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# Artificial Intelligence and the Paradigm Shift in Public Policy: Between Innovation Opportunities and Emerging Risks

***"L'intelligence artificielle et le changement de paradigme dans les politiques publiques : entre opportunités d'innovation et risques émergents "***

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**Abstract:**

This study aims to examine the paradigm shift brought about by artificial intelligence (AI) in public policy scholarship. It explores how machine learning, big data analytics, and generative AI reshape the core logic of policymaking across the policy cycle. The paper highlights the contribution of these technologies to enhancing predictive capabilities, optimizing data analytics, supporting decision-making, and streamlining policy implementation and evaluation. Consequently, it marks a transition from the conventional linear framework to a dynamic, proactive model driven by data and algorithms. The study further critically addresses the risks inherent in this transformation, particularly algorithmic bias, the lack of transparency, the "black box" problem, privacy concerns, and diminished accountability. Methodologically, the research employs a descriptive-analytical approach coupled with a systems framework. It concludes that while AI serves as a fundamental driver of this paradigm shift in public policy, its success remains contingent upon establishing a robust legislative, ethical, and institutional framework that strikes a balance between technical efficiency and human oversight, thereby advancing the public interest and safeguarding policy legitimacy in the digital era.

**Keywords:** Artificial Intelligence; Paradigm Shift; Public Policy; Policy Cycle; Algorithmic Governance; Decision-Making.

**Résumé :**

Cette étude vise à examiner le changement de paradigme induit par l'intelligence artificielle (IA) dans l'étude des politiques publiques. Elle explore la manière dont l'apprentissage automatique, l'analyse des mégadonnées (*big data*) et l'IA générative remodèlent la logique fondamentale de l'élaboration des politiques tout au long de leur cycle de vie. L'article met en évidence la contribution de ces technologies au renforcement des capacités prédictives, à l'optimisation de l'analyse des données, à l'aide à la décision ainsi qu'à la rationalisation de la mise en œuvre et de l'évaluation des politiques. Par conséquent, elle marque une transition du cadre linéaire conventionnel vers un modèle dynamique et proactif fondé sur les données et les algorithmes. L'étude aborde en outre de manière critique les risques inhérents à cette

transformation, notamment le biais algorithmique, le manque de transparence, le problème de la « boîte noire », les préoccupations relatives à la vie privée et l'affaiblissement de la responsabilité décisionnelle. Sur le plan méthodologique, la recherche adopte une approche descriptivo-analytique couplée à une démarche systémique. Elle conclut que, bien que l'IA constitue un moteur fondamental de ce changement paradigmatique dans les politiques publiques, sa réussite demeure tributaire de la mise en place d'un cadre législatif, éthique et institutionnel robuste, garantissant un équilibre entre efficacité technique et contrôle humain, afin de servir l'intérêt général et de préserver la légitimité des politiques publiques à l'ère numérique.
**Mots-clés :** Intelligence artificielle ; Changement de paradigme ; Politiques publiques ; Cycle des politiques publiques ; Gouvernance algorithmique ; Prise de décision.

## *1. Introduction:*

Contemporary societies are undergoing rapid technological transformations that necessitate a critical reassessment of the conventional paradigms governing political and administrative institutions. Artificial intelligence stands at the forefront of these transformations, driven by its capacity for big data processing, machine learning, predictive modeling, and complex pattern recognition. AI is no longer merely a tool for administrative optimization; it has become an influential driver reshaping governance mechanisms, decision-making, and public policymaking. It provides novel capabilities for issue detection, agenda prioritization, policy alternative simulation, outcome forecasting, and the refined implementation and evaluation of policies—significantly reflecting a departure from traditional linear processes toward a more dynamic and proactive data- and algorithm-driven architecture.

This transformation extends beyond the deployment of new technological tools to fundamentally alter the nature of knowledge, the roles of policy actors, and the human–machine dynamic within the public sphere. Despite the substantial opportunities AI offers for evidence-based policymaking, it raises critical concerns regarding algorithmic bias, decision transparency, data privacy, accountability, and the "black box" dilemma. These issues prompt fundamental questions regarding the extent of decision delegation to intelligent systems and emphasize the imperative of preserving meaningful human oversight and democratic accountability, particularly concerning decisions affecting individual rights and the public interest.

The significance of this study stems from the timeliness of the topic and the pressing need to understand the profound transformations driven by AI in public policy—a vital nexus where technical expertise intersects with political, legal, ethical, and societal dimensions. The study derives its academic value from its attempt to theoretically ground the concept of a paradigm shift in public policy in light of the transition toward algorithmic governance, to unpack the opportunities smart technologies offer for re-engineering the policy cycle, and to critically assess the risks that may impede the efficacy or undermine the legitimacy of this transition.

Accordingly, the central research problem is articulated in the following primary question:

***How do artificial intelligence technologies drive a paradigm shift in public policy scholarship?***

This central problem gives rise to several sub-questions:

1. To what extent can AI technologies reconfigure the sequential stages of the public policy cycle?
2. What are the principal risks and challenges that might impede the transition of public policy from its conventional model to an intelligent model grounded in algorithmic governance?

The study is guided by the primary hypothesis that artificial intelligence technologies drive a paradigm shift in public policy by transitioning from traditional decision-making models to algorithmic governance supported by machine learning, big data analytics, and predictive capabilities, thereby reshaping the various stages of the policy cycle. This is complemented by two sub-hypotheses:

- **First Sub-Hypothesis:** AI technologies can reconstruct the public policy cycle, converting it from a conventional linear trajectory into a more proactive, dynamic, and intelligent system.
- **Second Sub-Hypothesis:** This transformation confronts substantial structural challenges, foremost among them the absence of algorithmic transparency, inherent bias, inadequate legislative and regulatory frameworks, and the erosion of human oversight and accountability.

To address this problem and test the stated hypotheses, the study adopts a descriptive-analytical approach to delineate the conceptual parameters of the phenomenon and analyze the associated structural shifts. Additionally, it integrates a systems approach to conceptualize the public policy cycle as an interconnected matrix of inputs, processes, outputs, and feedback loops, examining how AI technologies reconfigure the relationships and interactions among these constituent elements.

Accordingly, the study is divided into three main sections:

1. The Chronological Development of the Concept of Artificial Intelligence.
2. The Paradigm Shift in Public Policy.
3. An Analysis of the Risks and Challenges Resulting from the Integration of Artificial Intelligence into the Field of Public Policy.

## *2. Chronology of the Conceptual Evolution of Artificial Intelligence*

The historical development of artificial intelligence (AI) represents an epistemological and technological evolution that has transcended speculative philosophy and science fiction to become a foundational pillar reshaping state structures and contemporary governance. Comprehending the current integration of algorithms into public policymaking requires tracing the conceptual origins and developmental stages of machine intelligence over time.

### *2.1. Historical Stages of Artificial Intelligence*

The conceptual trajectory of AI has evolved through several distinct phases:

**a.The Foundational Phase (1950–1960):** In 1950, Alan Turing published his seminal work, *Computing Machinery and Intelligence*, addressing the fundamental question: "Can machines think?" Turing proposed an operational imitation test, later known as the Turing Test, suggesting that a machine could be deemed intelligent if its conversational responses were indistinguishable from those of a human. This proposal served as the earliest experimental criterion for assessing

machine intelligence[1]. The field formally emerged at the Dartmouth Conference in 1956, where John McCarthy coined the term "Artificial Intelligence." The foundational assertion of the workshop was that every aspect of learning or intelligence could, in principle, be described precisely enough for a machine to simulate it. Key pioneers in attendance included Ray Solomonoff, Oliver Selfridge, Trenchard More, Arthur Samuel, Herbert A. Simon, and Allen Newell, all of whom became foundational figures in the discipline[2] .

b. **The Logic and Expert Systems Phase (1960–1970):** The 1960s and 1970s witnessed critical assessments of early neural architectures, notably highlighted by Marvin Minsky and Seymour Papert's work on Perceptrons. Concurrently, rule-based expert systems gained prominence for knowledge representation, automated reasoning, and domain-specific decision support, exemplified by early medical diagnosis systems developed by researchers such as Edward Shortliffe. Autonomous robotics also advanced, marked by Hans Moravec's development of early computer-controlled vehicles navigating structured obstacle courses[3] .

c. **The Backpropagation and Industrial Expansion Phase (1974–1990):** During the 1980s, the backpropagation algorithm—initially introduced in the 1970s—gained widespread adoption within artificial neural network research. By the mid-1980s, the commercial AI market exceeded one billion dollars. Simultaneously, initiatives such as Japan's Fifth Generation Computer Systems project prompted increased research funding in the United States and the United Kingdom. However, the subsequent contraction of specialized hardware markets, including the Lisp machine sector in the late 1980s, ushered in an "AI Winter" characterized by reduced investment[4].

d. **The Mathematical Rigor and Applied Algorithms Phase (1990–2000):** Through the 1990s and 2000s, AI focused on solving complex applied problems, delivering solutions across data mining, industrial automation, logistics, business intelligence, medical diagnostics, recommendation engines, and web search indexing. Researchers increasingly incorporated rigorous mathematical frameworks, drawing on optimization theory, probability, and operations research. This formal mathematical integration fostered closer interdisciplinary collaboration and established AI as a methodologically robust scientific domain.

e. **The Big Data and Deep Learning Phase (2000–2020):** In the mid-2000s, a paradigm shift occurred emphasizing the primacy of large-scale data over algorithmic design alone. In 2006, Fei-Fei Li challenged the prevailing assumption that algorithmic refinement should precede large-scale data collection. Under the premise that real-world complexity requires comprehensive empirical training sets, the ImageNet dataset was introduced in 2009, comprising

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[1] - Dimitar Delipetrev, Chrysi Tsinaraki, and Uros Kostic, *Historical Evolution of Artificial Intelligence* (Luxembourg: Publications Office of the European Union, 2020), p.8.

[2] - Dimitar Delipetrev, Idid.

[3] - Arun Singh, "The Concept of Artificial Intelligence," *Journal of Emerging Technologies and Innovative Research (JETIR)* 6, no. 3 (March 2019), p.576.

[4] - Arun Singh, Idid.

millions of categorized visual instances across structured hierarchical subtrees[5]. In 2011, IBM's Watson demonstrated advanced natural language understanding and large-scale information retrieval on structured knowledge bases, highlighting significant milestones in computational linguistics and question-answering systems[6].

Scholars suggest that AI continues to evolve rapidly, transitioning into widespread practical deployment across public and private sectors[7]. Contemporary applications span several key sectors[8]:

a. **Engineering:** Algorithmic optimization of structural designs, automated verification, and execution monitoring.
b. **Medicine:** Diagnostic imaging analysis, clinical pattern recognition, and therapeutic recommendations.
c. **Defense and Strategic Affairs:** Real-time situational analysis, tactical decision support, and operational resource planning.
d. **Education:** Automated tutoring environments, adaptive learning analytics, and institutional assessment.
e. **Industry and Commerce:** Automated supply chain management, predictive market modeling, pricing optimization, and automated quality control.

### *2.2. The Concept of Artificial Intelligence*

Defining artificial intelligence involves examining its linguistic roots, operational definitions, and academic conceptualizations.

#### *2.2.1. Defining Artificial Intelligence*

a. **Linguistic and General Definitions:** Linguistically, intelligence denotes cognitive adaptability, analytical comprehension, and problem-solving capability[9]. The term "artificial" refers to constructs produced through human ingenuity rather than occurring naturally[10] . From an organizational and operational perspective, AI denotes computer systems capable of performing tasks traditionally requiring human cognition, including visual processing, speech perception, contextual reasoning, linguistic translation, and self-correcting iterative learning[11].

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[5] - Delipetrev, Tsinaraki, and Kostic, *Historical Evolution of Artificial Intelligence*, p.11.

[6] - *The History of Artificial Intelligence,* (Avicena, 2024), p.4. Accessed March 13. https://avicena.tech/wp-content/uploads/2024/03/The-History-of-AI_Avicena.pdf

[7] - Mohamed Ali El-Sharkawy, *Artificial Intelligence and Neural Networks* (Egypt: 1996), p.28.

[8] - El-Sayed Nasr El-Din El-Sayed, *How Computers Think: A Smart Reader's Guide to AI* (Egypt: Dar El-Ain Publishing, 2006), p.10–11.

[9] - Louis Maalouf, *Al-Munjid fī al-Lughah al-ʿArabiyyah* (Beirut: Electronic Press, 2009), p.237.

[10] - Abou Bakr Khoualed et al., *Artificial Intelligence Applications as a Modern Trend to Enhance the Competitiveness of Business Organizations*, 1st ed. (Berlin: Arab Democratic Center, 2019), p.11.

[11] - Abou Bakr Khoualed et al., Idid.

**b. Scholarly Definitions:**

- Stuart Russell and Peter Norvig define AI as a subfield of computer science dedicated to designing systems that perceive their environment and execute actions that optimize the likelihood of achieving specified goals, encompassing logical inference, problem-solving, and language processing.
- John McCarthy defined AI as the science and engineering of creating intelligent machines, particularly intelligent computational programs designed to perform functions that would require human intelligence if executed by people.
- Dan W. Patterson characterizes AI as a branch of computer science focused on developing software and hardware architectures that exhibit traits associated with human intelligence, such as natural language comprehension, semantic deduction, and adaptive reasoning[12].

### *2.2.2. Core Artificial Intelligence Technologies in Public Policy*

In modern governance, smart technologies constitute an integrated ecosystem combining machine learning, Internet of Things (IoT) frameworks, big data analytics, and advanced telecommunications. This digital architecture enhances public service delivery, operational efficiency, and programmatic policymaking across governmental sectors[13].

Within public policy analysis, several core technologies are particularly influential in re-engineering the policy cycle:

**a. Machine Learning**: Machine learning (ML) is an interdisciplinary field situated at the intersection of statistics, mathematical optimization, computational algorithmics, and signal processing. While early applications focused on optical character recognition (OCR) and spam filtering, modern ML models underpin automated fraud detection, algorithmic recommendation engines, computer vision, and neural machine translation[14].

**b.** Within public governance, machine learning provides analytical infrastructure for optimizing public resource allocation, predicting natural disaster risks, enhancing transportation safety through automated systems, and improving energy efficiency within national environmental transition frameworks[15].

**c. Big Data Analytics**m Big data within public administration is conceptualized through three foundational dimensions[16]:

- **Volume, Velocity, and Variety:** The structural velocity, sheer volume, and multi-format nature of administrative and societal data streams.

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[12] - Oussama Ben Khedim and Issam Layadhi, "The Role of AI Applications in Improving Administrative Efficiency in Algerian Sports Institutions," *Journal of Administrative and Sports Sciences* 6, no. 2 (December 2024), p.59.

[13] - Chloé-Agathe Azencott, *Introduction au Machine Learning* (Lecture Notes, 2026), p.10. (accessed January 10, 2026). https://cazencott.info/dotclear/public/lectures/IntroML_Azencott.pdf

[14] - Chloé-Agathe Azencott, Ididp11.

[15] - Chloé-Agathe Azencott, Idd., p.11.

[16] - Adel Inezarene, "Challenges of Using Artificial Intelligence and Big Data in Public Policymaking," *Aleph: Langues, Médias et Sociétés* 11 (2024), p.607–627.

- **Technological and Analytical Infrastructure:** The computational platforms and specialized architectures required to aggregate, clean, and process large datasets.
- **Insight and Public Value Generation:** The analytical pipeline through which raw administrative data is converted into actionable, evidence-based policy insights.

Operationally, big data in public policy refers to extensive informational assets whose high volume, rapid generation rate, and structural diversity require advanced computational methods to extract actionable intelligence for public decision-making.

**d. Generative Artificial Intelligence:** Generative AI represents a class of models designed to produce novel textual, visual, code-based, or synthetic data outputs through natural language prompts. Rather than functioning solely as indexing or retrieval systems, these architectures synthesize multi-modal content based on patterns derived from large training corpora[17].

Building on transformer models and deep neural networks, generative AI moves beyond descriptive data processing to autonomous content drafting, legislative text summarization, policy scenario generation, and regulatory synthesis, marking a core technological development in modern digital governance[18].

### *3. The Paradigm Shift in Public Policy: Founding Smart Public Policy Scholarship*

Artificial intelligence (AI) has transitioned across numerous governmental sectors from theoretical abstraction into operational practice. It has driven critical advancements in enhancing bureaucratic efficiency, modernizing data governance, and optimizing policy outcomes. These practical deployments range from computer vision applications in critical infrastructure protection and automated document authentication to diverse developmental implementations across public policy domains.

In the sphere of public policy, AI applications denote the deployment of algorithms, automated data pipelines, and computational frameworks to guide how governments design, execute, and evaluate public programs. By deploying machine learning architectures and predictive analytics within core operational fields—such as welfare distribution, public transportation management, and regulatory compliance—AI facilitates the identification of latent behavioral patterns, forecasts policy outcomes, and enhances decision-making mechanisms to achieve greater administrative efficiency and equity[19] .

#### *3.1. Agenda-Setting*

During the initial stage of the public policy cycle, AI supports policymakers in identifying and prioritizing urgent societal issues by analyzing large-scale administrative datasets and crowdsourced public data streams. The structural trends and latent patterns revealed through these

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[17] - Baraka Mechnane and Imane Benkssir, "Generative Artificial Intelligence in Education: A Global Vision of Challenges and Opportunities," *Journal of Industrial Economy (Khadratec)* 15, no. 1 (2025), pp.239–240.

[18] - Lahcen Abdi, "Generative Artificial Intelligence and Curriculum Development," *Ataa Journal for Studies and Research*, Special Issue (April 2025), p. 75.

[19] - Adam Boros, "AI in Public Policy," *The Decision Lab*, accessed March 11, 2026, https://thedecisionlab.com/reference-guide/computer-science/ai-in-public-policy

computational analyses provide actionable insights that help align and prioritize the government agenda[20] .

Machine learning algorithms are increasingly utilized to analyze complex crowdsourced datasets. In Belgium, for instance, natural language processing (NLP) architectures have been integrated to assist civil servants in processing extensive civic input gathered through digital stakeholder consultation platforms. These AI systems aggregate, classify, and analyze civic contributions via real-time interactive dashboards, extracting key thematic trends disaggregated by demographic cohort and geographic jurisdiction. Similarly, public administrations in Bulgaria leverage spatial analytics and regional data indicators to monitor civic reporting trends, identifying critical urban service delivery bottlenecks[21] .

More broadly, AI and data-driven systems play an expanding role in the agenda-setting phase by processing continuous, large-scale data streams to detect early indicators of emerging public problems. By utilizing machine learning and natural language processing, intelligent architectures process both structured and unstructured inputs, including news archives, social media discourse, search engine trends, and citizen feedback loops, to identify emerging civic patterns or anomalous events requiring policy intervention. For example, during the COVID-19 pandemic, the State Government of Victoria in Australia implemented AI-driven syndromic surveillance to track reported clinical symptoms and inpatient demographic characteristics, enabling the detection of emerging public health risks in near real time. Similarly, the Queensland Fire and Emergency Services (QFES) developed the "Service Demand Forecasting Tool," which leverages supervised machine learning models to forecast emergency service demand based on longitudinal incident logs, demographic transitions, and localized environmental variables[22].

### *3.2. Policy Formulation*

Artificial intelligence directly enhances the policy formulation stage by generating evidence-based empirical insights. At this juncture, the predictive utility of AI serves as a powerful computational tool for evaluating the structural impacts of macroeconomic policies, estimating cost-benefit ratios across competing policy alternatives, and delineating target demographic cohorts. For instance, two-level deep reinforcement learning frameworks have been deployed to evaluate optimal tax policy designs; this AI architecture, known as the "AI Economist," has demonstrated clear practical feasibility in simulating complex economic interventions. Furthermore, recent empirical advancements demonstrate that calibrated machine learning models

[20] - Andre Wirjo and Sylwyn Calizo Jr., "Artificial Intelligence in Economic Policymaking," *APEC Policy Support Unit Policy Brief*, no. 52 (November 2022), p.2.
[21] - Andre Wirjo and Sylwyn Calizo Jr., Idid.
[22] - Jooho Lee and Yixin Dai, "Artificial Intelligence and Data-Driven Technology in the Public Policy Cycle: Comparative Applications, Opportunities, and Risk," *Journal of Comparative Policy Analysis: Research and Practice* 27 (2025), p.479.

can accurately forecast the downstream macroeconomic effects of green public spending, supporting the formulation of more sustainable fiscal strategies [23].

The policy formulation stage translates identified societal demands into concrete government programs and regulatory instruments. This process involves establishing strategic targets, evaluating alternative policy options, managing stakeholder negotiations, integrating scientific expertise, and drafting statutory texts. A critical domain where AI exhibits substantial utility is within formal legislative and regulatory processes. In recent scholarship, large language models (LLMs) have been deployed to simulate and evaluate the socioeconomic ramifications of regulatory frameworks. A notable case study involved assessing the European Union's *AI Act*, modeling its potential cross-sectoral impacts across the labor market, social welfare systems, community cohesion, and national security architectures. Additionally, AI systems streamline legal research and statutory drafting during the preliminary investigative phases by categorizing, indexing, and synthesizing extensive bodies of jurisprudence and statutory codes to support legislative drafting[24] .

Large language models further assist legislative drafters in maintaining statutory consistency and structural coherence across legislative texts. They detect statutory ambiguities, cross-reference intersections with existing statutory regimes, and categorize derived obligations, entitlements, licenses, and statutory penalties. Moreover, LLMs examine drafting conventions, recommend standardized technical terminology, and highlight drafting discrepancies. Finally, these models evaluate draft statutory instruments across functional dimensions, including digital readiness, technical interoperability, and compliance with statutory policy mandates such as gender neutrality in legal drafting[25] .

### *3.3. Policy Implementation*

The implementation stage represents the operational translation of adopted policy mandates into public programs and services. Following formal political adoption, administrative agencies and public institutions execute policies through operational programs, regulatory enforcement, and service delivery workflows. This stage requires multi-agency coordination across public departments, private actors, and non-profit organizations, alongside resource allocation, human capital management, and localized adaptation to fulfill the policy's core legislative intent[26] .

Artificial intelligence holds significant transformative potential for policy implementation by automating routine administrative tasks, optimizing dynamic resource allocation, and enabling data-driven compliance monitoring. A primary dimension of this operational impact is the automation of procedural workflows: robotic process automation (RPA) and AI pipelines process

[23] - Wirjo and Calizo Jr., "Artificial Intelligence in Economic Policymaking,"p.3.
[24] - Rony Medaglia, *Better Policy Making in the Age of AI* (Center for the Governance of Change, October 2025), pp. 10–11.
[25] - Rony Medaglia, Idid.
[26] - Lee and Dai, "Artificial Intelligence and Data-Driven Technology in the Public Policy Cycle," , pp.482–483.

administrative applications, archive and index public documentation, and dispatch formal notices rapidly with low error rates, freeing civil servants to focus on complex discretionary tasks. In parallel, AI-driven performance dashboards facilitate real-time administrative oversight by tracking operational key performance indicators (KPIs) and identifying emerging administrative bottlenecks or anomalies, providing public managers with actionable intelligence for rapid procedural interventions. Beyond administrative workflow optimization, AI also reshapes the operational discretion of front-line administrative personnel "street-level bureaucrats" executing public policy on the ground[27] .

The deployment of AI and big data within policy implementation is structured along two core dimensions: first, these technologies help identify operational priorities for targeted local deployment across varying operational scales; second, AI analytics augment the empirical data streams required to accelerate implementation workflows. Continuous real-time data processing enables broad optimizations in urban traffic coordination and infrastructure operations through automated control systems[28]. Consequently, public policy implementation achieves higher responsiveness in public service delivery, particularly through service personalization and behavioral profiling based on sociodemographic indicators. Within this operational context, tax administrations globally utilize predictive profiling on individual and corporate entities to combat tax evasion and fraudulent declarations by designing targeted compliance incentives. Similarly, law enforcement and municipal police authorities deploy AI-driven predictive systems to monitor public safety risks and identify spatial-behavioral patterns in criminal activity[29] .

### *3.4. Policy Evaluation*

The epistemological foundation of policy evaluation resides in evidence-based critical inquiry; public policy assessment is grounded in rationality and systematic empirical verification. The Foundation for Critical Thinking (2016) traces the intellectual roots of this analytical approach back twenty-five centuries to Socrates and the development of the Socratic method. Socratic inquiry established the necessity of probing empirical evidence, scrutinizing underlying assumptions, dissecting core conceptual premises, and tracing the logical implications of spoken arguments and actions. Today, Socratic questioning remains a foundational pedagogical strategy for cultivating systematic critical evaluation. Through this analytical model, Socrates highlighted the imperative of logical coherence and structural clarity by subjecting ungrounded assertions to rigorous examination, demonstrating that unverified rhetoric often conceals conceptual ambiguities, insufficient empirical evidence, and self-contradictory premises[30] .

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[27] - Lee and Dai, Idid.

[28] - David Valle-Cruz and Edgar A. Ruvalcaba-Gomez, "A Review of Artificial Intelligence in Government and Its Potential from a Public Policy Perspective" (Conference Paper, United Arab Emirates, June 18–20, 2019), p.96.

[29] - David Valle-Cruz and Edgar A. Idid.

[30] - Michael Quinn Patton, "Public Policy Evaluation: Origins and Evolution," in *Handbook of Public Policy Evaluation* (Edward Elgar Publishing, 2026).

In classical linear policy frameworks, formal evaluation is positioned as the final phase of the policy cycle, theoretically permitting early policy termination or iterative recalibration upon detecting programmatic failure. In operational practice, however, adjusting an enacted policy agenda carries high organizational and political risks; traditional business intelligence tools in the pre-big data era generally lacked the analytical latency required to justify agile interventions or early-cycle adjustments[31] .

Continuous evaluation is exemplified by the United Kingdom government's Performance Platform. Rather than merely publishing static open government data on public programs at disparate intervals, the platform utilizes dynamic data visualization frameworks to provide accessible, real-time assessment of operational public services. Although iterative in development and constrained by limitations in granular root-data access across specific modules, this performance platform illustrates the contemporary shift toward continuous, real-time policy evaluation[32].

### *3.5. Analytical Comparison: AI Re-Engineering Across the Policy Cycle*

To synthesize the transformative impact of artificial intelligence across the policy cycle, the table below delineates the structural alignment between policy stages, applied AI technologies, public policy domains, core institutional benefits, and associated operational risks:

| Policy Stage | Policy Domain | AI Application Type | Core Opportunity & Benefit | Associated Structural Risk |
|---|---|---|---|---|
| **Agenda-Setting** | Public Health, Emergency Services & Urban Affairs | NLP, Web Mining & Big Data Streams | Early detection of public issues; real-time civic sensing; dynamic agenda prioritization | Data bias; digital exclusion of marginalized voices; selective algorithmic attention |
| **Policy Formulation** | Fiscal Policy, Labor Regulations & Legislative Drafting | Deep Reinforcement Learning, Predictive Modeling & LLMs | Simulation of complex policy alternatives; empirical impact forecasting; legislative drafting coherence | Model opacity ("black box"); algorithmic hallucinations; over-reliance on speculative projections |

[31]- Johann Höchtl, Peter Parycek, and Ralph Schöllhammer, "Big Data in the Policy Cycle: Policy Decision Making in the Digital Era," *Journal of Organizational Computing and Electronic Commerce* 26, no. 1–2 (October 12, 2016), p.163.

[32] - Johann Höchtl, Peter Parycek, Idid.

| | | | | |
|---|---|---|---|---|
| **Policy Implementation** | Social Welfare, Tax Administration & Law Enforcement | RPA, Computer Vision & Predictive Profiling | Administrative workflow automation; service personalization; operational efficiency gains | Automated discrimination; loss of frontline administrative discretion; due process violations |
| **Policy Evaluation** | Public Service Delivery & Infrastructure Management | Real-Time Dashboards & Automated Analytics | Continuous, real-time performance evaluation; agile programmatic recalibration | Surveillance overreach; performance gaming; misinterpretation of spurious statistical correlations |

**Source: Prepared by the author**

***4. Risks and Challenges of Integrating Artificial Intelligence into Public Policy***

The integration of artificial intelligence (AI) into public policy is no longer a distant theoretical prospect; it represents an active operational reality. Governments and political actors globally are deploying and developing AI tools across various domains, ranging from healthcare diagnostics and fraud detection to electoral campaigns and public service delivery. While AI technologies promise enhanced operational efficiency, greater decision accuracy, and personalized public services, they also introduce critical structural risks. Issues surrounding bias, transparency, privacy, and accountability have emerged as central challenges, raising a fundamental question: *How can public institutions ensure that AI serves the public interest rather than exacerbating existing inequalities or amplifying administrative errors at scale?*[33]

Evaluating the deployment of AI and data science within the public sector carries high normative importance. Unlike private-sector interactions—where consumers retain the autonomy to engage with or boycott a firm—citizen interaction with the state is involuntary. Consequently, algorithmically mediated administrative decisions directly impact citizens' fundamental rights, from social welfare entitlements to criminal justice outcomes. Ensuring that these computational systems operate under principles of procedural fairness, transparency, and democratic values represents a structural challenge that demands immediate attention from policymakers[34] .

Integrating AI tools into public policy introduces several operational and institutional risks. Machine learning models and statistical frameworks can generate adverse policy outcomes.

[33] - Kenneth Benoit, "AI and Data Science for Public Policy," *LSE Public Policy Review* 3, no. 3 (November 4, 2024), p.40.
[34] - Kenneth Benoit, Idid.

Furthermore, the opacity surrounding algorithmic mechanisms risks eroding institutional trust and social capital. Additionally, algorithmically driven tools can be deployed in ways that undermine democratic deliberation and institutional pluralism[35] .

Machine learning models derive their analytical capacity from historical training datasets, meaning that empirical data inputs determine algorithmic parameters and downstream outputs. While these models are engineered to minimize error rates and optimize performance metrics, they can capture spurious correlations that coincide with specific training scenarios without establishing genuine causality. Consequently, models that demonstrate high predictive accuracy in aggregate populations may exhibit structural performance deficits when evaluating historically marginalized or underrepresented cohorts, producing discriminatory or exclusionary outcomes. For instance, researchers have identified and classified persistent forms of demographic, religious, and racial bias within datasets extracted from social platforms such as Reddit, which are frequently used to pre-train large language models[36] .

Public policymaking also faces systemic hurdles due to inherent environmental complexity and dynamic constraints, particularly when short-term political incentives take precedence over long-term strategic objectives. In this context, policymakers require structured frameworks to address recurring decision-making pathologies[37] :

a. **Difficulty in Building Consensus Among Policy Actors:** A challenge that can be mitigated by deploying algorithmic simulations to explore common policy ground.
b. **Cognitive Overconfidence in Subjective Judgments:** Where policymakers rely excessively on personal intuition rather than empirical recommendations from expert systems.
c. **External Attribution of Policy Failures:** The tendency to attribute unfavorable outcomes to exogenous factors rather than accepting institutional and administrative responsibility.

Additional structural challenges confronting decision-making in public policy include[38] :

a. **Predictive Uncertainty:** Difficulties in forecasting outcomes within complex, non-linear policy environments.
b. **Implementation Divergence:** Gaps in procedural precision during policy execution on the ground.
c. **Discretionary Bias in Decision-Making:** Systematic disparities observed in administrative enforcement, such as law enforcement stop-and-arrest rates.
d. **Administrative Corruption:** The reliance on unlawful mechanisms to execute or influence public policies.

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[35] - Santiago Velez, "Is Artificial Intelligence a Risk in Public Policy Work?," *LSE Public Policy Review* 3, no. 3 (November 4, 2024), p.41–43.
[36] - Santiago Velez, Idid.
[37] - Adel Inezarene, "Challenges of Using Artificial Intelligence and Big Data in Public Policymaking," *Aleph: Langues, Médias et Sociétés* 11 (2024), p.607–627.
[38] - Adel Inezarene, Idid.

The deployment of automated tools in policy formulation can also reinforce systemic policy discrimination. Predictive analytics and risk-scoring algorithms risk entrenching historical inequities when trained on biased administrative records. For example, when France's National Family Allowance Fund (*Caisse Nationale des Allocations Familiales* - CNAF) deployed an algorithmic risk-scoring system to detect overpayments and potential benefit fraud, civil society organizations challenged the system's legality. They demonstrated that the model generated disproportionately higher risk scores for single mothers, persons with disabilities, and low-income beneficiaries due to its underlying scoring variables. Furthermore, complex deep learning architectures—such as deep neural networks—generate predictions across multi-layered statistical interactions that are difficult to interpret. This dynamic creates a "black box" problem that obscures the rationale behind administrative determinations. In policy formulation, this opacity undermines institutional accountability and infringes upon core principles of procedural justice and due process[39].

During the agenda-setting phase, selective attention presents another critical hurdle. Determining which issues warrant urgent government action is often contested, raising fundamental questions about which epistemic voices and evidence streams shape the public agenda. Digital platforms and news media can amplify sensationalist topics while sidelining complex structural issues, skewing policy priorities toward heavily funded campaigns. Moreover, public officials frequently struggle to identify emerging societal problems early, increasing the risk that the concerns of underrepresented communities remain overlooked in favor of influential interest groups[40] .

Within this framework, the field of AI ethics provides normative guidelines for human–machine interactions. Examining the ethical dimensions of AI evaluates its broader social, economic, cultural, and political impacts, establishing guardrails for designing and deploying automated systems[41] .

The primary imperative within AI ethics is the creation of governance mechanisms that ensure meaningful human control over automated systems. This requirement is especially critical in public policy, where technological deployment can disrupt traditional institutional processes. Fulfilling this imperative requires operationalizing ethical standards into institutional governance instruments that preserve human agency. Maintaining a "human-in-the-loop" across all stages of

[39] - Rony Medaglia, *Better Policy Making in the Age of AI* (Center for the Governance of Change, October 2025), p.11.

[40] - Jooho Lee and Yixin Dai, "Artificial Intelligence and Data-Driven Technology in the Public Policy Cycle: Comparative Applications, Opportunities, and Risk," *Journal of Comparative Policy Analysis: Research and Practice* 27 (2025), p.479.

[41] - Fernando Filgueiras, *Artificial Intelligence and Public Policy: Disrupting Policy Sciences*, Cambridge Elements in Public Policy (Cambridge: Cambridge University Press, 2024), p.47.

the public policy cycle remains a central challenge, as the analytical frameworks produced by AI increasingly shape administrative behavior and state action[42] .

***5. Conclusion***

This study examined the paradigm shift brought about by artificial intelligence (AI) in public policy scholarship, tracing its transition from an auxiliary administrative mechanism into an epistemological and structural paradigm that reshapes the fundamentals of governance and decision-making. The systems analysis across the public policy cycle demonstrates that the integration of machine learning, big data analytics, and generative AI has established a clear departure from conventional linear models, transforming policy processes into dynamic, proactive architectures grounded in mathematical modeling, predictive simulation, and real-time adaptation.

However, the innovative potential of algorithmic governance remains strictly bounded by normative and ethical parameters. The expansion of algorithmic systems across the public sector introduces fundamental risks to procedural fairness and democratic accountability, particularly when decision-making rationales are obscured within "black-box" models or when societal inequities are perpetuated through historical training data. Consequently, the sustainability of smart public policy models does not depend on uncritical technological optimism, but rather on building an integrated governance framework that maximizes algorithmic operational efficiency without compromising human oversight and the sovereignty of the public interest.

Based on the theoretical and analytical examination of the relationship between artificial intelligence and public policy, the study reached the following findings: The deployment of artificial intelligence technologies has driven a paradigm shift in public policy, transitioning the discipline's epistemological center from classical bureaucratic models grounded in linear procedures and intuitive heuristics to algorithmic governance frameworks supported by empirical data, predictive analytics, and self-correcting machine learning.

1. Smart technologies have demonstrated significant capacity to reconfigure the policy cycle by facilitating early issue detection during agenda-setting, enabling legislative and economic simulation during policy formulation, streamlining automated service delivery and personalization during implementation, and replacing retrospective assessments with continuous, real-time evaluation.
2. The integration of AI faces substantial institutional and ethical challenges, most notably algorithmic bias inherited from historical training data, the absence of algorithmic explainability, and the "black box" phenomenon, which together threaten procedural justice, administrative accountability, and equity in public resource distribution.
3. The technical efficacy of artificial intelligence derives its institutional legitimacy solely through meaningful human oversight ("human-in-the-loop"). The successful integration of these systems remains fundamentally contingent upon robust legislative and ethical frameworks that safeguard individual rights and serve the public interest.

[42] - Fernando Filgueiras, Idid., p.48–50.

In light of the findings reached, the study proposes the following recommendations to ensure the responsible and effective integration of artificial intelligence into public policy:

1. Enact comprehensive national legislation governing the deployment of AI in the public sector, mandating strict algorithmic transparency, technical explainability, and non-discrimination audits across automated public welfare and service programs.
2. Prohibit the full automation of public policy decisions that directly determine individual legal status, socio-economic entitlements, or fundamental citizen rights, ensuring final discretionary authority rests with human decision-makers.
3. Require public agencies and algorithmic developers to implement continuous audits of training datasets to ensure statistical and demographic representation, actively identifying and mitigating historical, racial, socio-economic, and gender biases prior to administrative deployment.
4. Design specialized institutional training programs for policymakers and public administrators focused on critical evaluation of AI outputs, the structural logic of expert systems, and the legal and ethical implications of data-driven governance.

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