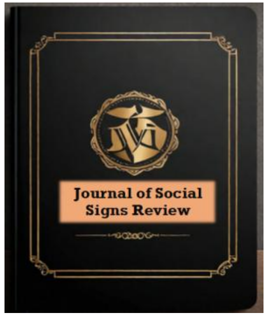
Vol. 3 No. 9 (2025)

Journal of Social Signs Review

Online ISSN 3006-4651

Print ISSN 3006-466X



Public Sector Knowledge Systems and Agentic AI: Institutional Learning and Policy Innovation

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Article Details:`

Received on 7 Aug , 2025
Accepted on 29 Aug ,2025
Published on 21 Sep , 2025

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Abstract

Public sector knowledge systems are undergoing rapid transformation as artificial intelligence (AI) becomes embedded in governance processes. AI technologies increasingly support administrative decision-making, policy analysis, and service delivery by enabling data-driven insights, predictive analytics, and automation within government institutions. As digital infrastructures mature, governments are moving beyond basic e-government models toward integrated knowledge ecosystems that enhance analytical capacity, cross-agency coordination, and citizen engagement. This article examines the intersection of public sector knowledge systems and "agentic AI"—AI systems capable of autonomous analysis, adaptive feedback generation, and iterative problem-solving. It argues that agentic AI represents a qualitative shift from rule-based automation toward dynamic institutional learning. By embedding AI within governance platforms, participatory mechanisms, and knowledge management processes, public institutions can strengthen policy experimentation, accelerate learning cycles, and foster evidence-informed innovation. However, technological capability alone does not guarantee institutional transformation. Effective integration depends on organizational capacity, legal and ethical safeguards, civil servant competencies, and leadership that aligns macro-institutional frameworks with micro-level implementation practices. Without deliberate institutional design, AI adoption may reinforce bureaucratic inertia or exacerbate governance risks related to transparency, accountability, and bias. The article proposes a conceptual framework linking knowledge infrastructures, agentic AI capabilities, and institutional learning loops to explain how public administration can transition from digitization and automation toward adaptive, innovation-oriented governance.

Keywords: Agentic AI; Public Sector Knowledge Systems; Institutional Learning; Policy Innovation; Digital Government; Knowledge Management; Governance Platforms; Policy Capacity; Administrative Reform; Ethical AI Governance

1. Introduction

Public sector organizations are undergoing profound transformation as digital technologies reshape the production, circulation, and application of knowledge in governance. Over the past two decades, the shift from traditional bureaucratic administration toward digital-era governance has redefined how governments coordinate internally and interact with citizens, markets, and civil society (Ajmal & Suleman, 2015a). Digital-era governance emphasizes reintegration, needs-based holism, and digitization as central organizing principles of contemporary public administration (Dunleavy et al., 2006). Within this transformation, artificial intelligence (AI) has emerged as a general-purpose technology with the potential to fundamentally alter decision-making, policy design, and institutional learning processes in the public sector (Ajmal & Suleman, 2015b).

AI applications in government now extend across domains including predictive analytics, automated decision support, natural language processing, fraud detection, and citizen engagement platforms (Ajmal, Islam, & Islam, 2024b). Empirical research demonstrates that AI can improve administrative efficiency, enhance service delivery, and enable more data-driven policy analysis (Wirtz et al., 2019). Similarly, studies of AI in public administration show that machine learning systems are increasingly embedded in regulatory oversight, welfare administration, urban management, and crisis response (Valle-Cruz et al., 2020). However, these technological advances also raise critical governance challenges related to transparency, accountability, bias, and institutional legitimacy (Veale & Brass, 2019).

Beyond efficiency gains, AI's deeper significance lies in its capacity to transform public sector knowledge systems. Knowledge systems in government encompass the infrastructures, data architectures, professional competencies, and institutional routines through which information is collected, interpreted, and translated into policy action (Ajmal, Islam, & Khalid, 2025a). The integration of big data analytics and algorithmic tools has altered how knowledge is generated and used in policymaking, enabling real-time monitoring, predictive modeling, and scenario simulation (Janssen & Kuk, 2016). These developments create new possibilities for evidence-informed governance but also require adaptive institutional arrangements capable of managing complexity and uncertainty (Ajmal, Islam, & Khalid, 2025b).

The concept of institutional learning provides a critical lens for understanding this transformation. Organizational learning theory emphasizes that institutions evolve not merely by adopting new tools but by revising underlying norms, routines, and decision-making frameworks (Fiol & Lyles, 1985). In the public sector, learning processes influence policy adaptation, reform trajectories, and innovation capacity. Research in public management highlights how performance information, feedback systems, and collaborative networks can foster policy learning when supported by conducive institutional conditions (Moynihan & Landuyt, 2009). Digital technologies—and increasingly AI—amplify these feedback mechanisms by accelerating information flows and expanding analytical capacity (Ajmal, Islam, & Khalid, 2025c).

Recent scholarship suggests that AI-enabled systems may contribute to new forms of policy innovation. Policy innovation labs, experimental governance models, and data-driven platforms illustrate how digital infrastructures can enhance analytical and operational policy capacity (McGann et al., 2018). AI systems can assist in identifying emerging social problems, modeling policy trade-offs, and evaluating outcomes at scale.

Vol. 3 No. 9 (2025)

Journal of Social Signs Review

Online ISSN Print ISSN

3006-4651 3006-466X

Yet technological integration alone does not automatically produce innovation (Ajmal, Islam, & Khalid, 2025d). Institutional environments, political incentives, administrative competencies, and governance norms shape whether AI becomes a tool for transformative learning or merely incremental automation (Ajmal, Khalid, & Islam, 2025b).

This article introduces the concept of **agentic AI** in the public sector—AI systems capable not only of executing predefined tasks but also of autonomously generating insights, adapting to new data environments, and iteratively supporting policy experimentation. Agentic AI differs from earlier forms of rule-based automation by incorporating elements of autonomy, continuous learning, and goal-oriented problem solving (Ajmal, Khalid, & Islam, 2025c). When embedded within robust knowledge infrastructures and accountable governance frameworks, such systems have the potential to accelerate institutional learning cycles and enhance policy innovation.

However, the integration of agentic AI into public sector knowledge systems raises significant normative and institutional questions. Algorithmic opacity may undermine democratic accountability; data biases may reinforce structural inequalities; and overreliance on automated systems may weaken professional judgment (Veale & Brass, 2019). Therefore, understanding AI's role in institutional learning requires attention not only to technical capabilities but also to governance design, legal safeguards, organizational culture, and ethical oversight(Ajmal, Khalid, & Islam, 2025d).

This study advances a conceptual framework linking public sector knowledge systems, agentic AI capabilities, and institutional learning processes. It argues that the transformative potential of AI in governance depends on aligning technological infrastructures with adaptive institutions, participatory mechanisms, and ethical regulatory regimes. By situating agentic AI within broader debates on digital government and policy innovation, the article contributes to emerging scholarship on how governments can move from digitization and automation toward adaptive, learning-oriented governance.

2.Literature Review

2.1. Digital Transformation and Public Sector Knowledge Systems

The digital transformation of public administration has fundamentally reshaped how governments generate, manage, and apply knowledge. The transition from New Public Management (NPM) to Digital-Era Governance (DEG) marked a shift toward reintegration of services, digital coordination, and data-driven administration (Dunleavy et al., 2006). DEG emphasizes the centrality of information infrastructures in reorganizing state capacity and enhancing citizen-centered service delivery.

Public sector knowledge systems can be understood as the socio-technical architectures through which governments collect data, produce policy-relevant knowledge, and institutionalize learning. These systems encompass digital platforms, databases, analytics tools, and professional competencies embedded in administrative routines (Islam, Ajmal, & Khalid, 2025a). Big data and open government initiatives have expanded the availability of administrative and real-time data, enabling predictive modeling and evidence-based decision-making (Janssen & Kuk, 2016). However, scholars note that digital transformation is not merely technical but institutional; it requires legal frameworks, interagency coordination, and adaptive organizational cultures (Mergel et al., 2019).
Research highlights that digital technologies strengthen analytical and operational capacities but can also create fragmentation if not aligned with governance structures

Online ISSN Print ISSN
3006-4651 3006-466X

(Mergel et al., 2019). Consequently, knowledge systems must be embedded within institutional arrangements that ensure interoperability, transparency, and sustained learning.

2.2. Artificial Intelligence in Public Administration

Artificial intelligence represents the next stage in the evolution of digital government. AI applications in public administration include predictive analytics, automated decision-support systems, chatbots, fraud detection, regulatory compliance monitoring, and crisis management tools (Wirtz et al., 2019). Empirical analyses show that AI can improve efficiency, reduce administrative burdens, and enhance service personalization (Islam, Khalid, & Ajmal, 2025a).

Valle-Cruz et al. (2020) argue that AI influences every stage of the public policy cycle—from agenda-setting and policy formulation to implementation and evaluation—by providing real-time analytics and forecasting capabilities. Similarly, Sun and Medaglia (2019) identify AI as a catalyst for data-driven governance, enabling governments to process complex datasets and generate actionable insights.

Despite these benefits, the literature consistently underscores significant risks. Veale and Brass (2019) caution that algorithmic governance may undermine transparency and democratic accountability if decision-making processes become opaque (Khalid, Islam, & Ajmal, 2025a). Concerns about bias, discrimination, and due process are particularly salient in welfare administration, policing, and immigration systems (Eubanks, 2018). Thus, AI integration requires robust regulatory oversight, ethical standards, and institutional safeguards.

2.3. Institutional Learning and Policy Innovation

Institutional learning theory provides a conceptual foundation for understanding how AI may reshape governance. Organizational learning involves the modification of routines, norms, and cognitive frameworks in response to feedback and environmental change (Fiol & Lyles, 1985). In public administration, learning processes influence policy adaptation, performance improvement, and reform sustainability (Ajmal, Islam, & Islam, 2024b).

Moynihan and Landuyt (2009) argue that public organizations learn when performance information is meaningfully integrated into decision processes and supported by leadership commitment and organizational culture. Similarly, Argyris and Schön (1996) distinguish between single-loop learning (incremental adjustments) and double-loop learning (transformative change in underlying assumptions). Digital tools, including AI, have the potential to accelerate both types of learning by expanding feedback mechanisms and analytical capacity (Ajmal et al., 2025).

Policy innovation scholarship further emphasizes the importance of experimentation, policy labs, and cross-sector collaboration in fostering adaptive governance (McGann et al., 2018). Innovation is not simply technological adoption; it requires institutional capacity, policy entrepreneurship, and supportive political environments. AI systems may support experimentation by simulating policy outcomes, identifying emerging trends, and enabling iterative design processes.

2.4. Governance, Ethics, and Algorithmic Accountability

The integration of AI into public sector knowledge systems raises complex governance and ethical questions. Algorithmic decision-making systems can reproduce systemic inequalities if trained on biased datasets (Eubanks, 2018). Moreover, opaque machine learning models challenge traditional principles of administrative law, such as reason-giving and procedural fairness (Veale & Brass, 2019).

Scholars argue that effective AI governance requires transparency mechanisms, explainability standards, participatory oversight, and regulatory capacity (Cath et al., 2018). Institutional readiness—defined by legal frameworks, digital competencies, and leadership support—is critical for responsible AI deployment (Mergel et al., 2019). Without these safeguards, AI may erode trust in public institutions rather than strengthen them.

The literature also emphasizes the importance of hybrid governance models that combine human judgment with algorithmic support. Rather than replacing administrators, AI should augment professional expertise and enhance deliberative processes. This human-in-the-loop approach supports accountability while leveraging computational advantages.

2.5. Toward Agentic AI and Adaptive Governance

While existing scholarship focuses largely on automation and predictive analytics, emerging discussions point toward more autonomous and adaptive AI systems. Such systems—referred to here as agentic AI—can autonomously generate recommendations, adapt to changing data environments, and support iterative policy experimentation.

From a knowledge systems perspective, agentic AI may function as a dynamic node within institutional learning cycles. By continuously processing feedback, identifying patterns, and simulating scenarios, these systems can enhance anticipatory governance and proactive policymaking. However, their transformative potential depends on integration with institutional learning structures, governance norms, and accountability mechanisms.

In sum, the literature suggests that AI's contribution to policy innovation is contingent upon three interrelated factors:

1. The robustness of public sector knowledge infrastructures;
2. Institutional capacity for organizational learning;
3. Governance frameworks that ensure ethical, transparent, and accountable AI use.

This review highlights a gap in existing research: while AI's operational impacts are well-documented, less attention has been paid to its role in reshaping institutional learning architectures. The concept of agentic AI provides a theoretical bridge between digital governance scholarship and institutional learning theory, offering a framework for analyzing how AI may catalyze adaptive, innovation-oriented public administration.

3. Conceptual Framework: Public Sector Knowledge Systems and Agentic AI

This section develops a conceptual framework linking public sector knowledge systems, agentic AI, institutional learning, and policy innovation. The framework integrates insights from digital governance, organizational learning theory, and algorithmic governance scholarship to explain how AI can move public administration from automation toward adaptive, innovation-oriented governance.

3.1. Public Sector Knowledge Systems as Socio-Technical Infrastructures

Public sector knowledge systems refer to the institutionalized arrangements through which governments collect data, generate information, interpret evidence, and translate insights into policy decisions. These systems consist of digital infrastructures (databases, platforms, analytics tools), organizational routines, legal frameworks, and professional competencies.

Digital-era governance theory argues that information integration and digital coordination are central to modern state capacity (Dunleavy et al., 2006). Big data architectures and interoperable systems enable real-time monitoring and cross-agency collaboration (Janssen & Kuk, 2016). However, knowledge systems are not merely technical structures; they are embedded in institutional norms and political contexts that shape how information is interpreted and used (Mergel et al., 2019).

Thus, the first dimension of the framework conceptualizes knowledge systems as **socio-technical infrastructures** composed of:

1. Data ecosystems (administrative, open, and real-time data);
2. Analytical capabilities (AI, predictive modeling, dashboards);
3. Institutional routines (decision protocols, feedback loops);
4. Governance safeguards (legal and ethical standards).

These elements jointly determine whether digital tools enhance institutional learning or remain isolated technological add-ons.

3.2. Agentic AI as an Evolution of Administrative Automation

Most existing AI applications in government focus on automation and predictive analytics. Research demonstrates that AI supports decision-making across policy-cycle stages, improving forecasting and evaluation (Valle-Cruz et al., 2020). Wirtz et al. (2019) categorize public sector AI applications into automation of processes, cognitive insights, and citizen interaction.

This framework extends that literature by introducing **agentic AI**, defined as AI systems capable of autonomous analysis, adaptive learning, and iterative recommendation generation within governance processes. Unlike rule-based automation, agentic AI systems:

- Continuously learn from new data inputs;
- Generate policy scenarios or optimization strategies;
- Support experimentation and feedback-based adaptation.

Conceptually, agentic AI aligns with adaptive governance theory, which emphasizes flexibility, anticipatory capacity, and iterative problem-solving in complex policy environments (Ansell & Gash, 2008). AI's capacity to simulate outcomes and identify emerging patterns enhances anticipatory governance, allowing institutions to move from reactive administration to proactive policy design.

However, algorithmic autonomy introduces accountability challenges. Veale and Brass (2019) argue that algorithmic systems may obscure decision rationales and weaken democratic oversight if not embedded in transparent governance frameworks. Therefore, agentic AI must operate within structured accountability regimes and human-in-the-loop oversight mechanisms.

3.3. Institutional Learning as the Mediating Mechanism

The framework positions institutional learning as the mediating process between AI capabilities and policy innovation. Organizational learning theory distinguishes between single-loop learning (incremental adjustments) and double-loop learning (revising underlying norms and assumptions) (Argyris & Schön, 1996).

Public organizations learn when performance information is integrated into managerial processes and supported by leadership commitment and supportive culture (Moynihan & Landuyt, 2009). AI systems enhance feedback mechanisms by processing large-scale performance data and identifying policy deviations in real time (Sun & Medaglia, 2019).

In this framework, agentic AI strengthens learning cycles through three mechanisms:

1. **Data Amplification** – Expanding the volume and granularity of performance information;

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Journal of Social Signs Review

Online ISSN Print ISSN

3006-4651 3006-466X

2. **Cognitive Augmentation** – Assisting administrators in identifying patterns, anomalies, and policy trade-offs;
3. **Scenario Simulation** – Enabling iterative experimentation and anticipatory modeling.

When embedded within supportive institutional conditions—such as digital competencies, cross-sector collaboration, and leadership support—these mechanisms facilitate double-loop learning and policy adaptation.

3.4. Governance and Ethical Moderators

AI's impact on institutional learning is moderated by governance and ethical frameworks. Research consistently highlights risks of bias, opacity, and procedural injustice in algorithmic governance (Eubanks, 2018; Veale & Brass, 2019). Ethical AI governance requires transparency standards, auditability, data protection safeguards, and inclusive design processes (Cath et al., 2018).

Institutional readiness—including digital literacy, regulatory capacity, and interagency coordination—also determines whether AI integration strengthens or destabilizes governance systems (Mergel et al., 2019). Without these safeguards, AI may reinforce bureaucratic rigidity or produce technocratic decision-making disconnected from democratic accountability.

Thus, governance structures act as **moderating variables** within the conceptual model. Strong safeguards enable agentic AI to enhance learning and innovation; weak safeguards increase the risk of institutional erosion.

3.5. Policy Innovation as the Outcome

Policy innovation refers to the development and implementation of new policy instruments, governance models, or service delivery approaches that improve public value creation. Innovation labs and design-thinking approaches illustrate how experimentation and data-driven methods can enhance policy capacity (McGann et al., 2018).

Within this framework, policy innovation emerges when:

- Knowledge systems provide integrated, high-quality data;
- Agentic AI supports adaptive analysis and experimentation;
- Institutional learning processes translate insights into revised norms and policies;
- Governance safeguards maintain legitimacy and accountability.

The model therefore conceptualizes innovation not as a direct product of AI adoption but as the outcome of **AI-enabled institutional learning embedded within accountable governance systems**.

3.6. Integrated Model

The conceptual framework can be summarized as a four-layer structure:

Layer 1: Knowledge Infrastructure

Digital data ecosystems + institutional routines

Layer 2: Agentic AI Capabilities

Adaptive analytics + scenario modeling + autonomous recommendation generation

Layer 3: Institutional Learning Processes

Feedback integration + single- and double-loop learning + organizational adaptation

Layer 4: Policy Innovation Outcomes

Adaptive governance + anticipatory policymaking + enhanced public value

Governance and ethical safeguards operate across all layers as cross-cutting moderators.

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Online ISSN Print ISSN

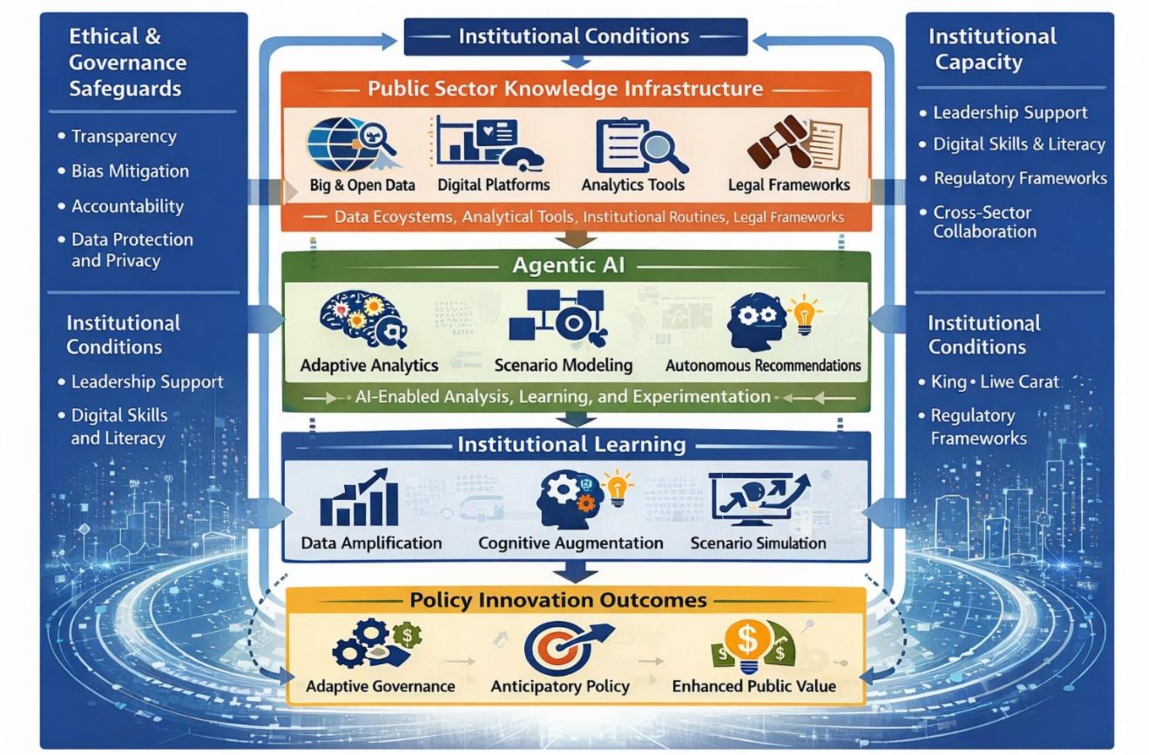
3006-4651 3006-466X

Theoretical Contribution

This framework advances existing scholarship in three ways:

1. It reconceptualizes AI as a structural component of public sector knowledge systems rather than a discrete technological tool.
2. It integrates organizational learning theory with digital governance research to explain AI's role in institutional adaptation.
3. It introduces agentic AI as a conceptual category bridging automation and adaptive governance.

By situating AI within institutional learning architectures, the framework clarifies the conditions under which AI can catalyze transformative policy innovation rather than incremental administrative efficiency.



4. Explanation of the Conceptual Model: Public Sector Knowledge Systems and Agentic AI

The model visualizes how **public sector knowledge infrastructures**, when integrated with **agentic AI capabilities**, can drive **institutional learning** and ultimately produce **policy innovation outcomes**, under the moderating influence of governance safeguards and institutional capacity. The framework synthesizes digital governance theory, organizational learning theory, and AI governance scholarship.

4.1. Institutional and Governance Conditions (Outer Moderating Layer)

The model places **ethical governance safeguards** and **institutional capacity** as cross-cutting conditions that shape every stage of AI integration.

4.1.1 Ethical & Governance Safeguards

Research consistently shows that AI deployment in the public sector requires transparency, accountability, bias mitigation, and data protection mechanisms. Algorithmic systems can undermine procedural fairness if decision logic is opaque (Veale & Brass, 2019). Ethical AI

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governance frameworks emphasize explainability, auditability, and democratic oversight (Cath et al., 2018).

These safeguards moderate whether AI strengthens legitimacy or erodes trust.

- Algorithmic opacity risks administrative injustice (Veale & Brass, 2019).
- AI governance requires ethical and regulatory oversight (Cath et al., 2018).

Thus, governance safeguards function as **system-wide moderators**, ensuring that AI-driven knowledge systems remain accountable and rights-preserving.

4.1.2 Institutional Capacity

Digital transformation depends on leadership commitment, digital skills, and regulatory readiness. Digital-era governance literature emphasizes that technological change must be accompanied by organizational restructuring and competency development (Dunleavy et al., 2006).

Empirical research shows that public sector digital transformation succeeds when supported by managerial leadership and digital literacy (Mergel et al., 2019).

Therefore, institutional capacity determines whether AI becomes a transformative force or a superficial technical overlay.

4.2. Public Sector Knowledge Infrastructure (Foundation Layer)

This layer represents the **socio-technical backbone** of governance.

4.2.1 Data Ecosystems and Big/Open Data

Modern governance relies on interoperable data systems and open data architectures that enhance analytical capacity (Janssen & Kuk, 2016). Integrated data environments enable cross-agency coordination and real-time monitoring.

Without robust data ecosystems, AI systems cannot function effectively. Thus, data integration is a prerequisite for AI-enabled governance.

4.2.2 Digital Platforms and Institutional Routines

Digital-era governance emphasizes reintegration and platform-based coordination (Dunleavy et al., 2006). Platforms standardize workflows, enable interoperability, and institutionalize feedback mechanisms.

Institutional routines determine how information is interpreted and acted upon. Knowledge systems must be embedded in formal decision processes to influence policy.

4.2.3 Legal and Regulatory Frameworks

Legal frameworks ensure that digital infrastructures comply with administrative law principles. AI integration must align with due process and procedural fairness norms (Veale & Brass, 2019).

Interpretation in the model:

The knowledge infrastructure layer represents the **structural precondition** for AI-driven learning. It transforms raw data into administratively usable knowledge.

4.3. Agentic AI Capabilities (Transformative Layer)

This layer introduces the model's novel contribution: **agentic AI**.

4.3.1 From Automation to Adaptive Intelligence

Existing literature documents AI applications across the public policy cycle, including forecasting, classification, and evaluation (Valle-Cruz et al., 2020).

Wirtz et al. (2019) categorize AI in government as automation, cognitive insight generation, and citizen interaction.

Agentic AI extends this by incorporating:

- Adaptive analytics

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3006-4651 3006-466X

- Scenario modeling
- Autonomous recommendation generation

This aligns with adaptive governance theory, which emphasizes flexibility and anticipatory capacity in complex policy systems (Ansell & Gash, 2008).

4.3.2 Cognitive Augmentation

AI does not replace administrators but augments their decision-making capacity (Sun & Medaglia, 2019). It processes complex datasets beyond human cognitive limits and surfaces patterns, anomalies, and optimization strategies.

In the model, agentic AI functions as a **dynamic analytical engine** embedded within institutional workflows.

4.4. Institutional Learning (Mediating Mechanism)

The model positions institutional learning as the **core mediating variable** between AI and innovation.

4.4.1 Organizational Learning Theory

Organizational learning involves updating routines based on feedback (Fiol & Lyles, 1985). Argyris and Schön (1996) distinguish:

- Single-loop learning: adjusting actions
- Double-loop learning: revising underlying assumptions

AI strengthens both by amplifying feedback loops and enabling scenario experimentation.

4.4.2 AI-Enabled Learning Mechanisms

The model identifies three learning mechanisms:

1. Data Amplification

Expanded real-time data improves performance monitoring (Sun & Medaglia, 2019).

2. Cognitive Augmentation

AI enhances analytical reasoning in policy evaluation (Wirtz et al., 2019).

4.3. Scenario Simulation

Predictive modeling enables anticipatory policymaking (Valle-Cruz et al., 2020).
When embedded in decision processes, these mechanisms facilitate adaptive governance and policy recalibration (Moynihan & Landuyt, 2009).

4.5. Policy Innovation Outcomes (Outcome Layer)

The final layer represents the systemic outcomes of AI-enabled learning.

4.5.1 Adaptive Governance

Collaborative and flexible governance structures respond more effectively to complex policy challenges (Ansell & Gash, 2008).

AI enhances anticipatory capacity and cross-sector coordination.

4.5.2 Anticipatory Policy

Predictive analytics supports proactive rather than reactive policymaking (Valle-Cruz et al., 2020).

4.5.3 Enhanced Public Value

Innovation labs and data-driven experimentation improve service delivery and policy effectiveness (McGann et al., 2018).
Importantly, innovation is not caused directly by AI. It emerges when:

- Knowledge systems are integrated
- Agentic AI enhances feedback
- Institutions learn adaptively
- Governance safeguards ensure legitimacy

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Integrated Theoretical Logic of the Model

The causal logic of the model can be summarized as:

Knowledge Infrastructure → Agentic AI Capabilities → Institutional Learning → Policy Innovation

Moderated by:

Governance Safeguards + Institutional Capacity

The framework integrates:

- Digital-era governance theory (Dunleavy et al., 2006)
- AI in public administration scholarship (Wirtz et al., 2019; Valle-Cruz et al., 2020)
- Organizational learning theory (Argyris & Schön, 1996; Fiol & Lyles, 1985)
- Algorithmic accountability research (Veale & Brass, 2019)

Theoretical Contribution

The model advances scholarship by:

1. Reframing AI as a structural component of knowledge systems
2. Positioning institutional learning as the central mediating mechanism
3. Introducing agentic AI as a bridge between automation and adaptive governance
4. Demonstrating how ethical safeguards condition innovation outcomes

Rather than viewing AI as a standalone technical tool, the model conceptualizes it as an embedded cognitive infrastructure shaping how governments learn and innovate.

5. Discussion

This study conceptualizes agentic AI as an embedded component of public sector knowledge systems that can reshape institutional learning and policy innovation. The discussion situates the model within existing scholarship on digital governance, organizational learning, and algorithmic administration, examining how the integration of adaptive AI capabilities may transform public administration dynamics.

First, the findings reinforce the argument that digital transformation in government is not merely a technological upgrade but an institutional restructuring process. Digital-era governance emphasizes reintegration, holistic service delivery, and data-driven coordination as defining characteristics of contemporary public administration (Dunleavy et al., 2006). The model presented here aligns with this perspective by positioning knowledge infrastructures—data ecosystems, digital platforms, and legal frameworks—as foundational layers that determine AI's functionality. Consistent with research on digital transformation, institutional readiness and organizational adaptation remain critical determinants of successful technological integration (Mergel et al., 2019).

Second, the discussion highlights that AI's transformative potential lies less in automation and more in its capacity to augment analytical and anticipatory governance. Prior studies demonstrate that AI applications now span the full public policy cycle, from agenda-setting to evaluation (Valle-Cruz et al., 2020). However, much of the empirical literature focuses on efficiency gains and service optimization (Wirtz et al., 2019). By introducing agentic AI as a capability for adaptive analytics and scenario simulation, the present model extends this literature toward understanding AI as a catalyst for institutional learning.

AI-enabled systems expand feedback loops by processing large-scale performance data and identifying emergent patterns (Sun & Medaglia, 2019). When embedded in decision routines, these systems strengthen both single-loop and double-loop learning processes as conceptualized in organizational learning theory (Argyris & Schön, 1996; Fiol

& Lyles, 1985). The capacity to simulate policy alternatives and generate iterative recommendations suggests that AI may enhance governments' ability to operate under conditions of complexity and uncertainty.

Third, the discussion underscores the mediating role of institutional learning in translating technological capabilities into policy innovation. Public organizations do not automatically innovate through technology adoption; learning mechanisms must be embedded within governance routines. Research on public sector performance management indicates that organizations learn when performance information is meaningfully integrated into managerial processes and supported by leadership commitment (Moynihan & Landuyt, 2009). The model reflects this insight by positioning institutional learning as the central pathway through which AI influences policy outcomes.

Fourth, governance and ethical safeguards remain essential boundary conditions. Algorithmic systems can generate unintended consequences, including bias amplification, opacity, and erosion of procedural fairness (Veale & Brass, 2019). Scholarship on AI governance stresses the importance of accountability mechanisms, transparency standards, and oversight structures to ensure legitimacy (Cath et al., 2018). The model therefore conceptualizes governance safeguards not as peripheral considerations but as cross-cutting moderators that shape every stage of AI-enabled knowledge production and learning.

The discussion also points to the evolving nature of public sector knowledge systems. Big and open linked data initiatives have expanded state analytical capacity but also increased the complexity of managing data flows and privacy risks (Janssen & Kuk, 2016). Agentic AI intensifies this complexity by introducing adaptive and autonomous analytical processes. This transformation shifts administrative practice from rule-based bureaucratic logic toward dynamic, data-responsive governance architectures.

Finally, the integration of AI into institutional learning cycles contributes to the broader evolution of collaborative and adaptive governance. Collaborative governance literature emphasizes cross-sector coordination and iterative problem-solving as responses to complex policy challenges (Ansell & Gash, 2008). Agentic AI may facilitate such collaboration by integrating heterogeneous data sources, modeling interdependencies, and supporting joint decision-making environments.

In summary, the discussion demonstrates that AI's contribution to public sector innovation is contingent upon its integration into knowledge infrastructures and learning systems, moderated by governance safeguards and institutional capacity. Rather than conceptualizing AI as an external technological intervention, the model frames it as an embedded cognitive infrastructure capable of reshaping how public institutions generate knowledge, adapt policies, and respond to societal complexity.

6.Theoretical Implications

This study advances theory at the intersection of digital governance, organizational learning, and artificial intelligence in public administration by reconceptualizing the role of AI within public sector knowledge systems.

6.1. Reframing AI as Cognitive Infrastructure Rather Than Administrative Tool

Existing literature largely conceptualizes AI in government as an instrument for automation, efficiency enhancement, or decision support (Wirtz et al., 2019; Valle-Cruz et al., 2020). The present framework extends this perspective by theorizing **agentic AI as an embedded cognitive infrastructure** within public sector knowledge systems.

By situating AI within socio-technical knowledge architectures—comprising data ecosystems, institutional routines, and legal frameworks—the study moves beyond a tool-based view and aligns AI with digital-era governance theory, which emphasizes reintegration and systemic restructuring of public administration (Dunleavy et al., 2006). This theoretical repositioning highlights AI's structural role in shaping how governments generate, interpret, and institutionalize knowledge.

6.2. Integrating Organizational Learning Theory with Digital Governance

A key theoretical contribution lies in linking AI capabilities with institutional learning processes. Organizational learning theory distinguishes between single-loop learning (incremental adjustments) and double-loop learning (normative transformation) (Argyris & Schön, 1996; Fiol & Lyles, 1985).

The framework suggests that agentic AI enhances both forms of learning by strengthening feedback loops, amplifying performance data, and enabling scenario simulation. This integration bridges a gap between digital governance research—which often focuses on technological adoption—and public management scholarship on learning and adaptation (Moynihan & Landuyt, 2009).

Thus, the model contributes a process-oriented explanation of how AI influences policy innovation: not directly, but through institutional learning mechanisms.

6.3. Extending Algorithmic Governance Theory

Algorithmic governance research emphasizes risks related to opacity, bias, and accountability (Veale & Brass, 2019). While this literature primarily examines the constraints and dangers of algorithmic administration, the present study extends it by incorporating governance safeguards as moderating conditions within a broader innovation framework.

By conceptualizing ethical and regulatory structures as cross-cutting moderators rather than afterthoughts, the model integrates accountability theory into the innovation process. This synthesis contributes to emerging debates on responsible AI governance (Cath et al., 2018) by demonstrating how legitimacy conditions shape the transformative potential of AI.

6.4. Advancing Adaptive and Anticipatory Governance Theory

Collaborative and adaptive governance theories emphasize iterative problem-solving, cross-sector coordination, and responsiveness to complexity (Ansell & Gash, 2008). The model contributes to this literature by identifying agentic AI as a mechanism that enhances anticipatory capacity through predictive modeling and scenario analysis.

This theoretical move reframes AI as an enabler of **anticipatory governance**, expanding the concept beyond institutional flexibility to include computational foresight embedded in decision processes.

6.5. Reconceptualizing Policy Innovation as a Learning Outcome

Policy innovation scholarship often focuses on policy labs, experimentation, and design thinking as drivers of reform (McGann et al., 2018). The present framework reframes innovation as the systemic outcome of AI-enabled institutional learning embedded within accountable governance systems.

This shifts theoretical emphasis from discrete innovation initiatives toward structural learning capacities supported by digital knowledge infrastructures.

6.6. A Multi-Level Governance Model

The model integrates macro-institutional conditions (legal frameworks, political environments), meso-level organizational structures (knowledge systems and routines), and micro-level cognitive processes (AI-supported analysis and learning).

By doing so, it contributes a multi-level theoretical architecture that connects:

- Digital transformation theory (Dunleavy et al., 2006; Mergel et al., 2019)
- Organizational learning theory (Argyris & Schön, 1996; Fiol & Lyles, 1985)
- AI governance scholarship (Veale & Brass, 2019; Cath et al., 2018)
- Policy innovation research (McGann et al., 2018)

This integrative framework advances theory by demonstrating how AI reshapes governance not merely through efficiency gains, but by altering the epistemic foundations of public administration.

7. Practical Implications

The conceptualization of agentic AI within public sector knowledge systems offers several concrete implications for governments, public managers, digital transformation units, and regulatory authorities.

7.1. Designing Integrated Knowledge Infrastructures

Public organizations should prioritize building interoperable data ecosystems and integrated digital platforms before scaling AI systems. Research on digital-era governance emphasizes reintegration and platform-based coordination as foundations for effective digital administration (Dunleavy et al., 2006). Similarly, big and open linked data architectures enhance cross-agency coordination and analytical capacity (Janssen & Kuk, 2016).

Practically, this implies:

- Standardizing data formats across agencies
- Investing in interoperable digital platforms
- Embedding AI tools within existing decision workflows rather than treating them as standalone systems

Without robust knowledge infrastructures, AI systems risk producing fragmented or unreliable outputs.

7.2. Embedding AI in Decision Routines, Not Parallel Structures

AI adoption should be institutionally embedded in formal policy processes. Evidence suggests that public organizations learn when performance information is meaningfully integrated into managerial decision-making (Moynihan & Landuyt, 2009).

Practically, governments should:

- Incorporate AI-generated analytics into policy briefings and regulatory reviews
- Use scenario modeling outputs during cabinet deliberations or legislative drafting
- Establish clear procedural protocols for human oversight of AI recommendations

Embedding AI within institutional routines strengthens organizational learning and prevents technological marginalization.

7.3. Strengthening Institutional Capacity and Digital Competencies

Digital transformation requires leadership commitment and workforce capabilities (Mergel et al., 2019). AI systems, particularly adaptive and agentic systems, require civil servants who understand data literacy, algorithmic logic, and ethical risk management.

Practical actions include:

- Continuous professional training in AI literacy

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Journal of Social Signs Review
Online ISSN Print ISSN
3006-4651 3006-466X

- Cross-sector recruitment strategies to integrate data scientists and policy analysts
- Creating interdisciplinary AI governance units

Capacity development reduces dependency on external vendors and enhances internal accountability.

7.4. Implementing Robust Governance and Accountability Mechanisms

Algorithmic governance can undermine procedural fairness if transparency and accountability mechanisms are absent (Veale & Brass, 2019). Ethical AI frameworks emphasize explainability, auditability, and bias mitigation (Cath et al., 2018).

Governments should therefore:

- Conduct algorithmic impact assessments prior to deployment
- Establish independent oversight bodies for high-risk AI systems
- Ensure explainability standards for automated recommendations
- Develop public reporting mechanisms to maintain trust

AI systems that lack legitimacy safeguards may provoke resistance or legal challenges, limiting innovation potential.

7.5. Leveraging AI for Anticipatory and Adaptive Policymaking

AI can enhance anticipatory governance by enabling predictive modeling and scenario analysis across the policy cycle (Valle-Cruz et al., 2020). Rather than focusing solely on administrative efficiency, public managers can use AI to explore long-term policy consequences, detect early warning signals, and simulate trade-offs.

Practical applications include:

- Early-warning systems in public health or environmental regulation
- Predictive analytics for welfare eligibility and service demand
- Simulation tools for budget forecasting and infrastructure planning

These uses align with collaborative governance approaches that emphasize iterative problem-solving in complex environments (Ansell & Gash, 2008).

7.6. Encouraging Policy Experimentation and Innovation Ecosystems

Public sector innovation labs demonstrate that experimentation enhances policy capacity (McGann et al., 2018). AI-driven simulation and feedback systems can scale experimentation beyond small pilot projects.

Governments can:

- Combine AI scenario modeling with innovation lab methodologies
- Test policy prototypes through simulated environments before implementation
- Use AI-generated feedback to refine regulatory frameworks

This approach supports adaptive governance without increasing systemic risk.

7.7. Managing Risk While Scaling Innovation

AI systems introduce new governance risks, including bias amplification and data misuse (Veale & Brass, 2019). Therefore, innovation must proceed alongside risk management strategies.

Practical risk-mitigation strategies include:

- Bias detection audits
- Privacy-by-design system architectures
- Clear escalation protocols for AI-related errors

Balancing innovation with responsible governance strengthens institutional legitimacy.

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