Defense University and Higher Research Institute of Strategic Studies, Tehran, Iran, Nesari.Morteza@sndu.ac.ir
2. Assistant Professor, Al-Mustansiriyah University, Baghdad, Iraq, abdulameer@uomustansiriyah.edu.iq
Corresponding author: Nesari.Morteza@sndu.ac.ir

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ABSTRACT

The rapid expansion of Generative Artificial Intelligence (GenAI) in the public sector presents opportunities for administrative efficiency and policy innovation, yet raises complex governance challenges concerning ethics, accountability, and institutional readiness. This study aims to develop a strategic governance model for GenAI adoption and management in public-sector organizations, with Iran serving as the primary contextual anchor within a broader cross-national sample of developing administrative systems. Employing a qualitative grounded theory approach, semi-structured interviews were conducted with 22 experts, policymakers, and senior specialists selected through purposive and snowball sampling until theoretical saturation. Data were analyzed using open, axial, and selective coding procedures. The findings reveal a paradigmatic model comprising causal, contextual, intervening, core, action/interaction strategies, and consequential categories. Institutional Adaptive Capacity emerged as the core phenomenon, operationalized through three interdependent dimensions: strategic data management, algorithmic accountability, and human–machine synergy. Key driving pressures, institutional enablers, and moderating factors (trust and risks) shape strategic responses and governance outcomes. Effective GenAI governance requires a proactive, multi-level, and context-sensitive framework centered on adaptive capacity. Such a framework supports responsible innovation, mitigates institutional and ethical risks, and strengthens transparency, accountability, and public trust in AI-enabled public services.

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1. Introduction

Technological transformations over the past decade, particularly in artificial intelligence (AI), have significantly reshaped governance structures, public management, and governmental decision-making systems. The emergence of generative AI (GenAI) represents a notable shift in government–technology–society relations. With capabilities to generate text, images, code, and complex analyses, GenAI is increasingly being incorporated into policymaking, public service delivery, and large-scale data analysis in government contexts (OECD, 2024; World Economic Forum, 2024).

Despite these opportunities, GenAI also introduces substantial governance challenges. Unlike earlier AI systems that primarily supported analytical or predictive tasks, generative models can produce policy content and shape how decision makers interpret information (Reuel & Undheim, 2024). This development complicates the boundary between a "decision support tool" and a "quasi decision-making actor" within public organisations, raising concerns related to accountability, transparency, explainability, and public trust (Wirtz, Weyerer, & Sturm, 2020).

From a theoretical standpoint, governance of emerging technologies refers to the institutional, legal, and managerial mechanisms through which technological development is directed toward public values. Within this context, the concept of AI governance has gained prominence as a framework for regulating the relationship between technological innovation and societal expectations. Scholars note that AI development is not purely technical but also institutional, ethical, and political in nature (Floridi et al., 2018). Similarly, international organisations emphasise the need for comprehensive governance frameworks to ensure responsible AI use in the public sector (OECD, 2024).

As governments expand the use of AI in areas such as resource allocation, public service management, citizen engagement, and policy analysis, the lack of appropriate governance mechanisms can create institutional risks, undermine public trust, and weaken the legitimacy of administrative decisions (Valle-Cruz et al., 2020). In response, global policy discussions increasingly emphasise the importance of coordinated governance approaches and encourage governments to move toward multilevel governance frameworks that integrate policy, strategic management, and institutional oversight (World Economic Forum, 2024).

1.1 Literature Review

1.1.1 Technology Governance and AI Governance

Governance, in its broad sense, refers to the set of mechanisms through which decision-making, control, and coordination are organised within complex social systems. As governments have become increasingly digitalised over the past decade, technology governance has gained greater importance in both policy and academic debates. In this context, technology is not treated as a neutral administrative tool. Rather, it is understood as a force that can redistribute power, reshape public decision-making, and alter the boundaries between the state, the market, and civil society (Wirtz et al., 2020; Sun & Medaglia, 2019).

In the field of artificial intelligence, governance is commonly understood as an integrated arrangement that connects policy objectives, technological capabilities, and institutional responsibilities. This perspective is particularly relevant in the public sector, where governments act not only as regulators that set rules and standards, but also as users that deploy AI systems for public purposes (Choi & Park, 2023). Trust, transparency, and accountability are therefore central to AI governance, since they help preserve democratic oversight and support public acceptance of AI-enabled public services (OECD, 2024). Empirical studies further suggest that the introduction of AI into the policy cycle has changed public decision-making processes by increasing the role of data-driven analysis and real-time analytics (Valle-Cruz et al., 2020).

At the international level, governance discussions increasingly emphasise the need for multilevel arrangements capable of addressing the cross-border societal implications of AI (UN AI Advisory Body, 2024). Adaptive governance models have also been proposed as a way to respond to rapid technological change without unnecessarily constraining innovation (World Economic Forum, 2024). Alongside these broader frameworks, more operational guidance has been developed for generative AI, with particular attention to safety, transparency, and practical risk mitigation (IMDA Singapore, 2024). Taken together, these contributions suggest that AI governance is not a one-size-fits-all construct, but a context-sensitive and multilayered endeavour that must balance innovation, public value, and institutional control.

1.1.2 Strategic Governance and Government Institutional Capacity

Strategic governance lies at the intersection of strategic management and public policymaking, focusing on the capacity of governments to navigate uncertainty, balance short-term operational demands with long-term societal objectives, and maintain coherence across multiple policy domains. Research on national AI strategies shows that governance choices are often shaped by underlying public values such as equity, efficiency, and democratic participation. These values influence how governments prioritise technological development, regulate risks, and define the broader goals of AI adoption, suggesting that strategic governance is not only a technical exercise but also a normative process reflecting societal priorities (Hjaltalin & Sigurdarson, 2024).

Despite widespread rhetorical commitment to strategic governance, empirical studies point to persistent implementation gaps. Analyses of public sector AI initiatives reveal a notable distance between high-level policy ambitions and operational realities. While policy strategies frequently outline comprehensive governance frameworks, practical implementation is often constrained by fragmented data infrastructures, organisational silos, and competing institutional incentives (Helmholz et al., 2024). Another frequently identified barrier is the shortage of specialised skills within public administrations. Without sustained investment in capacity building and organisational learning, governance frameworks risk remaining largely aspirational rather than operational (Trajkovski, 2024).

To address these gaps, scholars and policymakers have proposed more flexible regulatory instruments that allow experimentation alongside oversight. One example is the use of regulatory sandboxes, which enable governments to test AI applications within controlled environments before wider deployment. Such mechanisms can help balance innovation with regulatory caution

by allowing policymakers to learn from practical experimentation while maintaining safeguards (Gonzalez Torres & Sawhney, 2023). At the same time, policy analyses suggest that many governments remain institutionally underprepared for the governance challenges posed by generative AI. Strengthening strategic capacity therefore requires not only regulatory adaptation but also improvements in foresight capabilities, inter-agency coordination, and adaptive legal frameworks (OECD, 2024). Taken together, these studies indicate that effective governance of generative AI depends less on adopting a fixed governance template and more on developing institutional agility and long-term learning capacity.

1.1.3 Artificial Intelligence in the Public Sector and Governance Challenges

The growing use of artificial intelligence in the public sector has brought forward a range of structural challenges that extend well beyond technical deployment. Early analytical work in this area identifies three core barriers that shape the success or failure of AI adoption in government: data, skills, and trust. Data-related challenges include problems of quality, availability, interoperability, and privacy protection. Skills challenges refer to the limited availability of AI expertise within public organisations, while trust challenges concern both citizens' acceptance of AI-mediated decisions and the confidence of public managers in algorithmic outputs (Sun & Medaglia, 2019).

Subsequent studies suggest that AI is also reshaping the traditional policy cycle. Processes such as agenda setting, policy formulation, implementation, and evaluation are increasingly influenced by data-driven tools and computational analysis. Although this shift creates opportunities for more evidence-based policymaking, it also introduces new governance risks. These risks include algorithmic discrimination—where automated systems reproduce or amplify existing biases—reduced accountability resulting from opaque decision-making processes, and potential erosion of public trust when citizens are unable to understand or challenge algorithmic outcomes. Without appropriate safeguards, such developments may undermine core public-sector values such as transparency, fairness, and democratic accountability (Valle-Cruz et al., 2020; Wirtz et al., 2020).

More recent research highlights that many AI implementation challenges are fundamentally linked to data governance rather than to algorithms alone. Issues such as data provenance, lifecycle management, and the ethical use of data play a central role in determining whether AI systems function effectively in public administration. This perspective emphasises that AI governance should be understood as a broader socio-technical challenge that involves organisational processes, institutional arrangements, and data infrastructures alongside algorithm design (Nikiforova et al., 2025).

1.1.4 Generative AI and the Governance Paradigm Shift

The emergence of generative AI represents a qualitative shift in digital governance rather than a simple technological upgrade. Unlike predictive or classificatory AI systems, generative models can produce new outputs—such as text, images, code, or analytical suggestions—that often resemble human reasoning or creative work. This capability introduces governance challenges that differ from earlier forms of algorithmic automation. Recent research highlights that governing such systems requires more adaptive and flexible approaches, since their behaviour can be nonlinear,

context dependent, and occasionally difficult to anticipate. Under these conditions, traditional command-and-control regulatory approaches appear less suited to technologies capable of generating evolving and emergent outputs (Reuel & Undheim, 2024).

Comparative studies further show that governance responses to generative AI vary significantly across regions. National approaches range from cautious experimentation and pilot initiatives to more proactive regulatory development, reflecting differences in legal traditions, political cultures, and institutional risk tolerance (Luna et al., 2024). Policy analyses have also identified several governance challenges that are particularly associated with generative AI systems. These include the rapid spread of misinformation through convincingly generated but inaccurate content, limited transparency due to the technical complexity of large language models, and difficulties in oversight because outputs are not always easily traceable to specific inputs or decision rules (OECD, 2024).

In response to these challenges, policy discussions increasingly emphasise the need for multilayered and participatory governance arrangements that extend beyond government institutions to include technology developers, civil society actors, and affected communities (World Economic Forum, 2024). Practical governance initiatives have begun to translate these ideas into operational guidance. For example, risk management frameworks for generative AI have been proposed that prioritise safety, transparency, and continuous monitoring throughout the lifecycle of AI systems (IMDA Singapore, 2024). At the level of citizen–government interaction, emerging evidence suggests that generative AI tools can improve service delivery by producing more personalised responses, simplifying bureaucratic language, and reducing waiting times. At the same time, these potential benefits must be weighed against risks related to exclusion, manipulation, and the erosion of human discretion, which has led international policy bodies to stress the importance of coordinated and multilevel governance mechanisms (Yun et al., 2024; UN AI Advisory Body, 2024).

1.1.5 Public Trust, Ethics, and Accountability

Public trust is widely recognised as a central pillar of sustainable AI governance. Without trust, even technically advanced AI systems may encounter resistance, non-adoption, or political contestation. A comprehensive ethical framework for AI has been developed around principles such as beneficence, non-maleficence, autonomy, justice, and explicability. These principles respectively emphasise the promotion of well-being, the prevention of harm, the preservation of human decision-making, the assurance of fairness and non-discrimination, and the need to make AI decisions understandable. Rather than functioning merely as abstract norms, these principles translate into concrete governance requirements, including ethics-based algorithmic auditing (Floridi et al., 2018).

Ethics-based algorithmic auditing has also been proposed as a practical tool for regulating AI systems. Such auditing involves the systematic evaluation of AI models against predefined ethical criteria, including bias detection, fairness metrics, and transparency checks. However, the literature also notes important limitations: audits can be gamed, may fail to capture emergent behaviours, and require continuous rather than one-off implementation (Mökander et al., 2021).

Trust is also placed at the centre of contemporary AI governance recommendations, where it is framed both as a precondition for adoption and as an outcome of responsible governance (OECD, 2024). Empirical evidence similarly suggests that national AI strategies increasingly treat public trust as a key performance indicator. Nevertheless, building trust is not automatic; it requires transparent communication, mechanisms for redress, and demonstrable accountability (Hjaltalin & Sigurdarson, 2024). From a democratic governance perspective, algorithmic augmentation has been examined in relation to its capacity to enhance democratic values and the rule of law. While AI may improve deliberation and information processing, it may also undermine procedural legitimacy if it is not carefully integrated within existing democratic checks and balances (Burgess, 2022).

1.1.6 Research Background and Development of Governance Frameworks

Building on the theoretical and empirical insights reviewed above, several integrated governance frameworks have been proposed to guide the development and use of AI in the public sector. Existing research has emphasized the need to connect policy goals, technological capabilities, and institutional arrangements in ways that are both coherent and operationally viable (Choi & Park, 2023). At the same time, the literature has pointed to a persistent gap between policy rhetoric and implementation reality, suggesting that governance frameworks are only as effective as their practical operationalisation (Helmholz et al., 2024). Attention has also been drawn to the human dimension of governance, particularly the importance of public sector skills and organisational learning, without which governance frameworks risk remaining overly abstract and detached from practice (Trajkovski, 2024).

Innovative regulatory instruments, including regulatory sandboxes and experimental governance, have also been identified as useful mechanisms for balancing innovation and control, especially in fast-moving fields such as generative AI (Gonzalez Torres & Sawhney, 2023). The ethical foundations of responsible governance frameworks have been well established in the literature, particularly through principles related to transparency, accountability, and human-centred design (Floridi et al., 2018). At the same time, recent studies have shown that adoption challenges remain complex and multidimensional, often rooted less in algorithms themselves than in broader issues of data governance, institutional readiness, and administrative capacity (Nikiforova et al., 2025).

A more critical perspective in the literature has examined automated administrative decision-making in relation to the principles of good governance, highlighting both the potential synergies and the important trade-offs involved in replacing or augmenting human decisions with algorithms. These synergies include efficiency, consistency, and scalability, while the trade-offs concern transparency, administrative discretion, and legal contestability. The literature further suggests that not all administrative decisions are suitable for automation, particularly those involving high stakes, value conflicts, or the need for empathetic judgment. This limitation is especially relevant to generative AI, which may be deployed in precisely such complex public-sector contexts (Roehl & Balle Hansen, 2024).

1.2 Research Gap

Despite the theoretical and empirical advancements summarised above, four major gaps remain in the literature, which this study aims to address.

First, there is a conspicuous absence of a comprehensive framework that simultaneously encompasses the strategic, institutional, and technological dimensions of GenAI governance. Most existing frameworks focus on one dimension – ethics, regulation, technical standards, or organisational change – without adequately integrating them (OECD, 2024b; WEF, 2024).

Second, the literature lacks in-depth qualitative studies based on the lived experiences and expertise of practitioners – managers, policymakers, and technology leads who are actively grappling with GenAI implementation in public organisations. Much of the existing work is conceptual, normative, or quantitative, leaving a gap in grounded, context-rich accounts (Helmholz et al., 2024).

Third, there has been an excessive focus on ethics and technology at the expense of strategic management and institutional capacity. While ethical principles are essential, they are not self-implementing. Questions of organisational strategy, resource allocation, capability building, and change management have received comparatively less attention (Trajkovski, 2024).

Fourth, and finally, there is an absence of context-sensitive and locally grounded models for developing countries and non-Western administrative systems. Most existing governance frameworks originate from Western, industrialised contexts and may not transfer directly to different institutional, legal, and cultural environments (UN AI Advisory Body, 2024).

To address these gaps, the present study adopts a grounded theory approach, drawing on semi-structured interviews with 22 experts, policymakers, and senior public-sector specialists from Iran, China, Malaysia, and Turkey. This cross-national design enables the development of a context-sensitive model that captures both locally specific dynamics and shared governance patterns across developing administrative systems. The aim is to develop an empirically grounded, context-sensitive model of strategic GenAI governance, identifying its core dimensions, mechanisms, and the relationships among its constituent categories.

1.3 Problem Statement

Digital transformation has reshaped how governments deliver services, make decisions, and design policy. AI has become a central transformative technology. What pushes this transformation into a new phase is GenAI – a technology that not only analyses data but produces content, generates policy suggestions, simulates scenarios, and participates in quasi decision-making (Reuel & Undheim, 2024; OECD, 2024).

This transformation blurs the traditional boundary between "technological tool" and "institutional actor". Governments face fundamental questions: how to use GenAI to improve efficiency and effectiveness without undermining transparency, accountability, fairness, and public trust? These questions are compounded by GenAI's inherent opacity, data-driven nature, and unpredictability (Floridi et al., 2018).

International reports (OECD, 2024; World Economic Forum, 2024) indicate increasing AI adoption in citizen services, policy analysis, resource management, and decision support. However, they warn that without appropriate governance frameworks, institutional risks increase, public trust weakens, and legitimacy of administrative decisions declines. Technological development without parallel governance development generates unintended consequences.

Existing AI governance literature focuses on three areas: (1) ethical issues and guiding principles (Floridi et al., 2018); (2) policy analyses and macro-level frameworks (OECD, 2024; World Economic Forum, 2024); and (3) technical and organisational challenges (Sun & Medaglia, 2019; Wirtz et al., 2020). An important gap remains: no comprehensive, integrated model systematically explains strategic governance of GenAI in the public sector. It is unclear which dimensions, components, and mechanisms at the strategic level can simultaneously ensure organisational efficiency, technological innovation, and public values.

Many existing frameworks are prescriptive or policy oriented, lacking empirical grounding in managers' and policymakers' lived experiences. Yet GenAI's complexity, dynamism, and uncertainty demand governance models that are not solely top-down but informed by real experiences. OECD (2024) and Hjaltalin and Sigurdarson (2024) likewise call for adaptive, context-sensitive approaches.

Operationally, public organisations face challenges: absence of clear algorithmic standards, difficulties evaluating algorithmic decision consequences, limited institutional capacity to oversee intelligent systems, and lack of effective accountability and transparency mechanisms (Valle-Cruz et al., 2020; Wirtz et al., 2020). Adopting new technologies without an appropriate strategic governance framework cannot yield sustainable improvements.

Thus, strategic governance emerges as a key approach balancing short-term operational objectives with long-term public governance goals. Yet it remains unclear how to operationalise this concept for GenAI and which components shape it in the public sector.

Central research question**:** What are the dimensions, components, and mechanisms of strategic governance of generative artificial intelligence in the public sector, and how do these elements interact to form a coherent and effective governance model?

To address this, the study adopts a grounded theory approach to develop, based on interviews with experts, managers, and policymakers, a context-sensitive, empirically grounded model of strategic governance of GenAI – a model that contributes to theoretical literature and provides practical guidance for responsible, transparent, trust-enhancing use of GenAI in the public sector.

2. Methods

This This study was conducted using a qualitative approach and grounded theory methodology. The main objective was to discover and explain the dimensions, components, and mechanisms of strategic governance of generative artificial intelligence in the public sector. Given the emerging nature of the topic, the complexity of the phenomenon, and the lack of a comprehensive, context-

sensitive theoretical framework, a qualitative approach enabled the researcher to examine the phenomenon from the perspectives, experiences, and interpretations of key actors.

2.1. Sampling and Participants

Participants consisted of 22 experts, policymakers, senior public managers, and specialists in public administration, digital governance, artificial intelligence, technology policy, and information systems. All participants possessed substantial professional experience related to digital transformation, AI governance, public-sector innovation, or technology policy, representing governmental organizations, policy institutions, and academic environments.

A purposive sampling strategy was initially employed to identify information-rich participants with direct expertise in AI governance and public-sector transformation. Subsequently, snowball sampling was used to identify additional knowledgeable participants and refine emerging theoretical categories. Selection criteria included relevant professional expertise, executive or policy-making experience, involvement in digital governance initiatives, and familiarity with intelligent technologies in public organizations.

Interviews continued until theoretical saturation was achieved. In this study, initial theoretical saturation was identified after the 18th interview, at which point no new substantive codes or concepts emerged from ongoing constant comparison. To confirm the stability and completeness of the evolving categories, four additional interviews (interviews 19 to 22) were conducted, which yielded no substantially new dimensions or theoretical relationships. Saturation was determined based on three criteria: (a) no new open codes appearing in two consecutive interviews; (b) no new axial categories or theoretical properties emerging; and (c) the established relationships among categories within the paradigm model remained consistent and comprehensive.

2.2. Research Context and Data Collection

Adopting a cross-national perspective, this study draws on semi-structured interviews with 22 experts from Iran, China, Malaysia, and Turkey. Iran's public sector serves as the primary contextual anchor amid its evolving GenAI governance landscape, while international expertise provides a crucial comparative dimension—enabling the study to differentiate locally specific institutional dynamics from shared patterns across developing administrative systems.

Interviews (45–85 minutes) explored participants' experiences with GenAI adoption, institutional readiness, oversight, and accountability. All sessions were audio-recorded, transcribed verbatim, and supplemented with field notes. In line with grounded theory methodology, data collection and analysis proceeded concurrently, allowing iterative theoretical sampling and continuous category refinement based on emerging insights.

2.3. Data Analysis

Data analysis exclusively followed the systematic coding procedures proposed by Strauss and Corbin (1998), which are specifically designed for building substantive theory from qualitative data in complex organizational and policy contexts. No other grounded theory traditions were employed, ensuring methodological consistency throughout the analytical process.

Analysis began with open coding, during which interview transcripts were examined line by line and meaningful concepts were identified and labeled. Through constant comparison, similar concepts were grouped into preliminary categories. During axial coding, relationships among categories were explored and organized according to the grounded theory paradigm model, including causal conditions, contextual conditions, intervening conditions, action/interaction strategies, and consequences. In the final stage, selective coding was employed to identify the core category and integrate all major categories into a coherent theoretical framework explaining the strategic governance of generative artificial intelligence in the public sector.

Throughout the analytical process, constant comparison was used to refine categories, explore variations, and ensure that the emerging theoretical model remained empirically grounded in participants' perspectives. Analytical memos were maintained to document coding decisions, theoretical interpretations, and emerging relationships among categories.

2.4. Trustworthiness

Several strategies were employed to enhance trustworthiness. Credibility was strengthened through prolonged engagement with the data, member checking, and constant comparison throughout the analytical process. Selected participants reviewed preliminary interpretations and emerging categories to assess their consistency with lived experiences. Dependability was supported through a detailed audit trail documenting coding decisions, category development, analytical memos, and methodological reflections. Confirmability was enhanced by systematic documentation of the analytical process and continuous reflection on potential researcher assumptions. Transferability was facilitated through rich descriptions of the research context, participants, and analytical procedures, enabling readers to assess the applicability of findings to other settings. Repeated examination of transcripts and iterative refinement of codes further strengthened the coherence and rigor of the final conceptual model.

2.5. Ethical Considerations

Ethical considerations were observed throughout all stages of the research. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any stage. Informed consent was obtained from all participants prior to data collection. The confidentiality of participants' identities and organizational affiliations was ensured; interview data were used solely for research purposes. To protect anonymity, identifying information was removed during transcription and analysis. The researcher also sought to represent participants' views accurately and avoid any distortion or selective interpretation of their statements.

3. Results

This section presents the findings derived from the grounded theory analysis of the interview data. The analytical process involved open, axial, and selective coding, through which concepts, categories, and relationships were systematically identified and integrated into a conceptual model of the strategic governance of generative artificial intelligence in the public sector.

Before presenting the coding structure and the resulting theoretical model, the characteristics of the study participants are summarized in Table 1.

Table 1.
Profile of Expert Participants.

Participant Code	Participant Group	Area of Expertise	Professional Experience (Years)	n	Geographic Distribution (n)
P1–P5	Senior public-sector managers	Public administration and digital transformation	> 15	5	Iran (2), China (2), Malaysia (1)
P6–P9	Policymakers and decision-makers	Digital governance and technology policy	10–15	4	Iran (2), China (1), Turkey (1)
P10–P13	Artificial intelligence specialists	AI systems, data analytics, and algorithmic applications	5–10	4	Iran (1), China (2), Turkey (1)
P14–P16	Information technology specialists	Digital infrastructure and public information systems	10–15	3	Iran (1), China (1), Malaysia (1)
P17–P19	Academic faculty and researchers	AI, public management, and public policy	> 15	3	Iran (1), China (1), Malaysia (1)
P20–P22	Technology governance researchers and consultants	Technology governance and public-sector innovation	5–10	3	Iran (2), Turkey (1)
Total	-	-	-	22	Iran (9), China (7), Malaysia (3), Turkey (3)

As shown in Table 1, the study involved 22 expert participants from four countries with diverse professional backgrounds in public administration, digital governance, artificial intelligence, technology policy, information technology, and public-sector innovation. The participants included senior public managers, policymakers, technical specialists, academic researchers, and governance consultants. This composition provided a broad range of practical, technical, and scholarly perspectives on the governance challenges and opportunities associated with generative artificial intelligence in the public sector. The diversity of participants enhanced the theoretical richness of the data and supported the development of a comprehensive grounded theory model. Critically, the analytical process drew on the full cross-national dataset, identifying governance patterns that were consistently observed across the Iranian, Chinese, Malaysian, and Turkish cases, while also attending to context-specific variations where they emerged.

The findings indicate that the strategic governance of generative artificial intelligence in the public sector is a multi-layered phenomenon shaped by causal, contextual, and intervening conditions. These conditions influence the formulation of organizational and policy strategies, which in turn lead to governance-related outcomes such as improved administrative efficiency, enhanced transparency and accountability, increased institutional adaptability, and strengthened public trust. The categorized structure of the grounded theory analysis is presented in Table 2.

Table2.
Grounded Theory Coding Structure.

Categories	Selective Codes	Axial Codes	Representative Open Codes (Examples)	In-Vivo Codes
Causal Conditions	Government digital transformation pressure	Expansion of public digital services; increasing citizens' expectations for accountability; need to optimize administrative costs; international competition in government innovation; transition toward smart government	Digital service expansion; citizen-centric governance; cost-efficiency pressures; global benchmarking; smart government vision	*"The speed of technological change has surpassed our policy-making capacity"* (P1); *"The demand for faster public services forces us to adopt AI, whether we are fully prepared or not"* (P6)
	Emergence of generative artificial intelligence in governance	Application of large language models; development of automated content-generation tools; automation of repetitive decisions; expansion of artificial intelligence APIs; role of global technology companies	LLM integration; content automation; decision automation; API ecosystems; technology provider influence	*"Traditional policy cycles simply cannot keep up with the weekly updates in generative AI capabilities"* (P17)
	Increasing complexity of policy-making issues	Multidimensionality of public problems; increasing environmental uncertainty; dependence on big data; conflict of stakeholders' interests; acceleration of technological changes	Wicked problems; environmental volatility; data-driven policy; stakeholder tensions; technological velocity	*"The multidimensionality of today's problems makes traditional policy approaches obsolete"* (P6)
Contextual Conditions	Institutional capacity of government	Maturity of digital transformation; adequacy of data infrastructures; integration of information systems; flexibility of bureaucratic structure; level of intersectoral collaboration	Digital maturity assessment; data infrastructure readiness; systems interoperability; bureaucratic adaptability; cross-agency cooperation	*"Our main problem is not the lack of technology, but the absence of coordination among existing systems"* (P14)
	Organizational culture and innovation	Level of technology acceptance; continuous organizational learning; managers' attitudes toward innovation; willingness to change; intra-organizational social capital	Technology adoption readiness; learning orientation; leadership innovation mindset; change readiness; internal trust networks	*"Our bureaucratic culture often views AI as a threat rather than an enabler"* (P2)
	Legal and regulatory framework	Absence of a comprehensive artificial intelligence law; ambiguity in data ownership and privacy; weakness of ethical	AI legislation gap; data governance ambiguity; ethics standards deficit; regulatory	*"The legal vacuum in data privacy makes every AI project a risky experiment"* (P7)

Categories	Selective Codes	Axial Codes	Representative Open Codes (Examples)	In-Vivo Codes
		standards; institutional fragmentation of regulation; absence of a conformity assessment system	fragmentation; certification gap	
Intervening Conditions	Technological and algorithmic risks	Model error; data bias; lack of algorithmic transparency; security vulnerability; dependence on foreign technology	Model accuracy concerns; algorithmic fairness; opacity challenges; cybersecurity threats; technology sovereignty issues	*"Even if the model is accurate, contaminated data can distort the entire decision"* (P11)
	Level of public trust	Institutional trust in government; concerns about digital surveillance; previous experience with electronic services; public awareness of artificial intelligence; social acceptance of innovation	Government credibility; privacy anxieties; e-service track record; AI literacy; innovation receptivity	*"Citizens are worried about who sees their data when AI processes their applications"* (P20)
	Leadership and change management capacity	Digital skills of managers; transformational leadership style; capacity for cross-level coordination; management of conflicts of interest; evidence-based decision-making	Managerial digital competency; visionary leadership; vertical coordination; conflict resolution; data-driven management	*"Without leaders who understand both tech and administration, these projects are doomed to fail"* (P3)
Core Category	Institutional Adaptive Capacity	Strategic data management; Algorithmic accountability and transparency; Human–machine synergy in decision-making	Data governance; algorithmic oversight; human-AI collaboration; adaptive governance systems	*"If the data are not correct, even the best model will make the wrong decision"* (P12); *"Algorithmic transparency is not just a technical fix; it is a political necessity for institutional trust"* (P21); *"The goal is not to replace the expert but to augment their judgment with AI-driven insights"* (P18)
Action/Interaction Strategies	Designing an artificial intelligence governance framework	Formulation of utilization policies; development of ethical guidelines; definition of transparency standards; design of a risk assessment system; establishment of internal oversight mechanisms	Policy formulation; ethics codification; transparency standards; risk management frameworks; oversight structures	*"Without clear guidelines, the use of AI in organizations creates more confusion than productivity"* (P4)
	Development of organizational capacity	Specialized training of employees; recruitment of data specialists; enhancement of managers'	Workforce upskilling; talent acquisition; digital literacy programs;	*"Investing in digital literacy programs for mid-level managers has been our highest priority"* (P15)

Categories	Selective Codes	Axial Codes	Representative Open Codes (Examples)	In-Vivo Codes
		digital literacy; establishment of a digital transformation unit; infrastructural investment	transformation units; infrastructure modernization	
	Strengthening transparency and social trust	Publication of algorithmic reports; stakeholder participation; establishment of complaint-handling mechanisms; public communication; assessment of the social impact of policies	Algorithmic transparency; citizen engagement; grievance mechanisms; public outreach; social impact assessment	*"We established a dedicated AI ethics board to review all high-risk decisions before implementation"* (P8)
Consequences	Enhancement of public governance efficiency	Reduction in decision-making time; increased analytical accuracy; optimal allocation of resources; reduction of operational costs; acceleration of public service delivery	Decision speed; analytical precision; resource optimization; cost efficiency; service acceleration	*"We measured a significant reduction in processing time for standard permits after integrating AI assistance"* (P16)
	Increased legitimacy and public trust	Citizen satisfaction; acceptance of digital services; reduction of the gap between government and citizens; strengthening of social capital; increased public accountability	User satisfaction; digital adoption; trust building; social cohesion; accountability enhancement	*"When citizens know that decisions are explainable, their trust increases"* (P5)
	Structural transformation of governance	Transition toward smart government; redefinition of the role of bureaucracy; institutionalization of data-driven decision-making; transformation of managers' roles; digitalization of processes	Smart government vision; bureaucratic role evolution; data-driven culture; managerial transformation; process digitization	*"The shift towards data-driven indicators has fundamentally changed how we evaluate department performance"* (P19)

3.1. Causal Category: Driving Pressures Shaping Generative AI Governance

Interviewees identified three simultaneous causal pressures that create the foundational need for strategic governance of generative AI in the public sector: the pressure of government digital transformation, the emergence of generative AI technologies, and the increasing complexity of policy-making issues. These factors interact to push governments toward redesigning their governance mechanisms. Beyond domestic pressures, international competition in government innovation and the global push toward smart government were also cited as influential drivers, positioning national AI strategies within a broader comparative context.

One senior manager in digital transformation (P1) explained: *"The speed of technological change has surpassed our policy-making capacity, and it is no longer possible to make decisions using traditional models."* A policymaker (P6) added: *"The demand for faster public services forces us to adopt AI, whether we are fully prepared or not."* Furthermore, an academic researcher (P17)

noted: *"Traditional policy cycles simply cannot keep up with the weekly updates in generative AI capabilities."* Alongside this, the expansion of digital services and rising citizen expectations were frequently cited as drivers pushing governments toward greater efficiency. Simultaneously, the emergence of large language models and automated content-generation tools was described as fundamentally altering the nature of administrative decision-making and introducing a new level of complexity and uncertainty into the governance system.

3.2. Contextual Category: Institutional, Cultural, and Legal Bases of Governance

Participants highlighted that the feasibility of implementing strategic GenAI governance depends significantly on institutional, cultural, and legal conditions. The institutional capacity of government—specifically digital maturity, integration of information systems, and bureaucratic flexibility—was cited as a decisive factor. Additionally, the adequacy of existing data infrastructures and the level of intersectoral collaboration across government agencies were identified as critical factors influencing institutional readiness.

An IT specialist (P14) stated: *"Our main problem is not the lack of technology, but the absence of coordination among existing systems."* Echoing this, a senior manager (P2) remarked: *"Our bureaucratic culture often views AI as a threat rather than an enabler."* Additionally, a policymaker (P7) pointed to the legal dimension: *"The legal vacuum in data privacy makes every AI project a risky experiment."* Resistance to change, lack of organizational learning, and conservative attitudes toward technology were recurrently mentioned as major cultural barriers. Furthermore, the absence of comprehensive AI laws and ambiguity regarding data ownership were frequently raised as critical legal challenges.

3.3. Intervening Category: Risks, Trust, and Leadership Capacity

Interviewees identified a set of moderating factors that shape the trajectory of governance efforts, primarily technological risks, public trust, and leadership capacity.

A data specialist (P11) emphasized data vulnerability: *"Even if the model is accurate, contaminated data can distort the entire decision."* A technology governance consultant (P20) raised concerns about social acceptance: *"Citizens are worried about who sees their data when AI processes their applications."* Moreover, a senior leader (P3) highlighted managerial gaps: *"Without leaders who understand both tech and administration, these projects are doomed to fail."* Concerns about digital surveillance, reduced transparency, and algorithmic bias were recurring themes. Interviewees consistently indicated that managers' ability to understand technology, manage conflicts, and guide organizational change plays a decisive moderating role in the successful implementation of strategic governance.

3.4. Core Category: Institutional Adaptive Capacity

The analysis reveals that the core category explaining the governance phenomenon is Institutional Adaptive Capacity, which is structured around three integrated dimensions: strategic data management, algorithmic accountability and transparency, and human–machine synergy in decision-making.

An AI specialist (P12) underscored the first dimension: *"If the data are not correct, even the best model will make the wrong decision."* A technology governance researcher (P21) addressed the second dimension: *"We realized that algorithmic transparency is not just a technical fix; it is a political necessity for institutional trust."* Regarding the third dimension, a faculty member (P18) explained: *"The goal is not to replace the expert but to augment their judgment with AI-driven insights."* The findings position data as the foundational layer of governance, while accountability mechanisms ensure responsibility in AI-based decisions. Additionally, the model places human actors as final overseers (meaningful human control), with machines functioning as analytical support systems.

3.5. Action and Interaction Strategies: Institutional Responses to Governance Demands

To realize strategic governance, participants described a set of operational strategies. These are categorized into designing comprehensive governance frameworks, developing organizational capacity, and strengthening transparency and social trust.

A manager (P4) emphasized the necessity of formal guidelines: *"Without clear guidelines, the use of AI in organizations creates more confusion than productivity."* A policymaker (P8) detailed internal oversight: *"We established a dedicated AI ethics board to review all high-risk decisions before implementation."* An IT specialist (P15) focused on human capital: *"Investing in digital literacy programs for mid-level managers has been our highest priority."* These strategies encompass formulating utilization policies, establishing oversight mechanisms, specialized training, recruitment of data specialists, algorithmic reporting, and stakeholder participation mechanisms.

3.6. Consequences: Efficiency, Trust, and Structural Transformation

Interviewees reported that the successful establishment of strategic GenAI governance yields multiple outcomes across operational, social, and structural levels.

A senior official (P5) described the social outcome: *"When citizens know that decisions are explainable, their trust increases."* An IT specialist (P16) provided an operational metric: *"We measured a significant reduction in processing time for standard permits after integrating AI assistance."* An academic (P19) observed the structural shift: *"The shift towards data-driven indicators has fundamentally changed how we evaluate department performance."* The findings identify enhanced governance efficiency (reduced decision-making time, increased analytical accuracy, resource optimization), increased public legitimacy (citizen satisfaction, social capital), and deep structural transformation (movement toward smart government, redefinition of bureaucratic roles, and digitalization of core processes)

3.7. Summary of Findings

The paradigmatic model of strategic GenAI governance in the public sector is structured around the core category of **Institutional Adaptive Capacity**. Causal pressures—including digital transformation, technological emergence, and policy complexity—operate within enabling or constraining contextual conditions (institutional, cultural, and legal). These dynamics are further moderated by intervening conditions such as algorithmic risks, public trust, and leadership

capacity. In response, institutions deploy specific action/interaction strategies, encompassing governance frameworks, capacity-building, and trust mechanisms. The successful application of these strategies leads to the consequences of enhanced efficiency, public trust, and structural transformation. Figure ١ presents the final visual representation of this model, illustrating how the core category and its dimensions integrate these diverse conditions and strategic responses into a coherent framework for governance.

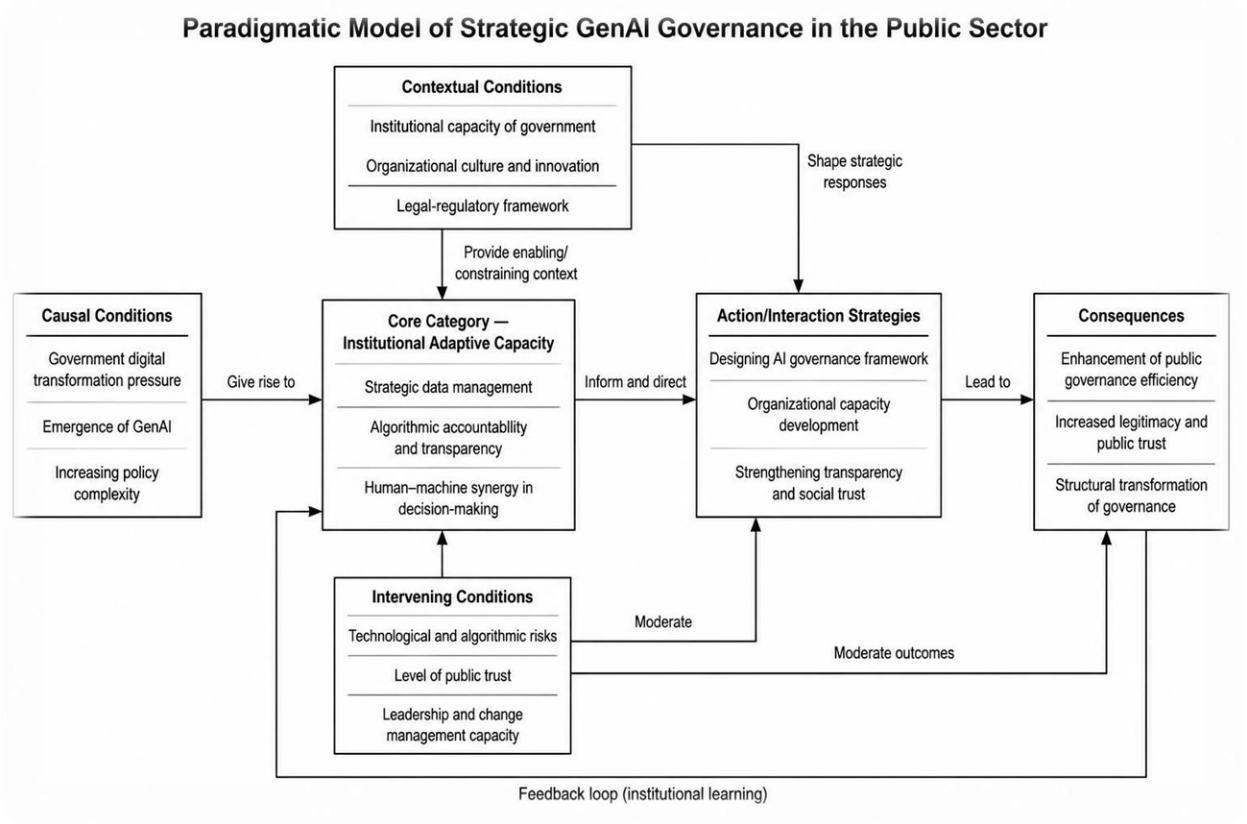

Fig. 1. paradigmatic model of strategic GenAI governance in the public sector.

4. Discussion

4.1. Theoretical Implications of the Paradigmatic Model

The paradigmatic model developed in this study advances the theoretical understanding of GenAI governance by conceptualizing it not as a static policy framework but as a dynamic, multilayered process of institutional adaptation. The findings indicate that the three causal pressures—digital transformation demands, the emergence of GenAI technologies, and policy complexity—do not merely create a need for new regulations; rather, they fundamentally disrupt the traditional bureaucratic logic of rule-based, hierarchical decision-making. This disruption compels public organizations to develop what we term Institutional Adaptive Capacity as the core category of governance response.

This conceptualization extends prior scholarly work that has primarily framed AI governance through ethical principles or technical standards. While such frameworks are valuable, they often

assume a stable institutional environment capable of implementing normative guidelines. The present study, however, reveals that in contexts where institutional infrastructures are still evolving, the core governance challenge is not the mere adoption of principles but the construction of organizational capacities to manage uncertainty, algorithmic fallibility, and rapid technological obsolescence. The interaction between contextual conditions (institutional maturity, culture, legal frameworks) and intervening factors (risks, trust, leadership) further shapes this capacity, suggesting that adaptive governance is inherently contingent and path-dependent. This finding challenges static, one-size-fits-all policy models and supports a processual view of governance as continuous institutional learning and recalibration.

4.2. A Context-Sensitive Innovation: Comparative Analysis with Western Governance Frameworks

One of the principal claims of this study is the development of a context-sensitive governance model for non-Western administrative systems. To substantiate this claim, it is necessary to explicitly compare the proposed framework with prominent Western models, particularly the European Union's AI Act and the OECD AI Principles.

The EU AI Act adopts a predominantly risk-based regulatory approach, categorizing AI applications into unacceptable, high, limited, and minimal risk, with legally binding obligations primarily focused on providers and deployers. Its logic is compliance-driven and ex-ante, relying on the existence of robust legal infrastructures, mature oversight bodies, and well-established market mechanisms. Similarly, the OECD framework emphasizes transparency, explainability, and human-centered values as overarching normative pillars, often presupposing high institutional trust and digital literacy.

By contrast, the model derived from this study reveals several distinct characteristics that render it specifically sensitive to non-Western public-sector contexts. Critically, these characteristics emerged consistently across the cross-national sample—comprising experts from Iran, China, Malaysia, and Turkey—indicating shared governance challenges among developing administrative systems, while simultaneously allowing for the identification of context-specific variations.

First, governance as capacity-building rather than compliance-driven regulation. While Western frameworks prescribe what organizations must do through legally binding obligations, our findings emphasize what they must be able to do. In the absence of comprehensive national AI laws—a condition explicitly noted by participants from Iran, Malaysia, and Turkey—the core governance mechanism shifts from legal enforcement to institutional capacity development. As one senior public manager from Iran observed: "Our main problem is not the lack of technology, but the absence of coordination among existing systems" (P2). A policymaker from Malaysia similarly noted: "We have the political will, but we lack the institutional scaffolding to translate principles into practice" (P8). This capacity-first orientation represents a fundamental departure from the compliance-driven logic of Western frameworks.

Second, the primacy of human–machine synergy over full automation. Western policy discourses frequently oscillate between promoting automation for efficiency gains and demanding human

oversight for ethical compliance. Our findings, however, indicate that in non-Western public sectors, "meaningful human control" is not merely a safeguard but an operational necessity. Given the contextual constraints of data fragmentation, infrastructural disparities, and rapid technological dependency on foreign providers—conditions widely reported by participants across all four countries—the role of human experts becomes indispensable for validating algorithmic outputs and maintaining institutional legitimacy. An Iranian AI specialist explained: "Even if the model is accurate, contaminated data can distort the entire decision" (P11). A Turkish policymaker echoed this concern: "We cannot trust algorithmic outputs blindly; our data systems are too fragmented" (P7). This positions human–machine synergy as a strategic governance pillar rather than a supplementary ethical afterthought—a distinction that reframes the governance challenge from "human-in-the-loop" (implying constraint) to "human-plus-machine" (implying augmentation).

Third, institutional architecture over technological fixes. Whereas Western models frequently emphasize algorithmic auditing, transparency checklists, and technical conformity assessments, the contextual conditions identified in this study—such as the "absence of coordination among existing systems" and "ambiguity in data ownership"—highlight that the fundamental governance barriers in non-Western contexts are primarily institutional rather than technical. An IT specialist from China observed: "Our systems were never designed to talk to each other; interoperability is our biggest bottleneck" (P15). A senior Iranian manager similarly noted: "Our bureaucratic culture often views AI as a threat rather than an enabler" (P2). The cross-national comparative dimension confirmed that these architectural deficits are not unique to Iran but represent shared challenges across Malaysia and Turkey as well, thereby underscoring the necessity of an institution-first governance logic.

Fourth, public trust as a structural intervening condition rather than a background variable. In established Western democracies, public trust is often treated as a relatively stable contextual factor. In this study, however, trust—alongside its associated concerns about digital surveillance, algorithmic bias, and social exclusion—emerged as a powerful intervening condition capable of derailing governance efforts regardless of technical sophistication. A technology governance consultant from Turkey explained: "Citizens are worried about who sees their data when AI processes their applications" (P20). An Iranian academic similarly noted: "Previous negative experiences with digital services have made our citizens skeptical of any new technology" (P18). A Malaysian policymaker added: "Building public confidence is not a one-time campaign; it requires sustained transparency and accountability" (P9). These findings reflect the socio-political sensitivities of transitioning societies where state-citizen relationships are historically complex, and where trust cannot be assumed.

In summary, while Western frameworks provide essential normative aspirations and valuable benchmarks, they presuppose institutional conditions—legal clarity, infrastructural integration, mature oversight bodies, and high social trust—that cannot be assumed in developing contexts. The proposed model contributes a systemic, institution-first perspective that addresses the unique interplay of legal ambiguity, infrastructural fragmentation, and expert dependency characteristic of non-Western public sectors. By grounding these distinctions in empirical evidence drawn from a cross-national sample (Iran, China, Malaysia, and Turkey), the model offers a contextually

grounded and practically actionable governance paradigm—one that acknowledges the shared realities of developing administrative systems while remaining adaptable to their evolving institutional capacities.

4.3. The Core Category and Its Dimensions: Unpacking Institutional Adaptive Capacity

The core category—Institutional Adaptive Capacity—is not a monolithic construct; rather, it is operationalized through three interdependent dimensions that together constitute its empirical and analytical substance. The identification of this capacity as the core category offers a theoretical synthesis that goes beyond the fragmented literature on 'data-driven governance' or 'algorithmic management.' These three dimensions are:

Strategic Data Management: As the findings show, data is not merely an input but the foundational layer of governance. In the absence of integrated databases and standardization, algorithmic outputs become unreliable. This dimension extends the concept of "data governance" beyond technical stewardship to include institutional mechanisms for data lifecycle management, accessibility, and quality assurance. The theoretical implication is that data management in the public sector is inherently a political and administrative act, not just a technical one.

Algorithmic Accountability and Transparency: Unlike private-sector applications, public-sector algorithmic decisions are subject to democratic scrutiny and legal contestation. The findings reveal that without explainability and clear legal responsibility, GenAI adoption risks eroding institutional legitimacy. This dimension aligns with the broader accountability literature but contextualizes it within the novel environment of probabilistic generative models, where assigning causality for automated decisions remains a persistent challenge. The model suggests that accountability must be embedded through continuous monitoring, auditing, and performance evaluation, rather than relying solely on pre-deployment compliance checks.

Human–Machine Synergy in Decision-Making: This dimension challenges techno-centric narratives that equate AI governance with automation. The findings empirically demonstrate that public-sector experts do not see machines as substitutes but as analytical complements. This synergy involves cognitive division of labor, where machines process patterns and probabilities while humans provide contextual judgment, ethical reasoning, and final oversight. Theoretically, this reframes the debate from "human-in-the-loop" (which implies constraint) to "human-plus-machine" (which implies augmentation), fostering a collaborative governance paradigm.

4.4. Strategic Action/Interaction Strategies and Governance Consequences

The action/interaction strategies identified—designing AI governance frameworks, developing organizational capacity, and strengthening transparency and trust—constitute the operational mechanisms through which Institutional Adaptive Capacity is enacted. The findings indicate that these strategies are not sequential but iterative and reinforcing. For instance, publishing algorithmic reports (transparency) can simultaneously enhance public trust and inform the continuous refinement of governance frameworks.

The consequences of successfully implementing these strategies—enhanced efficiency, increased legitimacy, and structural transformation—confirm that GenAI governance is a transformative

force capable of reshaping public administration. However, it is crucial to note that these consequences are conditional. Without adequate attention to intervening factors such as leadership capacity and risk mitigation, the same technological forces that enhance efficiency can also amplify biases, erode trust, and create new accountability gaps. This observation aligns with the established understanding of technology as a double-edged instrument in public governance and underscores the need for balanced, risk-aware governance strategies.

4.5. Significance and Contributions to Theory and Practice

The primary contribution of this study is the provision of an empirically grounded, integrative theoretical model that explains how and under what conditions strategic GenAI governance emerges and functions in the public sector. By shifting the focus from normative prescriptions to analytical descriptions derived from expert practice, the model bridges the gap between abstract AI ethics and practical public-sector realities.

Practically, the study offers actionable insights for policymakers. It argues that investments in GenAI should be preceded by institutional readiness assessments, cultural change programs, and legal gap analyses. Moreover, the emphasis on human–machine synergy suggests that public organizations should prioritize upskilling their workforce to work alongside AI, rather than focusing solely on procurement of advanced technologies. For developing countries, the model provides a strategic roadmap that prioritizes capacity-building over premature regulatory mimicry.

4.6. Limitations and Future Research Directions

Despite its contributions, this study has several limitations that must be acknowledged. First, as a qualitative grounded theory study, the findings are interpretive and contextually grounded, thus not intended for statistical generalization. The model should be viewed as an analytical framework for understanding processes, not a predictive instrument. Second, the reliance on expert interviews, while methodologically appropriate for exploring emergent phenomena, means that the perspectives of citizens, frontline service providers, and external private-sector actors are underrepresented. Future studies could employ surveys or mixed-method designs to validate the relationships identified here across larger and more diverse populations.

Third, the rapidly evolving nature of GenAI technologies represents a dynamic limitation. The governance challenges and strategies identified in this study are likely to evolve as models become more sophisticated, regulatory frameworks mature, and public expectations shift. Therefore, the proposed model should be treated as a living framework requiring periodic re-examination. Fourth, the study is confined to the public sector; the applicability of the findings to hybrid or private governance arrangements warrants further investigation. Finally, comparative cross-national studies are essential to test the context-sensitivity claims of the model. Examining how Institutional Adaptive Capacity varies across different administrative traditions, legal systems, and levels of technological infrastructure would significantly enhance the external validity and theoretical refinement of the proposed framework.

5. Conclusions

This study concludes that the strategic governance of generative artificial intelligence (GenAI) in the public sector constitutes a multilayered and systemic phenomenon shaped by the simultaneous interaction of technological, institutional, and human dimensions. Importantly, the empirical grounding of this model in a cross-national sample—comprising experts from Iran, China, Malaysia, and Turkey—reinforces its transferability and contextual robustness. While Iran served as the primary contextual anchor, the shared governance challenges identified across these diverse developing administrative systems suggest that the proposed framework offers practical relevance beyond a single national context, providing a strategic roadmap for capacity-building in similarly transitioning societies. Through a systematic grounded theory analysis based on the Straussian paradigm model, six interrelated categories—causal conditions, contextual conditions, intervening conditions, core category, action/interaction strategies, and consequences—were identified and integrated into a coherent conceptual framework. Together, these categories explain not only why strategic governance of GenAI emerges, but also how it is structured, operationalized, and institutionalized within public administration.

At the level of causal conditions, three primary driving forces were identified: the accelerating digital transformation of government, the emergence and diffusion of generative AI technologies, and the growing complexity of public policy problems. These forces collectively exert structural pressure on governments to reconsider traditional governance mechanisms. The findings suggest that GenAI does not merely enhance existing administrative processes; rather, it disrupts established decision-making logics by introducing probabilistic, adaptive, and data-intensive systems into public governance. As citizens' expectations for efficiency, responsiveness, and transparency increase, public institutions are compelled to redesign governance architectures capable of managing algorithmically mediated decision environments.

Contextual conditions—including institutional capacity, organizational culture, and legal-regulatory frameworks—were found to play a decisive role in shaping the feasibility and effectiveness of GenAI governance. Institutional maturity, digital infrastructure integration, bureaucratic flexibility, and regulatory clarity significantly influence whether strategic governance initiatives can be successfully implemented. The study demonstrates that technological capability alone is insufficient; governance outcomes are deeply contingent upon the broader administrative and normative environment within which GenAI systems are embedded. In this sense, strategic governance is fundamentally context-sensitive and cannot be detached from institutional realities. The cross-national dimension of this study further revealed that while each country exhibits unique institutional characteristics, the underlying structural challenges—such as fragmented data systems, bureaucratic rigidity, and regulatory ambiguity—are remarkably consistent across developing administrative systems.

The intervening conditions—namely technological risks, public trust, and leadership and change-management capacity—function as moderating variables that either facilitate or constrain implementation. The findings indicate that risks such as algorithmic bias, data quality deficiencies, model opacity, and cybersecurity vulnerabilities can undermine governance efforts if not

proactively managed. Simultaneously, public trust emerges as a central legitimacy resource: without transparency and explainability, algorithmic decision-making may generate skepticism and resistance. Leadership capability further determines whether institutions can navigate uncertainty, coordinate stakeholders, and sustain adaptive reform processes. Importantly, the study reveals that even robust infrastructures and formal frameworks cannot ensure success in the absence of trust-building and risk governance mechanisms. These intervening factors were consistently emphasized by participants across all four countries, underscoring their universal relevance in non-Western governance contexts.

At the core of the model lies the category of Institutional Adaptive Capacity, which represents the central explanatory construct of strategic GenAI governance. This capacity is operationalized through three interdependent dimensions: strategic data management, algorithmic accountability and transparency, and human–machine synergy in decision-making. Data is conceptualized not merely as an operational input, but as a governance infrastructure requiring regulation, quality assurance, and stewardship. Algorithmic accountability—including explainability, traceability, and responsibility allocation—emerges as essential for maintaining democratic oversight in AI-mediated decisions. Furthermore, human–machine synergy is framed as a structural necessity rather than a technical option. The findings indicate that meaningful human oversight stabilizes governance processes by balancing algorithmic efficiency with normative judgment and public accountability. Together, these three dimensions constitute the institutional backbone through which public organizations develop and sustain their adaptive capacity in response to GenAI challenges. The cross-national evidence confirmed that this tripartite structure is not idiosyncratic to Iran but represents a coherent governance logic observable across the sampled developing countries.

At the level of action/interaction strategies, public organizations respond to these conditions through the design of comprehensive AI governance frameworks, capacity-building initiatives, and mechanisms for enhancing transparency and social trust. These strategies operate as mediating instruments that translate contextual conditions into tangible governance outcomes. The study highlights that governance frameworks must integrate policy guidelines, technical standards, oversight bodies, and ethical safeguards, while simultaneously investing in organizational learning, digital literacy, and interdisciplinary collaboration. In doing so, institutions can align technological innovation with public values and strengthen their overall adaptive capacity. The comparative analysis further suggests that these strategies, while locally adapted, share common foundational principles that can inform a generalizable governance roadmap for developing countries.

Finally, the consequences identified in this study extend beyond improvements in administrative efficiency. While reduced decision-making time, enhanced analytical accuracy, and optimized resource allocation are important outcomes, the more profound impact lies in the structural transformation of public governance. The integration of GenAI contributes to redefining bureaucratic roles, reshaping authority structures, and embedding algorithmic systems into the architecture of public decision-making. Governments increasingly transition from traditional service providers to orchestrators of data and AI ecosystems. This transformation requires

rethinking classical concepts of legitimacy, accountability, and control in light of algorithmic power. Moreover, these consequences are not unidirectional; they reinforce the institutional adaptive capacity by creating feedback loops that inform continuous learning and policy refinement.

In sum, this study concludes that the strategic governance of generative artificial intelligence is not a static policy choice but an evolving institutional process. It unfolds at the intersection of innovation and public value, efficiency and legitimacy, automation and human oversight. By offering a grounded and integrated framework centered on Institutional Adaptive Capacity—empirically substantiated through a cross-national lens—the research provides a comprehensive analytical lens for understanding how public-sector institutions can navigate the transformative implications of generative AI while preserving accountability, trust, and democratic governance principles. The model contributes both theoretically and practically by emphasizing that governance capacity must be built, sustained, and adapted continuously in response to technological, institutional, and societal dynamics. For developing countries, this framework offers a pragmatic alternative to the compliance-driven approaches of Western regulatory models, prioritizing institutional readiness and adaptive learning over premature legal codification. Future research should test the applicability of this model across varied administrative traditions and explore its operationalization through longitudinal case studies, thereby further strengthening its external validity and practical utility.

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Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

The author was solely responsible for all stages of this research. This includes conceptualization of the research problem, development of the theoretical framework, design of the methodology, data collection through semi-structured interviews, qualitative coding and grounded theory analysis, interpretation of findings, visualization of the conceptual model, and preparation, review, and editing of the manuscript. The author assumes full responsibility for the integrity, accuracy, and originality of the work.

Data Availability Statement

The data supporting the findings of this study consist of anonymized interview transcripts, coding materials, and analytical memos generated during the grounded theory analysis of semi-structured interviews with 22 experts in public administration, digital governance, and artificial intelligence policy. To protect participant confidentiality and comply with ethical research commitments, the full dataset is not publicly available. However, anonymized excerpts or additional methodological details may be made available by the author upon reasonable request and subject to ethical approval and confidentiality considerations.

Declaration of Generative AI in Scientific Writing

During the preparation of this manuscript, the authors used the generative artificial intelligence tool Qwen (Alibaba) solely for language editing and minor improvements in clarity and readability. After using this tool, the authors carefully reviewed and edited the text and take full responsibility for the final content of the manuscript.

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