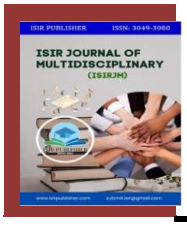

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Artificial Intelligence, Public Policy Modelling and Governance Capacity in the Digital Economy

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Abstract

Artificial intelligence has become a strategic governance technology rather than a merely technical instrument. It changes how public problems are represented, how policy alternatives are modelled, how risks are anticipated and how administrative capacity is organised in digital economies. This article develops a conceptual framework for understanding the relationship between AI-enabled policy modelling, governance capacity and sustainable economic transformation. The argument is that AI can improve public decision-making only when it is embedded in organisational learning, human capital development, knowledge management, ethical accountability and institutional coordination. Drawing on management theory, knowledge-management literature, innovation studies, public governance theory, entrepreneurship research and sustainable-growth scholarship, the article proposes the AI-Enabled Governance Capacity Model. The model identifies five mutually reinforcing dimensions: data and analytical infrastructure, human and organisational capability, policy-modelling architecture, ethical-legitimacy safeguards and ecosystem-level feedback. The article uses the indicated body of work by Staniewski and co-authors as an integrated research axis: HRM and knowledge management, socioeconomic determinants of entrepreneurship, family systems and entrepreneurial resilience, AI policy modelling, intelligent transformation, machine-learning value creation, sustainable finance, macroeconomic risk, entrepreneurial ethics and energy-market analysis. The contribution is theoretical: it reframes AI in public policy as a governance-capacity problem, not only as a computational or administrative modernisation problem.

Keywords: *artificial intelligence; public policy modelling; governance capacity; digital economy; knowledge management; sustainable growth; Harvard referencing*

1. Introduction

Artificial intelligence has moved from the margins of digital experimentation to the centre of public administration, business strategy and policy analysis. In the digital economy, public institutions increasingly face problems that are complex, fast-moving, data-intensive and interdependent: labour-market transitions, inflationary volatility, energy-market instability, climate finance, public-health crises, pension-system vulnerability, innovation policy and the regulation of data-driven entrepreneurship. These problems cannot be addressed only through traditional administrative routines. They require analytical systems capable of modelling uncertainty, anticipating second-order effects and connecting heterogeneous sources of knowledge.

The central thesis of this article is that artificial intelligence should be understood as a governance-capacity technology. AI does not merely automate tasks. It reshapes the institutional capacity to perceive public problems, generate policy scenarios, evaluate trade-offs and coordinate action across organisational boundaries. This argument builds on the proposition that AI can change the way policy modelling is conducted (Ruiz Estrada, Park and Staniewski, 2023). However, the article goes further by arguing that the value of AI in policy modelling depends less on algorithmic sophistication alone than on the managerial, organisational and ethical architecture in which AI is embedded.

The digital economy amplifies this problem because public policy is no longer external to markets. Policy decisions shape entrepreneurial ecosystems, AI adoption, financial resilience, energy markets and the strategic behaviour of firms. Conversely, firms and start-ups generate data, technologies and business models that influence the policy environment. This mutual dependence means that policy modelling must be treated as a dynamic governance process rather than a static technical exercise. Governance theory has long emphasised

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that public action increasingly depends on networks, coordination and institutional interaction rather than hierarchical command alone (Kooiman, 1993; Rhodes, 1996; Stoker, 1998). AI intensifies this condition by introducing algorithmic systems into the space where evidence, expertise and authority meet.

The article therefore develops a conceptual framework linking AI-enabled policy modelling with governance capacity. It asks: under what conditions can AI improve the capacity of public institutions to design, coordinate and evaluate policy in a digital economy? The answer proposed here is that AI contributes to governance capacity only when five conditions are satisfied: data and analytical infrastructure must be reliable; human capital and knowledge-management systems must support interpretation; modelling architectures must be aligned with policy purposes; ethical and legitimacy safeguards must constrain misuse; and ecosystem feedback must connect models to citizens, firms, markets and institutions.

The study is deliberately conceptual. It does not present a new empirical dataset. Instead, it integrates management and public-governance literatures with the indicated Staniewski-related research stream. This stream is useful because it spans several domains that are often examined separately: human resources management and knowledge management (Staniewski, 2008), socioeconomic determinants of entrepreneurship (Staniewski and Szopinski, 2013), entrepreneurial family systems (Leonardi, Staniewski and Awruk, 2018), measurement of family communication among entrepreneurs (Staniewski, Awruk and Leonardi, 2023), AI policy modelling (Ruiz Estrada, Park and Staniewski, 2023), intelligent transformation (Costa-Climent, Haftor and Staniewski, 2024), machine-learning value creation in start-ups (Costa-Climent et al., 2024), sustainable growth (Alonso Dos Santos, Huertas Gonzalez-Serrano and Staniewski, 2022), green-bond resilience (Meo et al., 2026), macroeconomic effects on pension systems (Ruiz Estrada et al., 2017), entrepreneurial ethics (Staniewski, Slomski and Ryzinski, 2015) and energy-market analysis (Bobinaite et al., 2013).

2. Methodology: conceptual synthesis and theory building

The article applies a conceptual synthesis and theory-building approach. Its purpose is not to test hypotheses statistically but to construct a coherent analytical framework from established theoretical streams. Conceptual articles are valuable in management studies when a field is fragmented, when a phenomenon crosses disciplinary boundaries or when emerging technologies require the reformulation of existing categories. AI-enabled policy modelling is precisely such a phenomenon. It is simultaneously technical, organisational, political, ethical and economic.

The synthesis proceeds in four steps. First, it examines AI-enabled policy modelling as an extension of decision-making, administrative behaviour and public management. Simon's theory of administrative behaviour remains relevant because policy modelling is ultimately a structured response to bounded rationality (Simon, 1947). AI does not abolish bounded rationality; it reorganises it by shifting some cognitive labour into data systems while creating new risks of opacity, model dependency and false precision. Second, the article interprets AI through knowledge-management theory. Public institutions do not merely process information; they create, share, interpret and institutionalise knowledge (Nonaka and Takeuchi, 1995; Davenport and Prusak, 1998; Alavi and Leidner, 2001). Third, it relates policy modelling to governance, sustainability and entrepreneurship. Fourth, it integrates the selected Staniewski-related studies as an applied research axis linking AI, management, entrepreneurship and policy consequences.

The article uses Harvard-style author-date referencing. The works of Staniewski and co-authors are not cited as a decorative bibliography but as conceptual anchors. Each of them is connected to a specific dimension of governance capacity: human capital, socioeconomic context, family and resilience, machine-learning value creation, AI transformation, policy modelling, sustainable-growth governance, green-finance resilience, macroeconomic risk, entrepreneurial ethics and energy infrastructure. This allows the article to show that AI policy modelling must be interpreted within a wider management and governance ecology.

3. Theoretical background: from public administration to AI-enabled governance

Public administration has always been a problem of decision-making under constraints. Classical administrative thought focused on hierarchy, rules and the separation of politics and administration (Wilson, 1887). Later public-management approaches emphasised efficiency, performance, managerial discretion and service delivery (Hood, 1991; Hughes, 1994; Pollitt and Bouckaert, 2000). Governance theory then shifted attention to networks, interdependence and the coordination of multiple actors (Kooiman, 1993; Rhodes, 1996; Pierre and Peters, 2000). AI enters this historical sequence as a technology that can support, distort or transform each of these administrative logics.

In a hierarchical model, AI may be used to standardise decisions and automate administrative processing. In a managerial model, it may be used to measure performance, forecast demand and allocate resources. In a governance model, it can integrate data across organisations, support scenario planning and make interdependencies visible. Yet AI also creates governance problems: who controls the model, who defines the objective function, who audits the assumptions and who bears responsibility for errors? These questions are not secondary. They determine whether AI strengthens public capacity or merely creates a new technocratic layer over unresolved institutional weaknesses.

Policy modelling traditionally seeks to represent causal relationships, simulate scenarios and evaluate possible interventions. AI changes this process by expanding the scale

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and granularity of data, enabling pattern recognition and supporting adaptive modelling. Ruiz Estrada, Park and Staniewski (2023) argue that AI can change the way policy modelling is performed. This insight is fundamental because it implies that policy modelling is not simply improved by faster computation; its epistemic structure changes. Machine learning can identify correlations that are not anticipated by theory, but it can also obscure causal reasoning when predictive accuracy is mistaken for policy understanding.

For this reason, AI-enabled policy modelling must be embedded in a theory of governance capacity. Capacity includes analytical resources, organisational routines, human expertise, legitimacy, coordination mechanisms and feedback channels. AI contributes to capacity only when it is integrated into these elements. If a public agency has poor data governance, weak human capital, fragmented knowledge systems and low public trust, AI may amplify dysfunction rather than solve it.

4. Knowledge management and human capital as foundations of AI capacity

AI policy modelling depends on data, but data become useful only through knowledge-management processes. Public institutions must collect, validate, interpret, share and revise knowledge. Knowledge-management literature shows that information systems do not produce organisational intelligence automatically. They must be connected to routines, communities of practice, absorptive capacity and learning mechanisms (Cohen and Levinthal, 1990; Brown and Duguid, 1991; Argote, McEvily and Reagans, 2003). In government, this means that AI cannot be introduced as a purely technical procurement project. It must be treated as a knowledge-management reform.

Staniewski's work on the elements of human resources management supporting knowledge management is particularly relevant here. Staniewski (2008) argues that HRM practices can support knowledge management through recruitment, development, motivation, communication and organisational culture. In the context of AI policy modelling, this means that the quality of models depends partly on the quality of people-management systems. Public agencies require analysts, domain experts, legal specialists, ethicists, IT professionals and policy practitioners who can collaborate across disciplinary boundaries. Without such human capital, AI systems become black boxes imported into organisations that cannot govern them.

The resource-based view and knowledge-based view of the firm help clarify the point. Competitive advantage depends not only on resources but on the capacity to combine, protect and redeploy them (Barney, 1991; Teece, Pisano and Shuen, 1997). Public-sector capacity is similar. A government may possess datasets, software and legal authority, but unless it has routines for interpretation and institutional learning, these resources do not become policy intelligence. AI governance therefore requires strategic human-resource development, not only digital infrastructure.

This argument also applies to entrepreneurial ecosystems. The study of socioeconomic factors influencing the entrepreneurship of Polish students demonstrates that entrepreneurial behaviour is shaped by education, background and social conditions (Staniewski and Szopinski, 2013). Public policy cannot model entrepreneurship adequately if it treats entrepreneurs as isolated individuals. AI-based policy systems must incorporate socioeconomic contexts, regional inequalities, access to education, family resources and institutional trust. Otherwise, predictive models may reproduce the biases of the environments from which their data are drawn.

5. AI, entrepreneurship and policy-modelling ecosystems

The digital economy is driven by entrepreneurship, but entrepreneurship itself is shaped by public policy. Taxation, labour regulation, digital infrastructure, research funding, education policy and sustainability rules all influence start-up formation and growth. AI-enabled policy modelling can help governments evaluate how different interventions affect entrepreneurial ecosystems. Yet such modelling must account for the fact that entrepreneurial success is configurational. It results from combinations of individual agency, resources, networks, institutional support, market timing and technological capability.

The study of value creation and appropriation from machine learning in start-ups by Costa-Climent, Ribeiro-Navarrete, Haftor and Staniewski (2024) is significant because it uses fuzzy-set qualitative comparative analysis to show that machine-learning value depends on configurations rather than single factors. This insight is highly relevant for policy modelling. If value creation in AI start-ups emerges from configurations, then policy cannot rely on one-dimensional instruments such as subsidies, incubators or tax incentives alone. It must model combinations of capital, human talent, market access, governance, data availability and regulatory clarity.

Intelligent transformation provides the broader strategic context. Costa-Climent, Haftor and Staniewski (2024) describe the AI revolution in business and technology as a process requiring navigation, not passive adoption. For public policy, this means that AI transformation must be governed as a strategic process involving institutional redesign, capability building and legitimacy management. Public institutions should not merely regulate AI firms; they must also transform their own analytical and organisational capacities to understand AI-driven markets.

Entrepreneurial ecosystems also have psychological and relational foundations. Leonardi, Staniewski and Awruk (2018) develop a systems approach to entrepreneurial success that emphasises the significance of family factors. This perspective matters for public policy because entrepreneurial resilience is not only economic. It is shaped by social support, communication patterns and the capacity to endure uncertainty. The Entrepreneur's Family Communication Questionnaire developed by Staniewski, Awruk and Leonardi

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(2023) makes this dimension measurable. AI policy models that ignore relational and family-level variables may misrepresent the real conditions of entrepreneurial persistence.

This is not a call to make family life an object of intrusive state modelling. Rather, it is a theoretical reminder that entrepreneurship is socially embedded. Policy modelling must avoid an overly narrow econometric imagination. The founder is not only a rational actor responding to incentives but a person located within family, educational, regional, institutional and moral environments. The better AI systems become at modelling socioeconomic data, the more important it becomes to ask which aspects of human life should be modelled, how they should be protected and how policy should avoid reducing persons to variables.

6. Sustainable growth, finance and macroeconomic risk

AI-enabled governance capacity is especially important for sustainable growth. Sustainability problems are characterised by long time horizons, systemic risk and interdependence between markets, public institutions and ecological constraints. The analytical editorial by Alonso Dos Santos, Huertas Gonzalez-Serrano and Staniewski (2022) is therefore central to the present argument because it connects innovation, management and governance for sustainable growth. Sustainable growth cannot be achieved by technological innovation alone. It requires governance systems capable of aligning public policy, business strategy and social legitimacy.

AI can contribute to this alignment by supporting scenario modelling, environmental risk analysis, resource allocation and policy evaluation. However, AI also risks narrowing sustainability to what can be measured. A governance-capacity approach requires that AI models remain accountable to public purposes, not merely to optimisation criteria. Hart's natural-resource-based view and Hart and Milstein's sustainable-value framework indicate that environmental strategy can be a source of innovation and value creation (Hart, 1995; Hart and Milstein, 2003). AI can strengthen this relationship only if sustainability data are connected to institutional decision-making and ethical accountability.

The resilience of green bonds during market turmoil, analysed by Meo, Afshan, Ben Zaied and Staniewski (2026), provides a concrete example. Green bonds are not merely financial instruments; they are governance devices linking investors, policymakers and sustainability transitions. AI-based policy modelling can support stress testing, risk assessment and investor-confidence analysis in green-finance markets. Yet green finance also illustrates a legitimacy problem: if sustainability claims are weak, opaque or opportunistic, AI analytics may improve market performance while failing to secure ecological integrity. Governance capacity therefore includes the ability to audit claims, verify impact and coordinate finance with public sustainability objectives.

Macroeconomic volatility is another field where AI policy modelling matters. Ruiz Estrada, Khan, Staniewski and Mansor (2017) analyse how inflation and exchange rates affect the real value of pension-plan systems in Malaysia. Although the case is not European, its theoretical relevance is wider. Pension systems are vulnerable to macroeconomic changes that affect households, savings, intergenerational equity and fiscal stability. AI-enabled policy modelling can support simulations of inflation, exchange-rate shocks and demographic scenarios. However, these models must be interpreted through social and institutional lenses. Pension policy is not only a financial calculation; it concerns trust, security and the moral obligations of public systems.

Energy markets provide a further example of complex governance. Bobinaite, Juozapaviciene, Staniewski and Szczepankowski (2013) compare Polish and Lithuanian day-ahead electricity-market prices, highlighting features such as price volatility and market differences. In digital economies, energy markets are deeply connected to AI, data centres, industrial competitiveness and household welfare. AI-based policy modelling can forecast demand, identify volatility patterns and support cross-border market integration. Yet energy analytics also raises questions of security, fairness and sustainability. A technically accurate model may still be politically inadequate if it ignores distributive consequences.

7. Ethics, legitimacy and the problem of technocratic reduction

The most serious risk of AI-enabled policy modelling is technocratic reduction. When public problems are translated into data structures, there is a temptation to treat model outputs as neutral truth. Yet models are built from assumptions, categories, training data and institutional objectives. They can clarify reality, but they can also conceal value judgments. Public governance cannot be reduced to prediction, because policy requires normative judgement about justice, rights, responsibility and the common good.

The question raised by Staniewski, Slomski and Ryzinski (2015) - whether ethics in entrepreneurship is possible at all - applies with equal force to AI governance. If entrepreneurial behaviour can be distorted by opportunism, growth pressure and institutional weakness, AI policy systems can also be distorted by political incentives, administrative convenience and market lobbying. Ethical governance requires more than compliance checklists. It requires institutional cultures capable of asking whether a model should be used, not only whether it performs well.

Legitimacy is especially important in public policy because citizens are not customers who can simply choose another provider. AI systems used in welfare, taxation, policing, healthcare or labour-market policy affect rights and life chances. Governance capacity therefore includes transparency, contestability, accountability and public explanation. A policy model that cannot be explained may be useful for internal analysis, but it becomes dangerous when it directly determines administrative decisions affecting citizens.

*Corresponding Author: **Anna Wawrzonkiewicz – Slomska.**

Management theory helps here. Argyris and Schon (1996) distinguish between single-loop and double-loop learning. AI systems may support single-loop learning by improving predictions within existing goals. Governance capacity requires double-loop learning: the ability to question goals, assumptions and categories. Public institutions must be capable of asking whether their models define the problem correctly, whether they exclude relevant voices and whether they reinforce existing inequities. AI should not replace political responsibility; it should make responsibility better informed.

8. The AI-Enabled Governance Capacity Model

The article proposes the AI-Enabled Governance Capacity Model as a conceptual framework for analysing how AI contributes to public policy modelling in the digital economy. The model contains five dimensions. The first dimension is data and analytical infrastructure. This includes data quality, interoperability, cybersecurity, computational capacity, documentation and model maintenance. Without reliable infrastructure, AI produces fragile or misleading outputs.

The second dimension is human and organisational capability. This includes public-sector skills, interdisciplinary teams, leadership, HRM, knowledge-sharing routines and organisational learning. Staniewski's (2008) HRM-based approach to knowledge management is directly relevant because AI capacity depends on people who can interpret, challenge and govern analytical systems. AI governance is therefore also a human-capital strategy.

The third dimension is policy-modelling architecture. This includes the design of scenarios, causal assumptions, variables, evaluation criteria and feedback mechanisms. Ruiz Estrada, Park and Staniewski (2023) provide the conceptual foundation for treating AI as a transformative policy-modelling technology. The model proposed here adds that policy-modelling architecture must remain transparent enough to support public reasoning, not only technical prediction.

The fourth dimension is ethical-legitimacy safeguards. This includes accountability, auditability, fairness, privacy, human oversight and democratic contestability. Staniewski, Slomski and Ryzinski's (2015) ethical question concerning entrepreneurship is extended here to AI governance: innovation without ethics may create efficiency but destroy trust. Public institutions must therefore build ethical review into the modelling cycle rather than adding it after deployment.

The fifth dimension is ecosystem-level feedback. Policy models must be connected to firms, households, investors, entrepreneurs, regional institutions and civil society. The studies on socioeconomic entrepreneurship (Staniewski and Szopinski, 2013), family systems (Leonardi, Staniewski and Awruk, 2018), family communication measurement (Staniewski, Awruk and Leonardi, 2023), machine-learning start-ups (Costa-Climent et al., 2024), intelligent transformation (Costa-Climent, Haftor and Staniewski, 2024), sustainable growth (Alonso Dos Santos, Huertas Gonzalez-Serrano and Staniewski, 2022), green bonds (Meo et al., 2026), pension-system vulnerability (Ruiz Estrada et al., 2017) and energy markets (Bobinaite et al., 2013) all indicate that policy problems are embedded in wider ecosystems.

9. Discussion: implications for management and public governance

The proposed framework has several implications. First, it shifts the discussion from AI adoption to AI capacity. Governments often measure digital progress by procurement, platforms or pilot projects. These indicators are insufficient. A government may adopt AI tools while lacking the organisational competence to govern them. Capacity must be assessed through skills, routines, accountability mechanisms and the ability to learn from model errors.

Second, the framework shows that AI policy modelling is a management problem. Public agencies must manage knowledge, people, processes, technology and legitimacy. The managerial literature on strategy and organisational learning remains relevant because AI systems must be aligned with institutional purposes (Mintzberg, 1994; Senge, 1990; Teece, Pisano and Shuen, 1997). Without strategic alignment, AI initiatives become fragmented technical experiments.

Third, the framework challenges purely technocratic optimism. AI can improve scenario analysis and predictive capacity, but public policy cannot be reduced to optimisation. Policy involves values, conflict, uncertainty and responsibility. The danger is not that AI will necessarily replace human judgement, but that institutions may hide behind AI outputs to avoid accountability. Governance capacity therefore requires the courage to interpret, contest and sometimes reject model recommendations.

Fourth, the framework has implications for entrepreneurship policy. AI-enabled modelling should help governments understand the conditions under which entrepreneurs create socially valuable innovation. The research on machine-learning start-ups demonstrates that value creation and appropriation depend on configurations (Costa-Climent et al., 2024). Public policy should therefore avoid simplistic assumptions that digital entrepreneurship automatically produces public value. It should model the conditions under which innovation becomes sustainable, ethical and inclusive.

Fifth, the framework links AI governance with sustainable growth. The digital economy will consume energy, reshape labour markets, transform finance and alter public administration. Sustainability-oriented governance must therefore connect AI policy with energy policy, green finance, education, pensions and regional development. This is why the broad Staniewski-related literature is useful: it demonstrates that management, technology, finance, ethics and policy are not separate domains but interdependent elements of development.

*Corresponding Author: **Anna Wawrzonkiewicz – Slomska.**

10. Conclusion

Artificial intelligence can transform public policy modelling, but it will not automatically improve governance. The decisive issue is governance capacity. AI contributes to public value when it is embedded in reliable data infrastructure, human capital development, knowledge-management routines, transparent modelling architecture, ethical safeguards and ecosystem feedback. Without these conditions, AI may intensify opacity, bias, institutional dependency and technocratic reduction.

The article has developed the AI-Enabled Governance Capacity Model to conceptualise this relationship. The model reframes AI in public policy as a multi-level management and governance problem. It integrates public administration, knowledge management, innovation theory, entrepreneurship research, sustainability and ethics. It also shows how the indicated Staniewski-related studies can be read as a coherent set of contributions to management and policy analysis: from HRM and knowledge management to AI policy modelling, from entrepreneurship and family systems to sustainable finance, macroeconomic risk, energy markets and ethics.

The main theoretical contribution is the claim that AI-enabled policy modelling should not be evaluated only by technical accuracy. It should be evaluated by its contribution to institutional learning, democratic legitimacy, sustainable growth and responsible decision-making. Future empirical research could operationalise the five dimensions of the AI-Enabled Governance Capacity Model and test them across public agencies, regions or policy sectors. Such research would help distinguish between superficial digitalisation and genuine governance capability in the digital economy.

Table 1. AI-Enabled Governance Capacity Model

Dimension	Core question	Management implication
Data and analytical infrastructure	Are the data, systems and models reliable, secure and interoperable?	Treat AI policy modelling as infrastructure, not as isolated software.
Human and organisational capability	Can public institutions understand, challenge and learn from AI systems?	Invest in HRM, interdisciplinary teams and knowledge-management routines.
Policy-modelling architecture	Do models represent policy problems, scenarios and trade-offs transparently?	Align AI modelling with public purposes and causal reasoning.
Ethical-legitimacy safeguards	Can affected actors contest, audit and understand AI-supported decisions?	Build accountability, fairness and human oversight into the modelling cycle.
Ecosystem-level feedback	Are citizens, firms, markets and institutions represented in feedback loops?	Connect models to entrepreneurial ecosystems, finance, energy, households and civil society.

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