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Data-Intensive and Ai-Mediated Anticipatory Governance: A Functional Typology of Institutional Capacity, Decision-Making, and Governance of Expertise

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DATA-INTENSIVE AND AI-MEDIATED ANTICIPATORY GOVERNANCE: A FUNCTIONAL TYPOLOGY OF INSTITUTIONAL CAPACITY, DECISION-MAKING, AND GOVERNANCE OF EXPERTISE

Abstract: Anticipatory Governance (AG) has emerged as a strategic approach for addressing uncertainty, systemic risk, and complexity in contemporary socio-technical systems. Governments and universities increasingly rely on Big Data, Data Science, and Artificial Intelligence (AI) to support future-oriented public decision-making, yet the institutional and societal implications of these technologies remain conceptually fragmented. This article addresses this gap through a Systematic Literature Review (SLR) that examines how data-intensive and AI-enabled capabilities become embedded across foresight, knowledge creation, policy design, and policy assessment. Rather than treating the generic technical differences among Big Data, Data Science, and AI as the principal contribution, the study develops a functional typology that distinguishes infrastructural observation and evidentiary integration, analytical modeling and interpretation, and AI-enabled decision mediation. The review analyzes how these functions respond to uncertainty, non-linearity, interdependence, and feedback; reshape informational, analytical, and decisional capacity; and redistribute epistemic and decisional authority. The findings indicate a cumulative but non-deterministic movement from expanded observability, to analytical structuring, to increasingly mediated action. We conceptualize this movement as decisional embedding: the degree to which technological systems enter the institutional production of alternatives, prioritization, recommendation, adjustment, or execution. The contribution lies in showing that technological integration in anticipatory governance is not merely an increase in computational capability, but a reconfiguration of knowledge, judgment, responsibility, and authority. The article concludes with implications for accountable, contestable, and human-governed hybrid decision architectures.

Keywords: Big Data, Data Science, AI, Anticipatory Governance, Foresight, Decision-Making, Responsible Innovation

1. Introduction

Contemporary governance increasingly operates within complex socio-technical systems characterized by uncertainty, non-linearity, interdependence, and dynamic feedback processes (Heo & Seo, 2021). Theoretical contributions in governance and resilience studies emphasize that complex adaptive systems generate emergent properties and unintended consequences that challenge traditional linear models of policy design and evaluation (Duit & Galaz, 2008; Walker et al., 2004). These structural features complicate institutional efforts to anticipate risks, coordinate interventions, and maintain adaptive capacity in rapidly evolving environments, and hence, both new approaches and technologies are required in this context.

In response to these conditions, Anticipatory Governance (AG) has emerged as a framework designed to strengthen institutional capacity for foresight, long-term strategic thinking, knowledge integration, and adaptive policy coordination (Fuerth & Faber, 2012; Guston, 2014; Panizzon & Janissek-Muniz, 2025). Rather than reacting to crises ex post, AG seeks to embed future-oriented reasoning into governance structures, enabling proactive engagement with systemic uncertainty and transformation. Empirical applications in environmental governance and resilience studies further demonstrate the relevance of anticipatory approaches in navigating socio-ecological complexity (Boyd et al., 2015).

Parallel to these institutional developments, governments and universities are increasingly integrating data-intensive, generative AI, geospatial AI, and algorithmic systems into public decision-making in order to cope with growing complexity. Yet the relevant transformation is not simply technological adoption. Big Data infrastructures can expand observational scope and data integration capacity (Kitchin, 2014; Janssen & Kuk, 2016; Liu et al., 2016), Data Science methodologies can support prospective analysis, predictive modeling, simulation, and probabilistic reasoning (Provost & Fawcett, 2013; Trujillo-Cabezas, 2020), and AI systems can become embedded in recommendation, prioritization,

and regulatory oversight (Danaher et al., 2017; Yeung, 2018; Wirtz et al., 2019; Xu et al., 2025). As these systems move closer to decision processes, however, they also reshape who or what produces evidence, frames alternatives, and influences legitimate action. Algorithmic logics therefore create not only technical opportunities but also institutional questions concerning opacity, delegation, accountability, and the governance of expertise (Giest & Klievink, 2024; Giest, 2017; Hughes et al., 2020; Pasquale, 2015; Dunleavy et al., 2006).

Despite growing scholarly attention to complexity in anticipatory governance, digital transformation, and algorithmic regulation, these literatures remain insufficiently integrated within a unified anticipatory-governance framework. The unresolved issue is not whether Big Data, Data Science, and AI have different technical characteristics; these distinctions are already recognizable in the technology literature. The deeper socio-technical problem is how different forms of technological embedding alter institutional visibility, epistemic framing, and the architecture of decision-making. The same computational technique may perform different institutional functions depending on where it enters a governance process. Consequently, the central question is not simply what a technology can compute, but how its use changes what becomes institutionally visible, whose interpretations become authoritative, how alternatives are structured, and where responsibility for action is located. The present study therefore focuses on functional and institutional differentiation rather than on mutually exclusive engineering categories. This is particularly relevant where anticipatory-governance frameworks depend on integrated and interoperable digital technologies to support universities and public-policy ecosystems (Panizzon & Janissek-Muniz, 2026).

This article addresses these gaps through a Systematic Literature Review (SLR) and develops a functional typology that organizes Big Data as primarily infrastructural and informational capacity, Data Science as primarily analytical and modeling capacity, and AI-enabled decision-mediating systems as increasingly embedded in recommendation, prioritization, adaptive adjustment, and partial execution. Agentic and generative AI are treated as subsets of this broader third layer when their primary institutional function is decision mediation. These macro categories are analytical functions rather than exclusive technical taxonomies: technologies such as machine learning may cross category boundaries depending on their institutional role. By mapping these functions across foresight, knowledge creation, policy design, and policy assessment, the study links systemic complexity to institutional capacity and to the redistribution of informational, epistemic, and decisional authority. We use decisional embedding as an integrative concept to describe the degree to which a technological system enters the institutional production of alternatives, prioritization, recommendation, adjustment, or execution. This continuum is not a maturity model and does not imply that greater automation is normatively preferable.

The contribution of the paper is threefold. First, it systematically synthesizes how data-driven and AI-enabled technologies are mobilized across the core functions of anticipatory governance. Second, it develops a functional typology relating technological roles to informational, analytical, and decisional capacity while clarifying overlaps among technical categories. Third, it theorizes decisional embedding as a socio-technical continuum and connects increasing technological mediation to delegation, accountability, epistemic authority, contestability, human oversight, and the governance of expertise in complex institutional settings. The resulting framework therefore links technological capability to the changing distribution of knowledge, judgment, responsibility, and authority.

2. Systematic Literature Review (SLR)

2.1 Review Design

This study employs a Systematic Literature Review (SLR) following PRISMA principles to identify, synthesize, and classify scholarly contributions at the intersection of Big Data, Data Science, AI technologies, and Anticipatory Governance in complex systems. The review uses a structured search and screening process, predefined inclusion and exclusion criteria, and a transparent coding framework aligned with the research questions. Because the study is interpretive as well as descriptive, the methodological account distinguishes between the a priori organizing categories used to code the literature and the relationships that were refined through synthesis of the reviewed studies.

2.2 Research Questions

The review is guided by five research questions:

RQ1: How do different technological layers address the structural challenges of complex systems - such as uncertainty, non-linearity, interdependence, and feedback dynamics - across the core functions of AG?

RQ2: How are Big Data, Data Science, and AI-enabled decision-mediating systems functionally mobilized across the four core functions of AG (foresight, knowledge creation, policy design, and policy assessment)?

RQ3: How do these technological layers contribute to the institutional goals of AG, including risk anticipation, epistemic integration, strategic coordination, responsiveness, and adaptation?

RQ4: In what ways do Big Data, Data Science, and AI-enabled decision-mediating systems reshape informational, analytical, and decisional capacity across the functions of AG?

RQ5: What are the implications of these technological configurations for delegation, accountability, epistemic authority, and the governance of expertise in data-driven AG?

2.3 Search Strategy, Database, and Boolean Operators

The search strategy employed a Boolean query in Web of Science, with data collection conducted during March 2026. The executed query used paired combinations of three technological domains (Big Data, Data Science, and Artificial Intelligence) with foresight and responsible innovation, and also included a standalone Anticipatory Governance branch. Consequently, database retrieval was broader than a strict technology-by-governance intersection; conceptual fit was subsequently enforced through title/abstract and full-text screening using the predefined inclusion and exclusion criteria. All retrieval counts reported in this article refer to the archived Web of Science export used by the authors at the time of data collection. The archived search returned 950 records. The exact search string applied was as follows:

("big data" AND foresight)
OR ("data science" AND foresight)
OR ("artificial intelligence" AND foresight)
OR ("big data" AND "responsible innovation")
OR ("data science" AND "responsible innovation")
OR ("artificial intelligence" AND "responsible innovation")
OR "Anticipatory Governance"

2.4 Inclusion and Exclusion Criteria

To ensure conceptual relevance and analytical consistency, the review applied a set of predefined inclusion and exclusion criteria. For inclusion criteria, the review included

a) Studies addressing governance, public administration, or public decision-making contexts;
b) Empirical, conceptual, or review articles examining the application of data-driven technologies within anticipatory, forward-looking, or future-oriented governance frameworks.

The following types of studies were excluded:

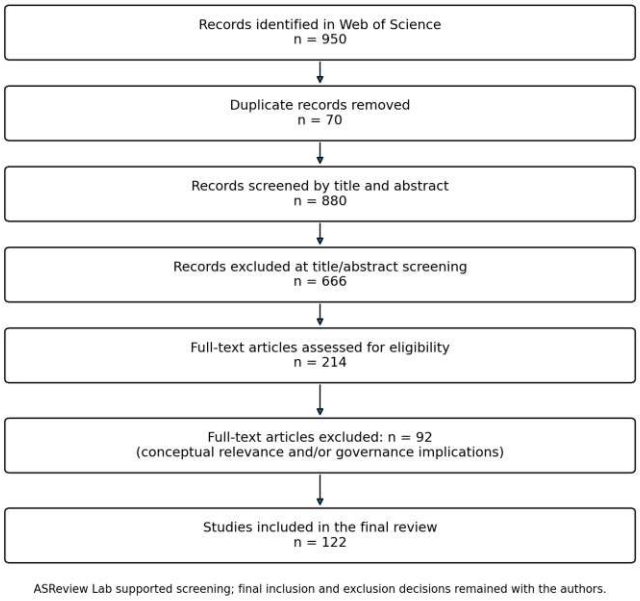
a) Purely technical computer science papers lacking explicit governance or policy implications;
b) Non-peer-reviewed materials, including reports, editorials, and conference abstracts without full academic validation;
c) Sector-specific case studies that did not provide broader conceptual or institutional insights relevant to anticipatory governance.

These criteria ensured that the final sample remained focused on the intersection between technological innovation and governance processes, while excluding studies that were either purely technical or too narrowly contextual to contribute to the broader analytical framework of anticipatory governance.

2.5 Results

The study-selection process was organized following PRISMA principles and is summarized in Figure 1. The archived Web of Science export contained 950 records. During data preparation, 70 duplicate records were identified and removed, leaving 880 records for title and abstract screening. Based on the predefined inclusion and exclusion criteria, 666 records were excluded. A total of 214 full-text articles were assessed for eligibility, of which 92 were excluded because they lacked conceptual relevance to the analytical framework and/or did not address governance implications. The final sample comprised 122 studies. ASReview Lab was used as an AI-assisted screening environment during this stage. The 'likely unique' indicator displayed by the ASReview interface is an internal heuristic and was not used as the formal duplicate count reported in the review flow; duplicate removal followed the workflow records maintained by the authors. Final inclusion and exclusion decisions remained under author responsibility.

Figure 1. Study-selection flow following PRISMA principles



2.6 Coding and Analytical Procedure

The selected articles were coded using a structured analytical framework aligned with RQ1-RQ5. The three macro technological categories - Big Data, Data Science, and AI-enabled decision-mediating systems - functioned as a deductive organizing frame informed by the prior literature and were established before the final synthesis. The third category includes agentic, generative, and adaptive AI systems when their primary institutional effect is decision mediation. The review was then used to refine the sublayers and to map how the categories relate to AG functions, dimensions of systemic complexity, institutional goals, decisional capacity, and normative concerns. Classification was therefore based on the primary institutional function performed in the governance process rather than on computational architecture alone. Each study was analyzed according to the following dimensions:

a) Technological layer (Big Data, Data Science, AI-enabled decision-mediating systems);
b) Anticipatory governance function addressed (foresight, knowledge creation, policy design, policy assessment);
c) Systemic complexity dimension engaged (e.g., uncertainty, non-linearity, interdependence, feedback dynamics);
d) Institutional goals referenced (e.g., risk anticipation, epistemic integration, coordination, responsiveness, adaptation);

e) Decisional implications identified (informational, analytical, or decisional capacity);
f) Normative and ethical concerns raised (e.g., accountability, transparency, bias, governance of expertise);

The coding process enabled the construction of five analytical tables corresponding to RQ1-RQ5, which form the empirical basis for the functional synthesis. Because category assignment involves interpretive judgment and technologies may perform more than one function, ambiguous and overlapping cases were reviewed in relation to their primary institutional effect. The study does not claim independent inter-rater reliability testing; this is acknowledged as a methodological limitation and motivates future validation of the typology with additional coders and empirical cases.

2.7 Use of Generative AI and Computational Tools

Python libraries were used as research-support tools after the filtered corpus had been defined. They assisted with organizing reviewed records, structuring information, checking consistency across coded material, and formatting draft analytical tables. Generative AI was also used as visual-design support in the preparation of Figure 2. The conceptual structure, technological layers, relationships, labels, and final interpretation represented in the figure were defined, reviewed, and validated by the authors. The AI system was not treated as an independent theoretical or empirical source, and its outputs did not substitute for the cited literature. The three macro technological categories used in coding were part of the authors' analytical framework; the mapping of sublayers, AG functions, institutional capacities, and governance implications was refined through the SLR. All AI-assisted outputs were checked, revised, and validated by the authors, who retain responsibility for inclusion decisions, classification, interpretation, writing, and presentation of results.

2.8 Descriptive Statistics

Table 1 reports the journal frequencies recorded for the final sample. The highest reported counts are associated with Sustainability, IEEE Access, and Technological Forecasting and Social Change, followed by Government Information Quarterly and Futures. This pattern is consistent with the interdisciplinary character of the review corpus and with the intersection of governance, sustainability, technological change, and decision-support research represented in the study.

Table 1. Journals represented in the final sample

Rank	Journal (Source Title)	Number of Articles	Main keywords/topics
1	**Sustainability**	22	sustainability; governance; innovation; AI; risk
2	**IEEE Access**	19	artificial intelligence; machine learning; analytics; decision-making; systems
3	**Technological Forecasting and Social Change**	14	foresight; forecasting; scenario analysis; emerging technologies; innovation
4	**Government Information Quarterly**	12	digital government; public policy; e-governance; transparency; data governance
5	**Futures**	11	futures studies; anticipation; scenario planning; strategy; uncertainty
6	**Expert Systems with Applications**	10	expert systems; prediction; decision support; optimization; intelligent systems
7	**Journal of Cleaner Production**	9	sustainability transitions; low-carbon innovation; environmental policy; circular economy; technology
8	**Information Sciences**	9	data science; algorithms; pattern detection; modeling; information systems
9	**Science of the Total Environment**	8	environmental monitoring; risk assessment; sustainability; complex systems; data analytics
10	**Decision Support Systems**	8	decision support; policy analytics; modeling; organizational decisions; AI

3. Results

3.1 Addressing Systemic Complexity in Anticipatory Governance (RQ1)

RQ1: How do different technological layers address the structural challenges of complex systems - such as uncertainty, non-linearity, interdependence, and feedback dynamics - across the core functions of Anticipatory Governance? The review shows that the contribution of technology varies according to the type of complexity being addressed. Under uncertainty, Big Data expands the range and timeliness of observable signals, while Data Science converts those signals into probabilistic estimates, trajectories, and scenarios; decision-mediating AI can then translate analytical outputs into ranked alerts or recommended responses (Muraro & Salles-Filho, 2024; McGregor et al., 2021; Kayser & Blind, 2017; Lukkien et al., 2024). The relevant distinction is therefore not simply between three technology labels, but between the governance functions of sensing, interpreting, and mediating action under uncertain conditions.

Non-linearity and interdependence are addressed most directly through analytical modeling. Systems modeling, simulation, geospatial analytics, network analysis, and scenario methods help represent indirect, cascading, and cross-domain effects that cannot be inferred from data aggregation alone (York et al., 2019; Francisco et al., 2022; Picavet et al., 2026; Cao et al., 2025). Big Data remains important because these models depend on integrated and sufficiently reliable inputs, while decision-support systems become relevant when modeled trade-offs are translated into policy options. In this sense, the layers are cumulative, but their value differs according to the structural problem being addressed. Feedback dynamics highlight the strongest difference in decisional embedding. Real-time data streams improve situational awareness; analytical techniques identify anomalies and estimate effects; and more agentic systems can recommend, prioritize, or conditionally trigger adjustments as new information enters the governance loop (David et al., 2024; Ulnicane et al., 2021; Webb et al., 2019). RQ1 therefore indicates a progression from observability to interpretability and, in selected applications, to operability. This progression does not eliminate uncertainty or complexity; rather, it changes how institutions sense, model, and respond to them, while simultaneously increasing requirements for transparency, oversight, and accountability (Table 2).

Table 2. Technological Layers x AG x Complexity

Technology Layer	Sublayer	Main contribution across AG functions in Complexity	Illustrative supporting references from the reviewed corpus
Big Data Infrastructure Layer	**Data Infrastructure**	Foresight: expands the detection of uncertainty and weak signals across domains. Knowledge creation: integrates dispersed information to reduce epistemic fragmentation. Policy design: provides systemic visibility over interdependent sectors and actors. Policy assessment: supports observation of large-scale system interactions and evolving feedback conditions.	Muraro & Salles-Filho (2024); McGregor et al. (2021); Christodoulou & Iordanou (2021)
	Real-Time Data Streams	Foresight: captures emergence and dynamic shifts in near real time. Knowledge creation: continuously updates knowledge under changing and uncertain conditions. Policy design: supplies time-sensitive inputs for interventions in volatile environments. Policy assessment: tracks immediate system responses and evolving feedback patterns.	Muraro & Salles-Filho (2024); McGregor et al. (2021)
	Data Governance Architecture	Foresight: stabilizes uncertainty-sensitive foresight through consistent data inputs. Knowledge creation: reduces epistemic fragmentation by improving comparability across sources. Policy design: supports coordination across interdependent systems through interoperable evidence. Policy assessment: enables more reliable tracking of systemic reactions over time.	Christodoulou & Iordanou (2021); David et al. (2024); Mahajan & Helbing (2026); Dara et al. (2022)
Data Science & Analytical Modeling	**Predictive & Statistical Modeling**	Foresight: reduces probabilistic uncertainty and risk estimation. Knowledge creation: identifies hidden systemic correlations and non-obvious patterns. Policy design: models cascading, indirect, and non-linear effects of interventions. Policy assessment: estimates systemic impacts and unintended consequences across interconnected settings.	Muraro & Salles-Filho (2024); Cao et al. (2025); Picavet et al. (2026)
	Systems Modeling & Simulation	Foresight: explores alternative future trajectories under uncertain and dynamic conditions. Knowledge creation: maps interdependence and causal complexity across system components. Policy design: stress-tests interventions in non-linear environments. Policy assessment: simulates feedback loops, adaptive responses, and path-dependent effects.	York et al. (2019); Picavet et al. (2026); Cao et al. (2025)
	Knowledge Extraction (NLP, Network Analysis)	Foresight: detects emergent issue clusters and weak signals. Knowledge creation: structures complex informational environments into interpretable patterns. Policy design: reveals relational patterns relevant to interventions in interdependent systems. Policy assessment: identifies anomalies, blind spots, and under-recognized systemic effects.	Kayser & Blind (2017); Picavet et al. (2026)
AI-Enabled Decision-Mediating Systems	**Decision Support Agents**	Foresight: prioritizes anticipatory responses under uncertainty. Knowledge creation: translates complex analytical outputs into actionable representations. Policy design: supports intervention choices in interdependent environments through option ranking. Policy assessment: recommends corrective action based on changing system performance and feedback signals.	Lukkien et al. (2024); Dara et al. (2022); David et al. (2024)
	Adaptive Governance Systems	Foresight: responds conditionally to emergent system states. Knowledge creation: updates operational knowledge as conditions change. Policy design: adjusts interventions within interdependent and evolving systems. Policy assessment: performs automated recalibration in response to feedback loops and adaptive system behavior.	David et al. (2024); Ulnicane et al. (2021); Webb et al. (2019)
	Generative Policy Agents	Foresight: constructs alternative futures under uncertain conditions. Knowledge creation: synthesizes diverse inputs into structured interpretations of complex situations. Policy design: proposes intervention packages under non-linear and interdependent constraints. Policy assessment: generates evaluative syntheses that support adjustment across iterative policy cycles.	Picavet et al. (2026); Ulnicane (2025); Cao et al. (2025)

3.2 Functional Positioning Across Anticipatory Governance (RQ2)

RQ2: How are Big Data, Data Science, and AI-enabled decision-mediating systems functionally mobilized across the four core functions of Anticipatory Governance? The pattern is best understood by AG function rather than as a quantitative distribution of mutually exclusive technology categories. In foresight, the reviewed studies combine broad environmental scanning and weak-signal capture with predictive modeling, scenario analysis, and, more recently, AI-assisted synthesis or recommendation (Muraro & Salles-Filho, 2024; Kayser & Blind, 2017; Picavet et al., 2026). The pattern is therefore one of increasing transformation of signals into structured anticipatory judgments.

In knowledge creation, the central movement is from evidentiary integration to epistemic structuring. Cross-domain data infrastructures consolidate fragmented sources, whereas clustering, text mining, network analysis, and related Data Science methods identify patterns and relationships within those sources (Kayser & Blind, 2017; Muraro & Salles-Filho, 2024). Generative or assistive AI contributes when these analytical outputs are synthesized into narratives, summaries, or policy-relevant options, although such synthesis remains dependent on human validation and contextual interpretation (Picavet et al., 2026; Ulnicane, 2025).In policy design, the strongest contribution comes from modeling alternatives and their consequences. Simulation, predictive analytics, and systems models allow institutions to compare interventions under non-linear and interdependent conditions, while AI-enabled decision support becomes relevant when alternatives are ranked, parameterized, or converted into actionable options (York et al., 2019; Cao et al., 2025; David et al., 2024). The institutional boundary between analytical support and decisional mediation is most visible at this stage because technological systems can begin to structure the choice architecture itself. In policy assessment, continuous data streams support monitoring, while analytical techniques enable anomaly detection, impact estimation, and identification of unintended effects. More deeply embedded AI systems can support adaptive recalibration when feedback is incorporated into repeated decision cycles (Lukkien et al., 2024; David et al., 2024; Ulnicane et al., 2021). Thus, assessment can move from retrospective evaluation toward feedback-sensitive institutional learning, provided that automated adjustments remain traceable and contestable.

Overall, RQ2 reveals patterned functional positioning: foresight emphasizes signal-to-judgment transformation; knowledge creation emphasizes evidentiary and epistemic integration; policy design emphasizes comparison and structuring of intervention alternatives; and policy assessment emphasizes monitoring, evaluation, and feedback. The three technological layers can contribute to each function, but their relative importance changes with the institutional task and degree of decisional embedding (Table 3).

Table 3. Technological Layers x AG Functions

Technology Layer	Sublayer	Foresight	Knowledge Creation	Policy Design	Policy Assessment	Illustrative supporting references from the reviewed corpus
Big Data	Data Infrastructure	Large-scale environmental scanning and signal aggregation	Cross-domain dataset consolidation	Evidentiary grounding for design alternatives	Monitoring architecture for performance tracking	Muraro & Salles-Filho (2024); McGregor et al. (2021); Christodoulou & Iordanou (2021)
	Real-Time Data Streams	Dynamic early-warning detection	Continuous updating of informational inputs	Time-sensitive evidence for adaptive planning	Real-time tracking of implementation outcomes	Muraro & Salles-Filho (2024); McGregor et al. (2021)
	Data Governance Architecture	Standardized and reliable forecasting inputs	Ensures interoperability and data integrity in knowledge production	Transparent evidentiary standards in design processes	Auditability and accountability mechanisms	Christodoulou & Iordanou (2021); David et al. (2024); Mahajan & Helbing (2026); Dara et al. (2022)
Data Science	Predictive & Statistical Modeling	Probabilistic analysis and risk estimation	Identification of systemic patterns and correlations	Scenario testing and policy option modeling	Counterfactual analysis and impact estimation	Muraro & Salles-Filho (2024); Cao et al. (2025); Picavet et al. (2026)
	Systems Modeling & Simulation	Exploration of alternative future trajectories	Mapping of causal and interdependent dynamics	Stress-testing policy interventions	Simulation-based evaluation of systemic effects	York et al. (2019); Picavet et al. (2026); Cao et al. (2025)
	Knowledge Extraction (NLP, Network Analysis)	Detection of emerging issue clusters	Structured synthesis of complex data ecosystems	Alignment of policy design with analytical insights	Identification of anomalies and blind spots	Kayser & Blind (2017); Picavet et al. (2026)

AI-Enabled Decision-Mediating Systems	**Decision Support Agents**	Ranked anticipatory recommendations	Prioritized and structured knowledge outputs	Option ranking and decision assistance	Recommendation of corrective adjustments	Lukkien et al. (2024); Dara et al. (2022); David et al. (2024)
	Adaptive Governance Systems	Dynamic updating of projections	Operational recalibration of knowledge inputs	Conditional execution of policy adjustments	Automated feedback-based recalibration	David et al. (2024); Ulnicane et al. (2021); Webb et al. (2019)
	Generative Policy Agents	Scenario narrative generation	Drafting and framing of policy-relevant knowledge	Proposal generation and structured intervention packages	Automated evaluative reporting	Picavet et al. (2026); Ulnicane (2025); Cao et al. (2025)

3.3 Technological Contributions to Institutional Governance Goals (RQ3)

RQ3: How do these technological layers contribute to the institutional goals of anticipatory governance, including risk anticipation, epistemic integration, strategic coordination, responsiveness, and adaptation? Across the corpus, technological contributions are better differentiated by the governance goal they enable than by repeating the generic definition of each layer. Risk anticipation depends on the combination of broad signal detection, probabilistic or scenario-based interpretation, and the translation of anticipatory outputs into timely alerts or options (Muraro & Salles-Filho, 2024; Cao et al., 2025; Picavet et al., 2026). Epistemic integration similarly depends on connecting heterogeneous evidence and then making relationships and assumptions visible enough to support institutional interpretation.

Strategic coordination is strengthened when shared evidence infrastructures are combined with models that represent interdependencies and clarify cross-sector effects. Decision-support systems can add a further coordination layer by ranking alternatives or structuring choices across organizational units, but this also introduces algorithmic influence into how priorities are established (York et al., 2019; David et al., 2024; Lukkien et al., 2024). Responsiveness, by contrast, is primarily a temporal challenge: real-time observation shortens detection time, analytics shorten interpretation time, and decision-mediating systems may shorten the interval between interpretation and institutional response.

Adaptation emerges when these capacities are connected through feedback. Monitoring provides updated inputs, evaluation supports learning and model revision, and adaptive systems can recommend or conditionally implement recalibration as circumstances change (Ulnicane et al., 2021; Webb et al., 2019; David et al., 2024). The contribution to AG goals is therefore cumulative but not automatically beneficial: greater speed and integration can strengthen responsiveness while simultaneously increasing dependence on model assumptions, data quality, and institutional safeguards.

Taken together, RQ3 shows that technologies support AG goals through different combinations of sensing, interpretation, coordination, and feedback-sensitive action. The key analytical point is not a fixed one-to-one correspondence between a technology and a governance goal, but how combinations of technological functions are institutionally assembled to support anticipation, integration, coordination, responsiveness, and adaptation (Table 4).

Table 4. Technological Layers x AG Goals

Technology Layer	Sublayer	Foresight (Risk Anticipation)	Knowledge Creation (Epistemic Integration)	Policy Design (Strategic Coordination)	Policy Assessment (Responsiveness & Adaptation)	Illustrative supporting references from the reviewed corpus
Big Data	**Data Infrastructure**	Early detection through large-scale signal aggregation	Consolidation of cross-domain datasets	Shared evidentiary platforms for coordinated design	Monitoring infrastructure enabling institutional responsiveness	Muraro & Salles-Filho (2024); McGregor et al. (2021); Christodoulou & Iordanou (2021)
	Real-Time Data Streams	Dynamic risk awareness via continuous updates	Ongoing integration of emerging information	Timely inputs for adaptive coordination	Real-time tracking of policy implementation	Muraro & Salles-Filho (2024); McGregor et al. (2021)
	Data Governance Architecture	Reliable forecasting inputs through standardized data	Ensures interoperability and epistemic consistency	Transparent evidentiary standards for coordinated decision-making	Accountability and auditability in performance evaluation	Christodoulou & Iordanou (2021); David et al. (2024); Mahajan & Helbing (2026); Dara et al. (2022)
Data Science	**Predictive & Statistical Modeling**	Probabilistic risk forecasting	Identification of systemic correlations	Scenario comparison and strategic alignment	Impact estimation and evaluative feedback	Muraro & Salles-Filho (2024); Cao et al.

						(2025); Picavet et al. (2026)
	Systems Modeling & Simulation	Exploration of long-term strategic futures	Integration of multi-level system dynamics	Stress-testing coordinated interventions	Anticipation of unintended systemic effects	York et al. (2019); Picavet et al. (2026); Cao et al. (2025)
	Knowledge Extraction (NLP, Network Analysis)	Detection of emerging risk clusters	Reduction of epistemic fragmentation	Alignment of policy framing with analytical insights	Identification of evaluative blind spots	Kayser & Blind (2017); Picavet et al. (2026)
AI-Enabled Decision-Mediating Systems	**Decision Support Agents**	Prioritized risk ranking and alerts	Structured synthesis of actionable knowledge	Option prioritization across institutional actors	Recommendation of corrective adjustments	Lukkien et al. (2024); Dara et al. (2022); David et al. (2024)
	Adaptive Governance Systems	Conditional anticipatory response	Operational recalibration of knowledge inputs	Execution of coordinated rule-based adjustments	Automated adaptive learning within feedback loops	David et al. (2024); Ulnicane et al. (2021); Webb et al. (2019)
	Generative Policy Agents	Narrative framing of strategic risks	Drafting integrative policy knowledge	Proposal generation for coordinated action	Automated evaluative summaries influencing next-cycle decisions	Picavet et al. (2026); Ulnicane (2025); Cao et al. (2025)

3.4 Informational, Analytical, and Decisional Capacity (RQ4)

RQ4: In what ways do Big Data, Data Science, and AI-enabled decision-mediating systems reshape informational, analytical, and decisional capacity across the functions of anticipatory governance? RQ4 synthesizes the preceding findings at the level of institutional capacity. Rather than restating the technologies by AG function, the analysis focuses on what changes in the decision architecture as technological systems become more deeply embedded. Informational capacity concerns what institutions can observe and stabilize as evidence; analytical capacity concerns how that evidence is transformed into representations, estimates, and alternatives; decisional capacity concerns how technological systems participate in prioritization, recommendation, adjustment, or execution.

Informational capacity is expanded through heterogeneous data integration, continuous monitoring, and data-governance mechanisms that improve comparability, traceability, and interoperability (Muraro & Salles-Filho, 2024; McGregor et al., 2021; Christodoulou & Iordanou, 2021). This capacity remains non-decisional in a formal sense, but it is institutionally consequential because data infrastructures influence what becomes visible, measurable, and credible as a basis for anticipatory action.

Analytical capacity is reshaped by predictive models, simulation, causal or network representations, and knowledge-extraction techniques that structure uncertainty and interdependence into interpretable forms (Kayser & Blind, 2017; York et al., 2019; Cao et al., 2025). These tools do not merely add information: they frame the decision space by making some trajectories, variables, and intervention alternatives more salient than others. Formal authority may remain human-centered while epistemic framing becomes increasingly model-mediated.

Decisional capacity changes when AI systems become embedded in the choice or feedback loop. Decision-support agents can rank alternatives, adaptive systems can recommend or trigger conditional adjustments, and generative systems can structure proposals or evaluative summaries (Lukkien et al., 2024; Picavet et al., 2026; Ulnicane, 2025). Three forms of mediation are especially relevant: prioritization, through ranking and alerting; conditional execution, through rule-based or adaptive adjustment; and narrative structuring, through the framing of proposals and interpretations. The result is a more hybrid distribution of judgment across human and algorithmic actors. RQ4 identifies the central integrative mechanism of the typology: increasing decisional embedding. The movement from informational capacity to analytical structuring and then to decisional mediation is not a deterministic technological sequence, nor does it imply that one layer replaces another. It is an institutional continuum describing how deeply technological systems enter the production of evidence, the framing of alternatives, and the enactment of responses. This continuum provides the bridge between the functional findings in RQ1-RQ3 and the governance-of-expertise issues examined in RQ5 (Table 5).

Table 5. Technological Layers x Decision Capabilities

Technology Layer	Sublayer	Foresight (Capacity Framing)	Knowledge Creation (Epistemic Structuring)	Policy Design (Decision Space Configuration)	Policy Assessment (Adaptive Decision Control)	Illustrative supporting references from the reviewed corpus
Big Data	Data Infrastructure	Expands situational awareness	Broadens the evidentiary base	Grounds design alternatives in large-scale data	Enables monitoring-based oversight	Muraro & Salles-Filho (2024); McGregor et al. (2021); Christodoulou & Iordanou (2021)
	Real-Time Data Streams	Increases temporal sensitivity	Continuously updates informational inputs	Supports timely adjustment framing	Enables rapid detection of deviations	Muraro & Salles-Filho (2024); McGregor et al. (2021)
	Data Governance Architecture	Stabilizes forecasting inputs	Ensures reliability, comparability, and integrity	Strengthens transparency in decision justification	Supports auditability and traceability	Christodoulou & Iordanou (2021); David et al. (2024); Dara et al. (2022); Mahajan & Helbing (2026)
Data Science	Predictive & Statistical Modeling	Structures probabilistic reasoning	Identifies systemic patterns and correlations	Models alternative intervention outcomes	Estimates policy impacts and unintended effects	Muraro & Salles-Filho (2024); Cao et al. (2025); Picavet et al. (2026)
	Systems Modeling & Simulation	Frames decisions through simulated futures	Maps causal interdependencies	Stress-tests policy robustness	Anticipates unintended systemic effects and feedbacks	York et al. (2019); Picavet et al. (2026); Cao et al. (2025)
	Knowledge Extraction	Highlights salient issues and emergent clusters	Reduces epistemic fragmentation	Influences agenda-setting and design framing	Identifies evaluation priorities and blind spots	Kayser & Blind (2017); Picavet et al. (2026)
AI-Enabled Decision-Mediating Systems	Decision Support Agents	Rank anticipatory options	Translate analytics into actionable outputs	Influence selection among policy alternatives	Recommend corrective adjustments	Lukkien et al. (2024); Dara et al. (2022); David et al. (2024)
	Adaptive Governance Systems	Update projections dynamically	Recalibrate operational parameters	Execute conditional adjustments	Perform automated feedback-based recalibration	David et al. (2024); Ulnicane et al. (2021); Webb et al. (2019)
	Generative Policy Agents	Frame future narratives	Produce structured policy drafts and syntheses	Shape proposal architecture and option space	Generate evaluative interpretations influencing next-cycle decisions	Picavet et al. (2026); Ulnicane (2025); Cao et al. (2025)

3.5 Governance of Expertise and Ethical Implications (RQ5)

RQ5: What are the implications of these technological configurations for delegation, accountability, epistemic authority, and the governance of expertise in data-driven anticipatory governance? The systematic review indicates that, as technological layers evolve from informational infrastructures to decision-mediating systems, governance challenges shift from concerns about data quality and representational bias to broader questions of delegation, accountability, epistemic authority, and institutional oversight. The integration of Big Data, Data Science, and AI-enabled decision-mediating systems reconfigures not only technical capacity but also the distribution of agency, responsibility, and expertise within anticipatory governance. Across the reviewed literature, the movement from infrastructural support to algorithmic mediation is associated with a progressive relocation of authority from data management to analytical framing, to hybrid human–machine decision processes (Christodoulou & Iordanou, 2021; Ulnicane et al., 2021; David et al., 2024).

Within the Big Data layer, normative concerns focus primarily on legitimacy and data authority. Data infrastructures and real-time streams expand institutional visibility and strengthen monitoring capacity, but they also risk amplifying incomplete, skewed, or uneven representations of social reality. In this layer, ethical concerns are tied to the reliability of data pipelines, the governance of standards, and the transparency of evidentiary inputs used in anticipatory processes (McGregor et al., 2021; Christodoulou & Iordanou, 2021). The sublayer of data governance architecture becomes especially important because standards, interoperability rules, and audit mechanisms help sustain traceability, accountability, and trust. Here, the authority at stake is primarily informational rather than decisional: the central issue concerns who controls the data, how quality is assured, and how legitimacy is maintained in the production of anticipatory evidence (Dara et al., 2022; Mahajan & Helbing, 2026).

Within the Data Science layer, normative tensions shift toward model authority and epistemic framing. Predictive and simulation models structure how risks are understood, which futures are considered

plausible, and how policy problems are rendered analytically visible. The reviewed studies show that tools such as text mining, predictive modeling, and scenario analysis strengthen anticipatory reasoning, but they also privilege certain variables, assumptions, and forms of evidence over others (Kayser & Blind, 2017; Muraro & Salles-Filho, 2024; York et al., 2019). This creates concerns regarding epistemic authority: who defines the models, who validates them, how uncertainties are communicated, and whether institutional actors can interpret and contest the outputs appropriately. Although decisions formally remain human, analytical systems often shape the boundaries of policy space in advance. In this sense, the review suggests that Data Science produces a form of epistemic delegation without full formal transfer of decisional authority.

The normative tensions intensify within the AI-enabled decision-mediating layer. Decision-support agents can rank options, adaptive systems may execute conditional responses, and generative or agentic systems can shape proposals, narratives, and evaluative summaries. In these contexts, AI systems are more deeply embedded within governance loops, influencing not only how institutions interpret complex environments but also how they prioritize and enact responses (Lukkien et al., 2024; Picavet et al., 2026; Ulnicane, 2025). This embedding generates three interrelated governance challenges. The first is delegation, namely the extent to which decisional authority is transferred to algorithmic systems or shared with them in practice. The second is accountability, since outcomes increasingly emerge from hybrid processes in which human judgment, data-driven models, and AI-generated recommendations are intertwined. The third is oversight and contestability, particularly in situations where automated or semi-automated adjustments occur within feedback-rich governance environments (David et al., 2024; Dara et al., 2022; Webb et al., 2019).

As AI systems move from advisory support to more direct forms of operational mediation, the governance of expertise becomes central. Expertise is no longer located exclusively in human officials, analysts, or institutions; instead, it becomes increasingly socio-technical, distributed across data infrastructures, models, and AI systems. This does not eliminate human responsibility, but it does complicate how responsibility is exercised and justified. Institutions must therefore manage hybrid decision architectures in which algorithmic systems participate in anticipatory reasoning, evaluative learning, and adaptive execution. The review suggests that the core normative challenge of data-driven anticipatory governance lies in ensuring that these socio-technical configurations remain transparent, accountable, and open to contestation, even as their operational role becomes more deeply embedded in governance practice (Ulnicane et al., 2021; Ulnicane, 2025; David et al., 2024).

Table 6 synthesizes the ethical and governance implications associated with the main technological layers identified in the review, linking each sublayer to specific concerns across the four core functions of anticipatory governance. It shows how Big Data raises issues of epistemic legitimacy and data authority, how Data Science reshapes authority through model-based framing and analytical prioritization, and how AI-enabled decision-mediating systems intensify questions of delegation, responsibility, accountability, and oversight. By associating each sublayer with illustrative supporting references from the reviewed corpus, the table grounds these normative concerns in the literature included in the study.

Table 6. Technological Layers x Governance of Expertise

Technology Layer	Sublayer	Foresight (Epistemic Legitimacy)	Knowledge Creation (Authority & Transparency)	Policy Design (Delegation & Responsibility)	Policy Assessment (Accountability & Oversight)	Illustrative supporting references from the reviewed corpus
Big Data	Data Infrastructure	Risk of biased signal detection	Data ownership and representational asymmetries	Dependence on data quality in design choices	Responsibility for data integrity	McGregor et al. (2021); Christodoulou & Iordanou (2021); Mahajan & Helbing (2026)
	Real-Time Data Streams	Over-reliance on immediate signals	Reduced deliberative depth	Pressure toward reactive interventions	Short-term performance bias	Muraro & Salles-Filho (2024); McGregor et al. (2021)
	Data Governance Architecture	Standardization and trust-building mechanisms	Transparency and interoperability safeguards	Clear evidentiary standards	Auditability and traceability mechanisms	Christodoulou & Iordanou (2021); Dara et al. (2022); David et al. (2024)
Data Science	Predictive & Statistical Modeling	Probabilistic opacity and model uncertainty	Interpretive dominance of model designers	Scenario framing constrains policy alternatives	Quantification bias in evaluation metrics	Muraro & Salles-Filho (2024); Kayser & Blind (2017); Cao et al. (2025)
	Systems Modeling & Simulation	Embedded assumptions in system representation	Technocratic influence in causal framing	Path-dependency via modeled futures	Limited transparency in complex simulations	York et al. (2019); Picavet et al. (2026); Cao et al. (2025)
	Knowledge Extraction	Algorithmic filtering of salient issues	Agenda-setting through analytical prioritization	Amplification of dominant narratives	Selective evaluative visibility	Kayser & Blind (2017); Picavet et al. (2026)
AI-Enabled Decision-Mediating Systems	Decision Support Agents	Algorithmic ranking shapes anticipatory authority	Mediation of actionable knowledge	Partial delegation of decision authority	Diffusion of responsibility	Lukkien et al. (2024); Dara et al. (2022); David et al. (2024)
	Adaptive Governance Systems	Automated responses under limited deliberation	Reduced human interpretive control	Execution of rule-based interventions	Challenges in auditing automated recalibration	David et al. (2024); Ulnicane et al. (2021); Webb et al. (2019)
	Generative Policy Agents	Narrative framing influences perceived futures	Reconfiguration of epistemic expertise	Soft delegation via AI-generated proposals	Attribution difficulty for AI-influenced outcomes	Picavet et al. (2026); Ulnicane (2025); Cao et al. (2025)

4. Discussion

4.1 Proposed Functional Typology

The preceding analyses show that Big Data, Data Science, and AI-enabled decision-mediating systems perform differentiated but overlapping institutional functions within anticipatory governance. The proposed typology should therefore be read as an organizing framework for institutional effects, not as a claim that the generic technical differences among these domains are themselves novel. Its contribution is to connect those differences systematically to the four AG functions, dimensions of systemic complexity, governance goals, degrees of decisional embedding, and governance-of-expertise risks. This makes it possible to compare technologies according to what they do within governance processes rather than according to product labels or computational architecture alone.

The typology is grounded in institutional effect. Big Data primarily supports observation and evidentiary integration; Data Science primarily structures interpretation through modeling, simulation, and knowledge extraction; and AI-enabled decision-mediating systems become analytically distinctive when systems are embedded in recommendation, prioritization, adaptive adjustment, or partial execution. Agentic AI is treated here as a subset of this broader layer rather than as a retrospective label for all AI-assisted decision support. These are ideal-typical functions rather than mutually exclusive categories. Machine learning, for example, may support data processing, analytical modeling, or decision mediation depending on its role in a specific governance arrangement. The analytical value of the typology therefore lies in tracing a continuum of decisional embedding and the corresponding shift in informational, epistemic, and operational authority (Table 7).

Table 7. Big Data, Data Science, and AI Technologies for AG in Complex Systems: A Functional Typology

Dimension	Big Data	Data Science	AI-Enabled Decision-Mediating Systems
Epistemic Function	Observation	Modeling and interpretation	Mediation and execution
Institutional Capacity	Sensing and informational capacity	Analytical capacity	Decisional capacity
Complexity Dimension Addressed	Primarily addresses uncertainty through signal detection and feedback visibility through monitoring	Primarily addresses non-linearity, interdependence, and structured forms of uncertainty through modeling and simulation	Primarily addresses feedback dynamics and adaptive complexity through iterative adjustment, conditional response, and operational mediation
Role Across AG Functions	Supports foresight through signal detection, knowledge creation through data aggregation, and policy assessment through monitoring	Enables forecasting, scenario simulation, pattern detection, and impact evaluation across governance functions	Recommends, prioritizes, and in some cases conditionally executes adaptive interventions across governance functions
Decisional Embedding	Non-decisional; indirectly frames choices through visibility and evidentiary input	Advisory; structures and constrains the decision space without formally replacing human judgment	Embedded in decision loops; partially mediates or enacts institutional responses
Governance Risk Focus	Data integrity, bias, interoperability, representational asymmetries	Model opacity, epistemic dominance, quantification bias, interpretive asymmetry	Delegation boundaries, accountability diffusion, authority redistribution, reduced contestability

4.2 Implications: Hybrid Decision Architectures, Epistemic Limits, and Governance of Expertise

The integration of Big Data, Data Science, and AI-enabled decision-mediating systems into anticipatory governance reflects more than technological modernization. It changes how institutions perceive, interpret, and act under uncertainty, non-linearity, interdependence, and feedback. Hybrid architectures that combine structured and unstructured data, statistical inference, simulation, human judgment, and machine computation can broaden anticipatory capacity (Limongi et al., 2025), but they also relocate important parts of evidence production and decision framing into socio-technical systems. The central issue is therefore not simply whether these technologies improve prediction, but how their institutional embedding changes what can be known, whose interpretations become authoritative, and how action is justified.

This perspective is consistent with arguments that contemporary decision-making increasingly depends on combinations of analytical techniques rather than isolated tools. In AG, multimodal arrangements involving GeoAI, Generative AI, predictive analytics, and interoperable data infrastructures may connect spatial, temporal, semantic, and institutional information across foresight, policy design, and adaptive coordination (Limongi et al., 2025). Yet integration should not be equated with epistemic completeness. More data and more sophisticated models can improve observation and analysis while still leaving ambiguity, deep uncertainty, contested values, and emergent dynamics unresolved.

The functional typology makes this distinction visible by separating informational enhancement, analytical structuring, and decisional mediation. The progression from observation to interpretation to mediated action describes increasing institutional embedding, not an inevitable maturity path. A system may legitimately remain at an informational or advisory level when uncertainty, legal authority, ethical stakes, or the need for deliberation make automated mediation inappropriate. Decisional capacity is therefore an analytical lens for examining delegation boundaries rather than a normative claim that greater automation is desirable.

Viewed through the typology, Big Data technologies performs a foundational role in anticipatory governance by expanding institutional visibility. Its main contribution lies in large-scale signal detection, cross-domain data integration, and continuous monitoring, thereby improving how institutions perceive emerging issues and dynamic changes. In complex systems terms, this layer primarily helps institutions manage uncertainty by broadening the informational base available for early detection and situational awareness. However, the typology also clarifies that Big Data remains largely non-decisional: it does not directly determine policy choices, but indirectly frames them by shaping what is visible, measurable, and institutionally salient. The central governance risks at this level concern data integrity, representational bias,

interoperability, and informational asymmetries, since errors or distortions at the infrastructure level can affect all subsequent stages of anticipatory governance.

The typology also clarifies the distinctive role of Data Science technologies, which move beyond information accumulation toward modeling and interpretation. At this layer, technologies such as predictive analytics, simulation, and knowledge extraction help institutions identify systemic patterns, estimate risks, model indirect effects, and explore alternative futures. Data Science therefore, contributes most strongly to analytical capacity, particularly in relation to the complexity challenges of non-linearity and interdependence. Rather than merely informing institutions about what is happening, it structures how institutions understand what might happen and which intervention pathways appear plausible. This function is especially important in policy design and assessment, where models shape scenario comparison, impact estimation, and the framing of strategic alternatives. Yet the typology also shows that Data Science remains primarily advisory: it structures and constrains the decision space without fully replacing human judgment. Its main governance risks lie in model opacity, epistemic dominance, quantification bias, and interpretive asymmetry, since models can privilege certain assumptions and forms of evidence while obscuring uncertainty and contestability.

The role of AI-enabled decision-mediating systems becomes clearer still through the typology because this layer marks a shift from analytical support toward mediation and, in selected configurations, execution. At this layer, AI systems do not only process information or model future scenarios; they may participate in the prioritization, formulation, and adaptive adjustment of institutional responses. Decision-support agents can rank options and produce recommendations, adaptive systems can enable conditional recalibration, and generative or agentic systems can frame proposals and evaluative summaries. In complex-systems terms, this layer is especially connected to feedback dynamics because it operates within iterative loops of monitoring, evaluation, and response. Its analytical distinction therefore lies in stronger decisional embedding: systems are incorporated into governance loops in ways that can partially mediate, and in some settings conditionally enact, institutional action. The associated governance risks center on delegation boundaries, accountability diffusion, authority redistribution, and reduced contestability.

A critical implication is that none of the layers is neutral with respect to power or knowledge. Data infrastructures determine which populations, events, and signals become legible to institutions; analytical models privilege particular variables, assumptions, causal representations, and definitions of relevance; and decision-mediating systems can influence agenda setting by ordering options, alerts, and narratives. These effects connect the typology to broader concerns about data authority, model opacity, algorithmic regulation, and the politics of AI governance (Kitchin, 2014; Pasquale, 2015; Yeung, 2018; Ulnicane, 2025). Consequently, increased technological capacity may also produce new asymmetries between those who design, operate, audit, and contest anticipatory systems.

The epistemological limits of anticipation are equally important. Uncertainty in complex systems is not always reducible to a probability distribution, and weak signals are often ambiguous, fragmented, and dependent on contextual sensemaking. The review therefore does not imply that greater volumes of data or more autonomous AI remove uncertainty. Human curation, deliberation, and contestation remain necessary, particularly where emerging signals can support multiple interpretations or where policy choices involve conflicting values (Janissek-Muniz et al., 2025). This limit reinforces the need to evaluate technological integration not only in terms of predictive or operational performance, but also in terms of transparency, interpretability, pluralism, and institutional capacity to challenge automated outputs.

By distinguishing these layers functionally, the typology clarifies that anticipatory governance in complex systems is not simply becoming “more digital” or “more intelligent.” Rather, it is being reorganized through a cumulative layering of informational, analytical, and decisional technologies. Big Data strengthens the institutional capacity to sense complexity. Data Science strengthens the capacity to interpret complexity. AI-enabled decision-mediating systems increasingly shape the capacity to act within complexity through mediated and adaptive intervention. This layered view helps explain why governance challenges also evolve across the technological spectrum: from concerns about evidence quality and legitimacy, to questions of epistemic authority and model-based framing, and finally to problems of delegation, oversight, and accountability in hybrid human–machine decision architectures.

The typology of this study, therefore, provides an important conceptual clarification for the study of Big Data, Data Science, and AI technologies in anticipatory governance. It demonstrates that these technologies should not be treated as interchangeable tools, but as analytically distinct forms of institutional embedding that reshape governance in different ways. This clarification is especially important for complex systems research because it shows how each technological layer addresses different structural challenges while also introducing different normative and institutional risks. More broadly, the typology highlights that the future of anticipatory governance depends not only on better prediction, but on how institutions govern the transition from observation to analytical structuring, to algorithmically mediated action. Based on this set of typologies, we can better organize technology classes for each function. However, within the context of anticipation and foresight, this expansion must be approached with caution, particularly regarding the perception of weak signals. While Big Data amplifies the capacity to capture emerging cues, the identification and interpretation of weak signals remain highly dependent on processes of human curation and intervention, given their inherently ambiguous, fragmented, and sensemaking-dependent nature, which cannot be fully automated (Janissek-Muniz et al., 2025).

Table 8. Functional Typology of Tech. Layers, Sublayers, Tech. Classes and Illustrative AG Applications

Technology Layer	Sublayer	Technology Classes	Illustrative Example in Anticipatory Governance Functions and Context of Complexity
Big Data Infrastructure Layer: Increasing Observability and Evidentiary Integration	**Data Infrastructure**	1. Distributed storage systems 2. Data lakes/data warehouses/lakehouses 3. Cloud infrastructure 4. Data integration pipelines (ETL/ELT) 5. Distributed databases / NoSQL systems	Foresight/uncertainty: a government integrates climate, mobility, health, and economic data into a shared platform to detect emerging systemic risks. Knowledge creation/interdependence: cross-sector datasets are combined to reveal how vulnerabilities in one domain affect others.
	Real-Time Data Streams	1. Event streaming platforms 2. IoT data ingestion systems 3. Real-time analytics engines 4. Message brokers 5. Stream processing frameworks	Foresight/feedback dynamics: live sensor, social media, and emergency data are streamed to detect early warning signals of floods or disease outbreaks. Policy assessment / non-linearity: authorities track immediate effects of interventions as conditions change in real time.
	Data Governance Architecture	1. Metadata and data catalog systems 2. Data lineage and audit trail tools 3. Data quality and validation frameworks 4. Interoperability and API governance standards 5. Access control, privacy, & compliance systems	Knowledge creation / epistemic fragmentation: interoperable standards allow multiple agencies to use comparable evidence in anticipatory planning. Policy assessment/accountability under complexity: lineage and audit tools make it possible to trace which data informed adaptive policy adjustments.
Data Science & Analytical Modeling: Analytical Structuring and Interpretation	**Predictive & Statistical Modeling**	1. Regression and classification models 2. Time-series forecasting models 3. Risk scoring systems 4. Anomaly detection models 5. Causal and counterfactual analytics	Foresight/uncertainty: predictive models estimate the probability of hospital overload, unemployment spikes, or wildfire spread. Policy design / non-linearity: counterfactual models compare likely outcomes of alternative interventions before implementation.
	Systems Modeling & Simulation	1. System dynamics models 2. Agent-based models 3. Discrete-event simulation 4. Monte Carlo simulation 5. Digital twins	Policy design/interdependence and feedback: a city simulates how transport, housing, and energy policies interact over time. Policy assessment/path dependence: digital twin or simulation tools test how small changes may generate unintended long-term systemic effects.
	Knowledge Extraction (NLP, Network Analysis)	1. Text mining 2. Topic modeling 3. Named entity recognition 4. Sentiment/stance analysis 5. Network and graph analytics	Foresight / weak signals: NLP is used to scan policy reports, media, and public consultations for emerging issues. Knowledge creation/complexity: network analysis maps relationships among stakeholders, institutions, and risks to identify hidden clusters and coordination gaps.
AI-Enabled Decision-Mediating Systems: Algorithmically Mediated Action	**Decision Support Agents**	1. Recommender systems 2. Ranking and prioritization engines 3. Intelligent decision dashboards 4. Case-triage and routing agents 5. Multi-criteria decision-support agents	Policy design/uncertainty and interdependence: an AI assistant ranks policy options according to risk, cost, equity, and implementation feasibility. Policy assessment / adaptive correction: the system recommends where to intensify inspections or redirect resources based on evolving performance signals.
	Adaptive Governance Systems	1. Closed-loop decision systems 2. Rule-based adaptive systems 3. Reinforcement learning systems 4. Automated threshold-trigger systems 5. Dynamic resource allocation engines	Policy assessment/feedback dynamics: a governance system automatically recalibrates drought restrictions or traffic measures when thresholds are crossed. Foresight-to-action / adaptive complexity: interventions are continuously adjusted as the system responds to new data and changing conditions.
	Generative Policy Agents	1. LLM-based drafting agents 2. Scenario generation systems 3. Policy memo and report generation tools 4. Consultation summarization agents 5. Proposal generation agents	Foresight/uncertainty: a generative system produces alternative future scenarios for food, energy, or migration governance. Knowledge creation and policy design/complexity: it synthesizes diverse evidence into draft policy options, trade-off summaries, and evaluative reports for iterative decision cycles.

4.3 Illustrative Application of the Typology to Technology Classes

To illustrate the practical use of the typology, this section applies it to an Anticipatory Climate Resilience Governance vignette in a university context, drawing on Panizzon & Janissek-Muniz (2026). Table 9 is explicitly illustrative rather than evidentiary: the named technologies are examples of implementation possibilities and were not validated by the SLR as preferred products or as a complete technical architecture. The purpose is to show how technology classes can be mapped to the three functional layers and the four AG functions. Because products evolve rapidly and often combine multiple capabilities, classification should follow the institutional function performed in a given configuration rather than the commercial label of a tool.

Table 9. Illustrative Technology Classes and University Anticipatory-Governance Vignette

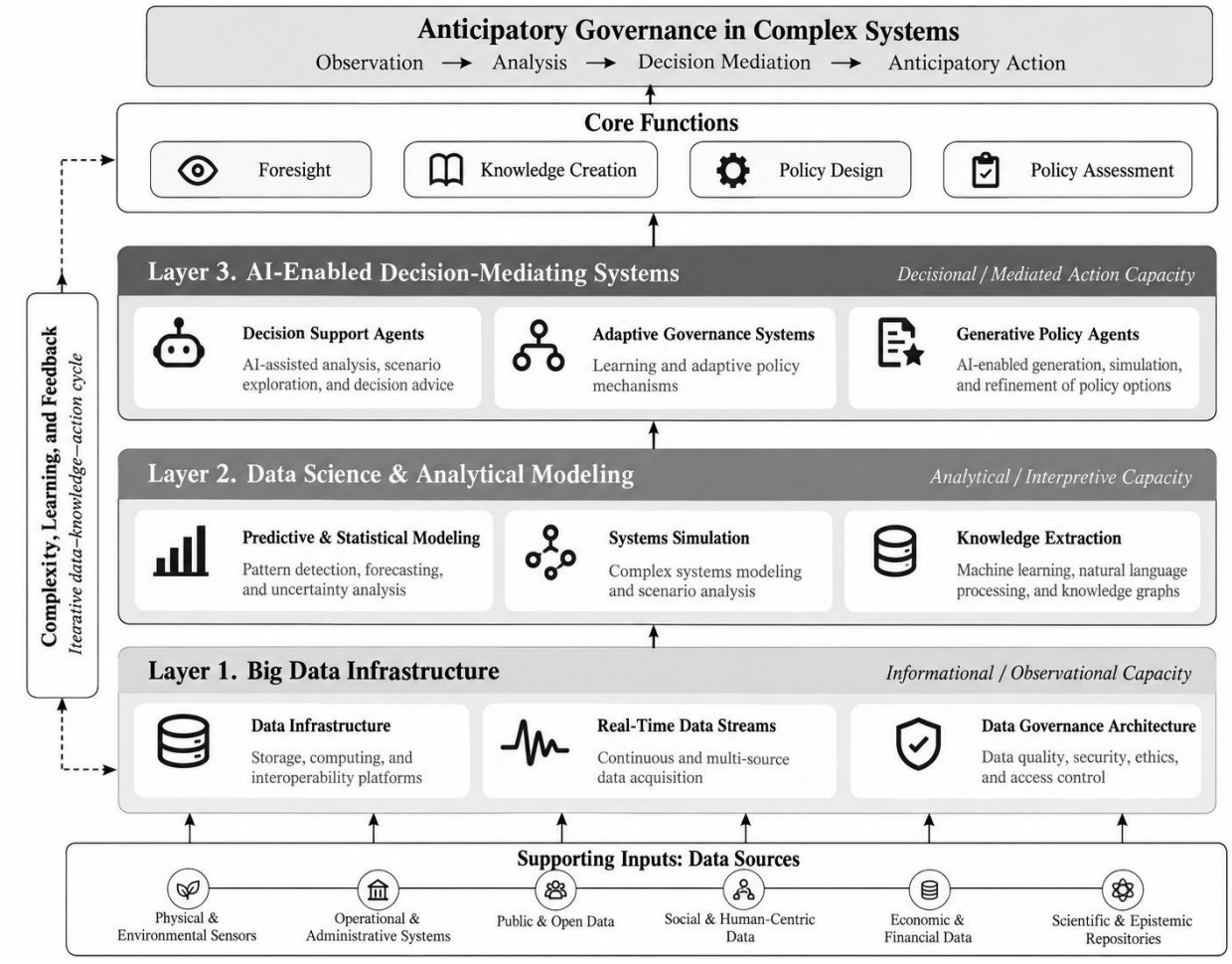
Technology Layer	Sublayer	Technology Classes and Illustrative Implementation Examples	Specific Illustrative Vignette in AG Functions and Context of Complexity
Big Data Infrastructure Layer: Increasing Observability and Evidentiary Integration	**Data Infrastructure**	1. Distributed storage systems - Hadoop HDFS 2. Data lakes/data warehouses/lakehouses - Databricks 3. Cloud infrastructure - AWS 4. Data integration pipelines (ETL/ELT) - Apache Airflow 5. Distributed databases / NoSQL systems - Apache Cassandra	Foresight/uncertainty: the university integrates campus energy data, rainfall records, drainage maps, student mobility data, building occupancy, and local public health indicators into a shared resilience data platform to identify which facilities and populations are most exposed to flood and heat risks. Knowledge creation/interdependence: these linked datasets reveal how extreme weather affects not only infrastructure, but also class continuity, transport access, student wellbeing, and research operations across interconnected systems.
	Real-Time Data Streams	1. Event streaming platforms - Apache Kafka 2. IoT data ingestion systems - Azure IoT Hub 3. Real-time analytics engines - Apache Flink 4. Message brokers - RabbitMQ 5. Stream processing frameworks - Spark Streaming	Foresight/feedback dynamics: the lab streams data from weather stations, river-level sensors, classroom heat sensors, electricity systems, and municipal emergency alerts into a live dashboard to detect early signs of flash floods or dangerous indoor heat conditions. Policy assessment / non-linearity: decision-makers monitor in real time whether measures such as cooling-room activation, class suspension, or traffic rerouting actually reduce disruption as conditions evolve.
	Data Governance Architecture	1. Metadata and data catalog systems - DataHub 2. Data lineage and audit trail tools - Apache Atlas 3. Data quality and validation frameworks - Great Expectations 4. Interoperability and API governance standards - WSO2 API Manager 5. Access control, privacy, and compliance systems - Ms Purview	Knowledge creation / epistemic fragmentation: the university adopts shared metadata, interoperability, and access rules with city agencies, civil defense, utilities, and local health authorities so that climate and vulnerability data can be interpreted consistently across institutions. Policy assessment/accountability under complexity: lineage and audit mechanisms allow the university to trace which evidence-informed decisions such as remote teaching activation, emergency closure, or targeted support for vulnerable student groups.
Data Science & Analytical Modeling: Analytical Structuring and Interpretation	**Predictive & Statistical Modeling**	1. Regression and classification models - scikit-learn 2. Time-series forecasting models - Prophet 3. Risk scoring systems - SAS 4. Anomaly detection models - PyOD 5. Causal and counterfactual analytics - DoWhy	Foresight/uncertainty: the university develops models to estimate the probability of flood-related building closure, heat-related absenteeism, peak electricity demand, and disruption to campus transport access during extreme weather events. Policy design / non-linearity: counterfactual analysis compares whether investments in shading, drainage upgrades, remote teaching protocols, or backup power would reduce risk more effectively under different climate scenarios.
	Systems Modeling & Simulation	1. System dynamics models - Vensim 2. Agent-based models - NetLogo 3. Discrete-event simulation - Simul8 4. Monte Carlo simulation - @RISK 5. Digital twins - Azure Digital Twins	Policy design/interdependence and feedback: the lab simulates how a severe heatwave or major flood affects interconnected systems, including mobility, dormitory safety, electricity demand, water supply, food services, health services, and academic continuity. Policy assessment/path dependence: simulation helps test whether short-term emergency measures, such as temporary closures or water rationing, create long-term resilience gains or instead generate new dependencies and vulnerabilities.
	Knowledge Extraction (NLP, Network Analysis)	1. Text mining - NLTK 2. Topic modeling - BERTopic 3. Named entity recognition - spaCy 4. Sentiment/stance analysis - Hugging Face Transformers 5. Network and graph analytics - Neo4j	Foresight / weak signals and emergence: the university analyzes climate assessments, municipal plans, campus incident reports, student complaints, and social media posts to identify recurring concerns about heat exposure, flooding, water scarcity, and service failures. Knowledge creation/complexity: network analysis maps how university units, utilities, NGOs, municipal agencies, and neighborhood associations interact, helping identify coordination bottlenecks and under-recognized vulnerable communities.
AI-Enabled Decision-Mediating Systems: Algorithmically Mediated Action	**Decision Support Agents**	1. Recommender systems - TensorFlow Recommenders 2. Ranking and prioritization engines - OptaPlanner 3. AI-enabled decision dashboards with recommendation/ranking modules 4. Case-triage and routing agents - Drools 5. Multi-criteria decision-support agents - 1000minds	Policy design/uncertainty and interdependence: an AI decision-support system helps university leaders and municipal partners rank resilience options such as green roofs, cooling centers, drainage retrofits, revised academic calendars, or targeted transport support, using criteria such as cost, urgency, equity, feasibility, and expected impact. Policy assessment / adaptive correction: the system also recommends where to deploy emergency staff, generators, transport assistance, or health outreach when climate risks intensify.

	Adaptive Governance Systems	1. Closed-loop decision systems - Apache NiFi 2. Rule-based adaptive systems - Drools 3. Reinforcement learning systems - Ray RLlib 4. Automated threshold-trigger systems - Node-RED 5. Dynamic resource allocation engines - Google OR-Tools	Policy assessment/feedback dynamics: when heat thresholds, flood alerts, or electricity stress indicators are exceeded, the university's resilience system automatically escalates alerts, opens cooling spaces, restricts access to exposed buildings, or shifts selected classes online. Foresight-to-action / adaptive complexity: these adjustments are continuously recalibrated as new environmental and operational data arrive.
	Generative Policy Agents	1. LLM-based drafting agents - Llama 2. Scenario generation systems - LangChain 3. Policy memo and report generation tools - GPT-based assistants 4. Consultation summarization agents - Haystack 5. Proposal generation agents - RAG-based policy copilots	Foresight/uncertainty: the lab uses a generative policy agent to produce alternative scenarios such as recurrent flooding of access roads, prolonged drought affecting water supply, or multi-day heat emergencies disrupting teaching and research. Knowledge creation and policy design/complexity: the system synthesizes scientific evidence, campus operations data, and stakeholder input into draft resilience plans, trade-off summaries, and briefing notes for university leadership and local government partners.

Although the article does not develop or validate a full technical architecture, the typology has architectural value because it encourages a systemic view of anticipatory-governance technologies. The reference architecture in Figure 2 is therefore a conceptual synthesis rather than an engineering specification. It illustrates how infrastructural, analytical, and decision-mediating components can be articulated within an interoperable socio-technical arrangement. The layers are grouped by their primary governance output rather than by underlying computational technique:

a) Layer 1: visibility, integration, monitoring;
b) Layer 2: modeling, simulation, interpretation;
c) Layer 3: recommendation, prioritization, adaptive adjustment;

Figure 2. Big Data, Data Science, and AI Technologies for Anticipatory Governance to address Complex Systems: Reference Architecture



5. Conclusion

Anticipatory governance has emerged as a strategic response to complex socio-technical systems marked by uncertainty, non-linearity, interdependence, and feedback dynamics (Duit & Galaz, 2008; Guston, 2014; Panizzon & Janissek-Muniz, 2025). At the same time, the growing integration of data-intensive and AI-driven technologies into public decision-making has generated conceptual ambiguity regarding not only the distinct roles of Big Data, Data Science, and AI, but also the institutional consequences of embedding computational systems in the production of evidence, interpretation, and action. This article addressed that gap through a systematic literature review and the development of a layered functional typology.

The main contribution of the study is not the generic technical distinction among Big Data, Data Science, and AI-enabled decision-mediating systems, but the systematic explanation of how these capabilities become institutionally embedded across anticipatory-governance functions. The proposed typology links infrastructural, analytical, and decision-mediating roles to informational, analytical, and decisional capacity and formalizes decisional embedding as the degree to which computational systems participate in the production of alternatives, prioritization, recommendation, adjustment, or execution. This lens makes visible how technological integration redistributes informational, epistemic, and decisional authority in hybrid socio-technical systems without treating the three categories as mutually exclusive engineering taxonomies.

The review findings indicate a cumulative but non-deterministic pattern. Big Data infrastructures broaden observability and stabilize evidentiary inputs; Data Science structures interpretation through modeling, simulation, and knowledge extraction; and AI-enabled decision-mediating systems become distinctive where algorithmic systems participate more directly in recommendation, prioritization, adaptive adjustment, or partial execution (Kitchin, 2014; Provost & Fawcett, 2013; Danaher et al., 2017; Yeung, 2018). These functions may coexist, overlap, or remain deliberately separated depending on institutional context. The relevant transformation is therefore not a simple progression toward greater automation, but a reconfiguration of where informational, epistemic, and decisional authority is located.

This perspective also clarifies the limits of technologically augmented anticipation. Hybrid architectures can expand foresight and adaptive capacity, but they do not eliminate ambiguity, deep uncertainty, emergent dynamics, or value conflict. As technological systems move from informational support toward decisional mediation, questions of delegation, accountability, epistemic authority, contestability, and oversight become more consequential. Anticipatory governance in the age of AI therefore requires not only interoperable technical capacity but institutional arrangements that preserve meaningful human judgment, make model assumptions and decision pathways traceable, allow affected actors to contest consequential outputs, and assign responsibility for decisions that emerge from hybrid human-machine processes.

The study also offers practical implications. Governments and universities should differentiate governance safeguards according to the function performed by a technological system and its degree of decisional embedding. Data infrastructures require mechanisms for integrity, interoperability, provenance, representational fairness, and legitimate data authority; analytical systems require scrutiny of model assumptions, uncertainty communication, interpretive bias, validation, and epistemic pluralism; and decision-mediating systems require explicit delegation boundaries, traceability, meaningful human oversight, and procedures for contesting, overriding, or reversing automated recommendations and adjustments. This function-based approach avoids equating the adoption of a specific technology with a desirable level of institutional autonomy.

This study has several limitations. First, the review relies on Web of Science as a single bibliographic database, which may exclude relevant scholarship indexed elsewhere and makes the corpus sensitive to database coverage and query design. The executed query also included a standalone Anticipatory Governance branch, broadening retrieval beyond records that explicitly paired governance terms with the three technology terms; relevance was therefore enforced during screening. Second, the functional coding is interpretive and, although author-validated, was not subjected to an independent inter-rater reliability test. Third, the boundaries among Big Data, Data Science, and AI-enabled decision-

mediating systems are analytically useful but porous; the same computational technique may perform different institutional functions across settings. Fourth, the rapidly evolving agentic and generative AI literature creates temporal instability in terminology and available applications. Finally, as an SLR, the study does not provide direct empirical validation of how the proposed configurations operate in real governance settings. Future research should test the typology across institutional cases, compare coding across independent researchers and additional databases, examine how delegation boundaries and accountability mechanisms operate in practice, and investigate how generative and agentic systems affect policy framing, agenda setting, contestability, human judgment, and the governance of expertise. Anticipatory governance in the age of AI is therefore not simply about improving prediction, but about governing how layered technological capacities shape what institutions can observe, whose interpretations become authoritative, which alternatives become actionable, and how responsibility for consequential decisions is ultimately assigned and justified.

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