
From Resistance to Readiness: Conceptualizing AI-Human Synergy as a Systemic Capability in Integrated Healthcare Governance

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Abstract: Public healthcare systems increasingly invest in artificial intelligence (AI) that holds promise to improve efficiency and generate organizational innovation. However, these efforts often fail and may even reinforce institutional rigidity. This study approaches this paradox by examining how AI interacts with human decision processes in complex governance environments. Drawing on an abductive qualitative study in healthcare, the findings suggest that the adoption barriers are not primarily technological but structural, and that AI adoption can become a useful diagnostic mirror indicating organizational readiness and revealing rational – and, importantly, addressable – adoption challenges. Rather than representing implementation failures, challenges related to fragmentation, documentation and trust signal misalignment between algorithmic logic and institutional practices, revealing how AI-human synergy, when reached, forms a systemic capability. Introducing the AI-Human Capability Loop, a conceptual framework elucidating co-evolution of cognitive understanding, collaborative confidence, and ethical adaptability, this study contributes to existing knowledge on innovation management for adaptive governance.

Keywords: AI-Human Synergy; Algorithmic Governance; Healthcare Innovation; Digital Health; Adaptive Governance; Innovation Management; Human-AI Collaboration; Public Sector Innovation; Systemic Capability; Integrated Care Systems.

1 Introduction

Public governance is confronted with a paradox: while AI and advanced analytics promise significant improvements in efficiency and quality and organizational innovation, their implementation in public sector organizations often leads to increased rigidity rather than enhanced adaptability (Haesevoets et al., 2025; Mergel et al., 2024). This tension is particularly visible in publicly funded healthcare and wellbeing systems, where substantial investments in data infrastructures and digital capabilities have not consistently translated into improved system-level coordination or decision quality (Wirtz et al., 2019; van Noordt & Misuraca, 2022). In particular, rather than reducing complexity, AI adoption has exposed challenges of traditional administrative rationality characteristic for healthcare organizations, revealing persistent tensions between algorithmic optimization and the situated, context-dependent nature of healthcare decision processes (Sun & Medaglia, 2019; Selten & Klievink, 2024). A relevant challenge is persistent gap between data production and organizational use, indicating that analytical capabilities may improve while remaining disconnected from meaningful decision processes (Topol, 2019).

In healthcare contexts, privacy issues and other regulation challenge data management and sharing, intensified by hierarchy and professional siloes (Hurmelinna-Laukkanen et al., 2021). In the context where decisions carry profound ethical and societal implications, trust becomes a central condition for AI integration (Bærøe et al., 2020; Banerjee et al., 2022). Trust does not emerge from technical performance alone, however, but is shaped through the interaction between data, human interpretation, and institutional accountability. This perspective connects with broader discussions on AI governance that emphasize transparency, accountability, and human oversight in complex decision environments (Floridi et al., 2018; OECD, 2019; European Commission, 2020).

Following this line of thinking, this study embraces the view that AI adoption in the public sector cannot be understood as a purely technical process but must be approached as a socio-technical transformation shaped by organizational structures, governance arrangements, and institutional norms (Grover et al., 2022; Duus et al., 2026). This view warrants examination specially in the healthcare and wellbeing sector. While rapid advances can be observed in clinical AI and predictive analytics (Jiang et al., 2017; Esteva et al., 2019; Topol, 2019), transition toward data-driven, adaptive governance requires a fundamental shift in organizational cognition, coordination, and institutional logics (Sousa-Zomer et al., 2020; Warner & Wäger, 2019). Existing research still provides only partial insight into how AI-human interaction develops over time, particularly in multi-actor environments characterized by distributed authority and fragmented information structures.

To address this gap, we adopt the view that anticipatory governance and future preparedness can be understood as collective capabilities emerging from continuous interaction between human and technological cognition. Organizations must develop the capacity to interpret signals, respond to uncertainty, and learn from feedback over time (Hiltunen, 2013; Kuusi et al., 2015). Accordingly, this study conceptualizes AI as a mechanism for augmenting collective intelligence within complex governance systems, and asks if and *how the interaction between human reflexivity and AI-driven intelligence may evolve into a systemic capability that supports adaptive governance* especially in the context of complex public sector environments.

To answer this research question, we rely on abductive qualitative study. Empirical insights from a Finnish wellbeing services county system, which represents a recent large-

scale administrative reform aiming to integrate health and social care services under unified governance structures, are reflected to existing scholarly literature on the dynamic capabilities (Teece, 2007; 2017) and on human-AI collaboration (Jarrahi, 2018; Dellermann et al., 2019; Raisch & Krakowski, 2021; Daugherty & Wilson, 2024).

Theoretically, this study contributes to understanding how algorithmic reasoning, human reflexivity, and institutional learning co-evolve within socio-technical systems. Practically, it shows how resistance, rather than being eliminated, can be leveraged as a feedback mechanism that strengthens organizational learning and coordination (Yan et al., 2026). In doing so, the study advances the view that adaptive governance emerges from the development of technological and relational capabilities that integrate cognition, collaboration, and ethical responsibility (Leavitt et al., 2024; Schilke et al., 2017).

2 Theoretical background

2.1 AI adoption and organizational challenges

Research on AI adoption has largely framed AI as an instrumental enabler of evidence-based control, process optimization, administrative automation, and performance enhancement, positioning AI primarily as a technical solution embedded within existing bureaucratic and managerial logics (Wirtz et al., 2019). While such technology/efficiency-oriented perspective has advanced understanding of AI's operational benefits (Grover et al., 2022; Duus et al., 2026), it provides only a partial account of the organizational and systemic challenges associated with its adoption (see Table 1).

Healthcare governance, for example, constitutes a complex multi-actor environment in which decision processes are distributed across administrative, clinical, and political domains, each shaped by distinct logics, incentives, and accountability structures (Kashyap et al., 2021; Liao et al., 2022; Zhu & Vartiainen, 2025). In such contexts, AI becomes entangled with professional judgment, institutional norms, and fragmented information systems, rather than functioning as a standalone innovative technical solution. Addressing these problematics, Engin et al. (2025) emphasize that the central challenge of AI adoption lies not in implementing individual tools but in reconfiguring the institutional rules and structures that govern their use. AI systems are not neutral instruments but components of broader governance architectures that shape how decisions are made, how authority is distributed, and how knowledge is legitimized within organizations (see also Liao et al., 2022; Mills & Sætra; 2025). Resistance to AI adoption in such settings may stem from limited trust in how AI works and whether the data is secured and reliable outcomes can be reached. Similarly, Leavitt et al. (2024) demonstrate how human actors sustain legitimacy and trust in algorithmic systems through reflective interpretation, underscoring the central role of human judgment in AI-enabled decision-making.

Considering the above insights, AI implementation often highlights, rather than resolves, underlying coordination problems (Sun & Medaglia, 2019; Kashyap et al., 2021; Ramadan et al., 2024). Raisch and Krakowski (2021) describe an automation-augmentation paradox, where increasing reliance on automation may reduce opportunities for human learning and weaken the capabilities required for oversight and adaptation. In complex public sector organizations, such as healthcare systems, this paradox becomes particularly pronounced. While AI may enhance efficiency at the task level, it may simultaneously

challenge system-level coherence and innovation, reduce transparency of decision processes, and create new dependencies on algorithmic outputs. These tensions can also be understood as manifestations of broader learning dynamics, where organizations must balance exploration and exploitation in the development of AI-enabled capabilities (Yan et al., 2026). From this perspective, AI supports decision-making, but also reshapes how knowledge is produced, validated, and enacted (Selten & Klievink, 2024), challenging governance models built around control and compliance typical for public sector healthcare organizations (Ansell & Gash, 2008; Kooiman, 2003). This also indicates that resistance to AI implementation may signal limited capabilities at system level that call for attention (see Table 1).

Table 1. Dominant research perspectives on AI adoption in organizations

<i>Research Perspective</i>	<i>Focus</i>	<i>Limitations</i>
<i>Technical implementation</i> Esteva et al., 2019; Jiang et al., 2017; Kashyap et al., 2021; Grover et al., 2022; Duus et al., 2026	Algorithms, data infrastructure	Neglects organizational learning
<i>Change management</i> Venkatesh et al., 2003; Hassan et al., 2024; Ramadan et al., 2024; Haesevoets et al., 2025; Pulkkinen et al., 2025; Yan et al., 2026	User adoption and resistance	Focus on behavioral barriers
<i>Socio-technical systems</i> Bostrom & Heinen, 1977; Dellermann et al., 2019; Jarrahi, 2018; Raisch & Krakowski, 2021; Sun & Medaglia, 2019; Selten & Klievink, 2024	Interaction between technology and actors	Limited governance perspective
APPLICATION IN THIS STUDY:		
<i>Theoretical basis</i> Teece, 2007; Teece, 2017; Sousa-Zomer et al., 2020; Uhl-Bien & Arena, 2018; Engin et al., 2025; Leavitt et al., 2024; Ansell & Gash, 2008; Mergel et al., 2024; van Noordt & Misuraca, 2022; Rozenblit et al., 2025; Topol, 2019; Duus et al., 2026	<i>Focus</i> AI-human synergy as systemic capability	<i>Benefit</i> Explains resistance as learning signal for improving governance

2.2 Towards systemic capability

Recent research emphasizes the reconfiguration of decision-making processes as a core condition for innovative adaptability in complex governance environments (Schilke et al., 2017; Sousa-Zomer et al., 2020). In this regard, AI adoption can be considered a process of cognitive augmentation (Jarrahi, 2018) that aligns with the notion of complementary intelligence, with AI contributing analytical precision and pattern recognition and humans providing contextual interpretation, ethical reasoning, and accountability (Daugherty & Wilson, 2024). Hence, organizations must not only adopt AI but continuously reconfigure how human and algorithmic intelligence interact across decision processes. This reconfiguration involves the development of organizational capabilities that integrate

technological resources, human competencies, and governance structures into coherent decision-making systems (Inan & Yilmaz, 2025; Gupta et al., 2025).

These aspects become visible in complex organizational contexts. Although AI is frequently positioned as a tool for efficiency, its effective integration in public healthcare governance depends on more reflective, participatory, and system-level approaches (Sun & Medaglia, 2019; van Noordt & Misuraca, 2022). In public healthcare governance, where decision-making is distributed across professional groups, deploying AI requires integration into existing practices of sensemaking, communication, and responsibility, supported by appropriate organizational and infrastructural arrangements (Kashyap et al., 2021; Liao et al., 2022). This perspective suggests that adaptation and resilience depend on systemic capability: the organizations' ability to continuously learn from interactions among data, human expertise, and organizational structures (Agyapong Siaw & Ali, 2024; Sousa-Zomer et al., 2020; Teece, 2017; Warner & Wäger, 2019). Rather than operating as separate components, these capabilities evolve over time through iterative and interactive feedback and learning, forming a relational process unfolding in socio-technical systems, that shapes how decisions are interpreted, validated, and enacted within organizations (Dellermann et al., 2019; Zhu & Vartiainen, 2025; Yan et al., 2026). Consequently, human-AI collaboration can be understood as an embedded component of systemic capability building rather than a discrete technological function.

Despite growing recognition of augmentation and complementary intelligence, existing research provides limited insight into how human-AI collaboration evolves into a sustained systemic capability within public governance. In particular, the mechanisms through which socio-technical interactions translate into collective learning, coordination, and adaptive decision processes remain underexplored in complex, multi-actor environments. Therefore, we next turn to empirical examination for new insight.

3 Empirical evidence - Method and context

To examine how AI-human synergy may evolve into a systemic capability in public healthcare governance, we adopted a qualitative, abductive research design suited to conceptually emerging phenomena that cannot be fully explained through a single theoretical lens (Timmermans & Tavory, 2012). As AI-human synergy can be considered a multi-dimensional phenomenon spanning cognitive, institutional, and technological domains, its examination warrants iteration between theoretical concepts and empirical observations.

With the goal to develop a conceptually grounded understanding, the theoretical basis was built on a literature review enabling structured integration of prior research while remaining responsive to emerging empirical insights (Webster & Watson, 2002; Page et al., 2021). In terms of empirical insight, we utilized case study logic to examine the phenomenon in its real-life organizational context (Yin, 2014) where the boundaries between technology, governance, and decision processes are analytically intertwined.

3.1 Empirical data

The empirical setting is the North Savo Wellbeing Services County in Finland, a relevant case due to its ongoing structural transformation, high information intensity, and active

efforts to strengthen data-driven coordination across services. Particular attention was given to the emerging ASSA 2.0 data coordination center, which functions as a real-world testbed for hybrid intelligence in healthcare governance. Rather than treating ASSA 2.0 as a stabilized institutional model, it was approached as an evolving coordination structure. This aligns with broader perspectives on governance as a dynamic, multi-actor process shaped by interaction and institutional adaptation (Ansell & Gash, 2008; Kooiman, 2003).

The empirical material consists of complementary data sources (see Table 2). First, policy documents, strategic roadmaps, and organizational development materials related to the Finnish healthcare reform and regional data coordination initiatives were analysed to contextualize the governance environment and identify formal expectations for data-driven management and anticipatory coordination (Valtioneuvosto, 2025). Second, semi-structured interviews and discussions provided insight into how these expectations are interpreted and enacted in practice. The data were collected by the first author in 2025, complemented by informal expert discussions within ongoing organizational development work. Third, the study incorporates an exploratory information capability survey conducted in 2025 as part of Reform 4 (R4), a regional initiative focused on restructuring specialized medical care and the university hospital system to strengthen integration, coordination, and data-driven management within the wellbeing services county. The reform emphasizes system-level decision-making and anticipatory governance across organizational boundaries. The survey designed to identify perceived information needs, reporting gaps, and coordination challenges across organizational domains rather than for statistical generalization generated utilized narrative format. This enabled the identification of both structural and cognitive dimensions of information capability, highlighting the role of user perspectives in shaping technology use (Venkatesh et al., 2003).

Table 2. Summary of the empirical data sources

<i>Data Source</i>	<i>Description</i>	<i>Purpose in Analysis</i>
Strategic policy documents	Regional digitalization and AI strategies (n = 13; total of 248 pages)	Understanding governance structures
Organizational roadmaps	Development plans for analytics and data use (n = 8; total of 135pages)	Contextualizing AI adoption
Management interviews	Interviews with senior managers (n = 24; total of 20 pages)	Identifying organizational tensions
Information capability survey	R4 capability survey (physicians, managers in specialized med care (n = 25)	Assessing data and analytics readiness

3.2 Data Analysis

In data analysis, we followed the principle of systematic combining where theory development and empirical inquiry evolve in parallel through continuous iteration between framework, field material, and interpretation (Dubois & Gadde, 2002). This approach reflects socio-technical perspectives that emphasize the interdependence of technological systems, organizational arrangements, and human practices in shaping outcomes (Bostrom & Heinen, 1977). In the analysis, the literature review functioned as an evolving analytical

resource rather than a static background as the analysis proceeded through iterative thematic interpretation.

Empirical materials were examined in relation to recurring themes, and early observations such as information and data fragmentation, interpretive gaps, trust in analytics, coordination challenges, uneven analytical maturity, challenges in collective decision processes, and the need for shared decision-support structures informed the (refined) selection of literature. In turn, literature on AI adoption, human-AI collaboration, socio-technical systems, and dynamic capabilities was used to interpret the empirical material and refine the emerging conceptual framework. Through this process, the study developed a conceptual understanding of AI-human synergy as an evolving systemic capability embedded in governance structures, organizational learning, and anticipatory public management.

4 Findings: Systemic Tensions in AI Adoption

The findings illustrate specific challenges related to data use, decision-making, and coordination during AI implementation. When connected to existing literature, they point toward the relevance of resistance as a productive factor signalling the root-causes of challenges and indicate how AI-human interaction unfolds over time, generating a loop that denotes synergies that form systematic capability development. The identified barriers and challenges are summarized in Table 3.

Table 3. Barriers and challenges (survey and interviews)

<i>Dimension</i>	<i>Barrier Category</i>	<i>Empirical Examples</i>	<i>Implications</i>
Cognitive understanding	Fragmented data environment	Data distributed across multiple systems, units, and domains; reliance on manually compiled reports (e.g., Excel)	Difficulty forming a coherent and timely situational picture; weak connection between data and decision-making
	Limited real-time visibility	Data primarily retrospective; lack of access to real-time operational insights	Reduced ability to anticipate, respond, and support proactive decision-making
Collaborative confidence	Inconsistent documentation and metrics	Variation in recording practices, classifications, and indicators across units	Limited comparability of data; duplication of work; reliance on informal validation practices
	Low trust in data and reports	Conflicting reports and uncertainty in interpreting analytics outputs	Reduced willingness to rely on AI-supported recommendations; weakened confidence in analytics

Ethical adaptability	Limited analytical capability	Skill gaps in data interpretation and analytics; uneven capabilities across units	Low organizational readiness for AI; difficulties in integrating analytics into decision processes
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A central finding concerns the *fragmentation of information environments*. Information relevant for decision processes was found distributed across multiple systems, organizational units, and professional domains. Respondents reported difficulties with accessing consistent data and referred to *limited real-time visibility*, often leading to reliance on manually compiled reports to support decision processes: “*Data is fragmented across systems, and we still depend on manually compiled reports, which makes it difficult to form a reliable and timely basis for decision-making*”. The absence of shared, integrated views was found to limit the development of common situational awareness and to slow down organizational response. This indicates that while available, data was weakly connected to decision practices. Similar patterns have been identified in prior research, where fragmented infrastructures, interoperability limitations, and siloed architectures constrain the effective use of AI in healthcare and public sector contexts (Hassan et al., 2024; Pulkkinen et al., 2025; Sun & Medaglia, 2019; van Noordt & Misuraca, 2022; Wirtz et al., 2019).

The empirical material likewise highlighted *inconsistencies in documentation practices and low trust in data and reports*. Respondents described variation in how data is recorded, classified, and interpreted across organizational contexts, leading to uncertainty regarding data reliability: “*Different units record and interpret data in varying ways, resulting in inconsistencies that make the data difficult to compare and trust*”. This was found to result in parallel reporting practices, duplicated work, and a continued reliance on informal knowledge to validate information. Such inconsistencies limited the usability of data for analytics and reduced confidence in system-generated outputs. These findings align with existing research emphasizing that the effectiveness of AI systems depends on stable, standardized, and interoperable data practices, which are often lacking in complex socio-technical environments (Dellermann et al., 2019; Hassan et al., 2024; Pulkkinen et al., 2025).

A further key tension emerged in relation to *Limited analytical capability*. The empirical material revealed uncertainty and scepticism toward analytics outputs, particularly in situations where algorithmic recommendations are not transparent or do not align with professional judgment: “*Different reports produce conflicting results, which weakens confidence in analytics*.” The interviews and survey respondents described difficulties in interpreting results, questioning their validity and clarification responsibility for decisions based on data: “*It is often unclear how the results should be interpreted and who is responsible for decisions based on them*.” Along these lines, earlier literature has noted that trust and legitimacy are critical conditions for AI adoption, particularly in contexts where decisions carry ethical and professional implications (Jarrahi, 2018; Raisch & Krakowski, 2021).

Noteworthy is, that the expressions of scepticism, (reverting to) reliance on manual processes, and hesitation toward analytics revealed tensions between algorithmic logic, often oriented toward efficiency, control, and compliance, and the human need for contextual interpretation, professional judgment, and ethical reflection. When expressing resistance, the informants referred not so much to technical adoption challenges, but those

related to the fit to the organizational needs: “AI currently has no official role in the organization, and its use is largely uncoordinated”. The empirical findings hence suggest that the *emerging resistance revealed structural rather than technical barriers to AI adaptation*, and implied what remedies could be employed. These insights align with research showing that stakeholder interpretations shape the use and impact of algorithmic systems (Sun & Medaglia, 2019), and that governance structures influence how authority, accountability, and legitimacy are distributed (Engin et al., 2025; Mills & Sætra, 2025). Importantly, resistance provided insight into where alignment between data, decision processes, and institutional logics remained incomplete. However, the value of resistance as a diagnostic signal depends on the organization’s capacity for reflexive engagement, that is, the ability to critically examine and question the assumptions and limitations of algorithmic outputs in relation to professional judgment and institutional context (see Leavitt et al., 2024).

Next to the finding that resistance reveals structural challenges in AI-human collaboration, another relevant insight is how the *observed tensions are not isolated issues but form a systemic pattern that can elucidate unfolding of the development of systemic capabilities*. Fragmentation of information environments contributes to inconsistencies in documentation, which in turn undermines trust in analytics and reinforces legitimacy challenges, which may reinforce perceptions of fragmentation and documentation issues. This interconnectedness reflects the socio-technical nature of AI adoption (Bostrom & Heinen, 1977; Dellermann et al., 2019), indicating how challenges in one domain propagate across others, limiting the system’s ability to translate data availability into actionable intelligence. This systemic misalignment can be illustrated as a breakdown in the flow from data to decision-making, where information loses coherence as it moves across organizational boundaries (Figure 1).

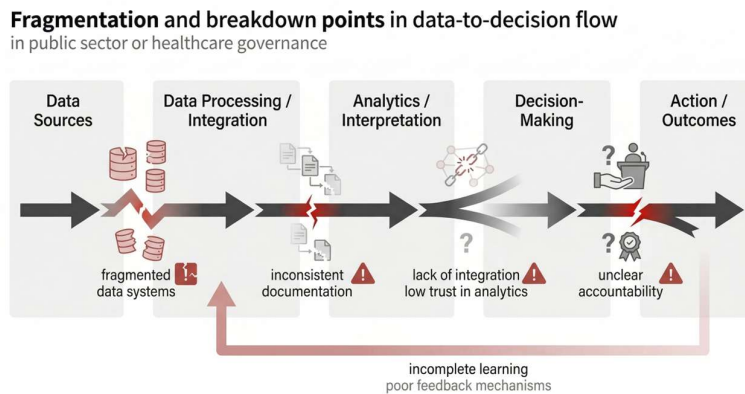


Figure 1. Fragmentation and breakdown points in data-to-decision flow.

Interpreted through the theoretical framework developed in Section 2, the empirical insights point to the emergence of *three interrelated dimensions of AI-human synergy that jointly form the basis of a systemic capability* when the challenges are addressed. First, fragmented information environments reflect limitations in *cognitive understanding*, as actors lack a shared basis for interpreting analytical outputs as contextual insights rather than objective representations (Leavitt et al., 2024; Jarrahi, 2018). Inconsistent

documentation practices and coordination challenges indicate weak *collaborative confidence*, where trust, accountability, and the capacity to critically engage with algorithmic outputs remain underdeveloped (Engin et al., 2025; Mills & Sætra, 2025; Raisch & Krakowski, 2021). Tensions related to limited analytical capability reveal constraints in *ethical adaptability*, referring to the ability to integrate AI into decision processes while preserving professional judgment, transparency, and responsibility (van Noordt & Misuraca, 2022). Importantly, these dimensions interact in a recursive rather than linear manner. Limitations in one dimension reinforce constraints in others, indicating that also the opposite holds: improving trust, coherence and documentation have the potential to create a dynamic pattern in which organizational learning, trust formation, and ethical reasoning co-develop into a systemic capability: This interaction reflects the early formation of a capability loop, where human interpretation and algorithmic outputs continuously shape one another contributing to adaptive governance. Yet misalignment prevents the loop from stabilizing into a fully functional system. These insights provide the empirical foundation for the conceptual framework presented in the following section, where AI-human synergy is conceptualized as a dynamic capability emerging from the interaction of cognitive understanding, collaborative confidence, and ethical adaptability.

5 Discussion: The AI-Human Capability Loop

The findings of this study indicate that the challenges of AI adoption in public healthcare governance are not primarily technological but systemic. Data readiness, organizational coordination, and cultural readiness must co-evolve, as misalignment between these constrains the effective use of AI despite technological advances. Our study suggests that AI-human synergy can be seen as a relational and evolving capability that originates from resistance to emerging tensions; such resistance allows identifying the dimensions where capability building is needed and facilitates a recursive loop in which human cognition and algorithmic intelligence continuously shape one another.

More specifically, while AI adoption challenges reflect systemic misalignments in data, governance, and organizational practices, resistance indicates how these misalignments are interpreted and responded to. Hence, rather than representing failure, it functions as a diagnostic signal that reveals misalignment between algorithmic outputs and institutional logics (Engin et al., 2025; Sun & Medaglia, 2019). Through iterative engagement, tensions can be interpreted, addressed, and gradually transformed, enabling organizations to move from resistance toward systemic readiness for adjustment, that is, a systemic capability. The AI-Human Capability Loop conceptualizes the socio-technical process through which tensions, such as data fragmentation and inconsistency and lack of trust, are not eliminated but transformed into sources of organizational learning and adaptive capacity (Figure 2).

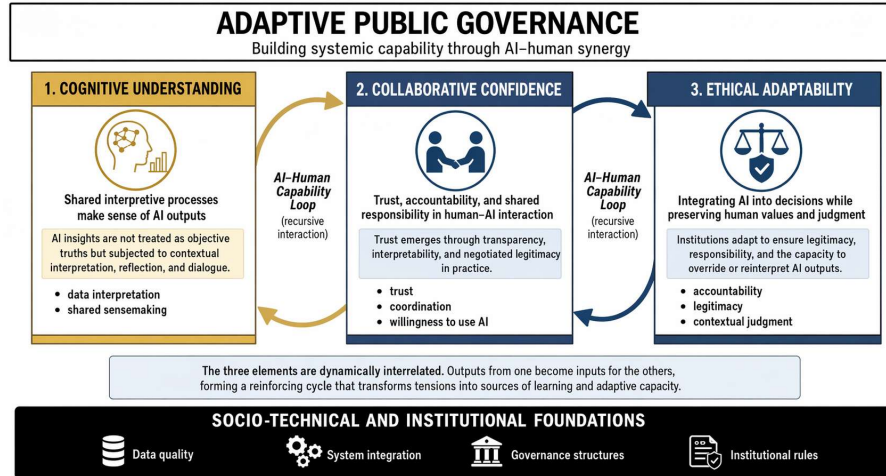


Figure 2. Systemic capability structure for adaptive governance.

Within the capability loop, three interdependent elements – cognitive understanding, collaborative confidence, and ethical adaptability – form a reinforcing cycle in which outputs from one become inputs for the others. At the core of the loop is *cognitive understanding*, referring to the shared interpretive processes through which actors make sense of algorithmic outputs: AI-generated insights are not treated as objective truths but are subjected to contextual interpretation, reflection, and dialogue. This aligns with research emphasizing reflexive interpretation as a mechanism through which algorithmic systems gain meaning in organizational settings (Leavitt et al., 2024), as well as with broader sensemaking perspectives in socio-technical environments (Sun & Medaglia, 2019). Through these processes, data is translated into institutional knowledge, enabling collective learning and strengthening decision quality (Uhl-Bien & Arena, 2018). This interpretive process is reinforced by AI’s capacity to complement human intelligence in transforming tacit knowledge into explicit and actionable organizational assets, thereby enabling the dynamic reconfiguration of knowledge resources in line with sensing and learning processes (Agyapong Siaw & Ali, 2024).

However, the transition from understanding to trust is neither automatic nor linear; it unfolds through a socio-technical mediation process in which interpretation must be collectively validated and enacted in practice. Trust, therefore, is not a property of the AI system itself, but an outcome of interaction, built through transparency, interpretability, and the negotiated legitimacy of algorithmic outputs within organizational practice. Building on this interpretive foundation, *collaborative confidence* captures the emergence of trust, accountability, and shared responsibility between human and algorithmic actors. Human-AI interaction involves an ongoing process of calibration, reflecting the notion of human-AI symbiosis (Jarrahi, 2018). In this way, it aligns with research on complementary intelligence, where human judgment and algorithmic analysis co-produce outcomes (Daugherty & Wilson, 2024). At the same time, this dimension must be understood through the automation-augmentation paradox, where increasing reliance on AI may weaken human oversight if not actively managed (Raisch & Krakowski, 2021).

The third dimension, *ethical adaptability*, extends the concept of dynamic capabilities into the domain of governance, legitimacy, and responsibility (Teece, 2017). Ensuring ethical adaptability requires that the division of labor between human expertise and algorithmic systems is governed by clearly defined accountability structures and ethical standards, mitigating risks related to limited analytical applicability such as bias, excessive monitoring, and the erosion of professional judgement (Agyapong Siaw & Ali, 2024). It refers to the institutions' ability to integrate AI into decision-making processes while preserving moral judgment, professional autonomy, and the capacity to override or reinterpret algorithmic outputs when necessary (Ahmad, 2025; Engin et al., 2025; Rozenblit et al., 2025; van Noordt & Misuraca, 2022).

From innovation management perspective, the AI-Human Capability Loop reframes AI adoption and AI-based innovation as a continuous process of capability formation instead of a bounded implementation process focused on efficiency and automation (Wirtz et al., 2019; Dellermann et al., 2019). The framework shifts attention toward how organizations design and govern the interaction between human and algorithmic intelligence over time, enabling alignment between data, interpretation, and decision processes across organizational boundaries. In this sense, AI adoption becomes an ongoing coordination challenge, where value emerges through the continuous calibration of cognitive understanding, collaborative confidence, and ethical adaptability rather than through discrete implementation stages.

By conceptualizing AI-human synergy as a dynamic and relational capability, the suggested framework provides a foundation for understanding how organizations can move toward integrated and adaptive governance. Fundamentally, it suggests that the core task of innovation management in AI-enabled environments is the continuous design of socio-technical interaction through which learning, coordination, and adaptive capacity emerge.

6 Conclusions

As illustrated in Table 1, existing research on AI implementation clusters around technological, human-centric, and capability-oriented perspectives, yet provides limited understanding of how these dimensions interact. This study examines understanding of AI in public governance by reframing AI adoption as a systemic capability instead of a technological implementation challenge. In this sense, our study also addresses a broad limitation in prevailing digital transformation approaches, where technological capability is often assumed to directly produce organizational performance (Vial, 2019).

The theoretical contribution of this study lies in combining the technological, human-centric, and capability-oriented perspectives. First, challenging efficiency-focused views of AI adoption in the public sector (Wirtz et al., 2019; van Noordt & Misuraca, 2022), our study emphasizes the need for alignment along technological, organizational, and cognitive dimensions. Our findings show that fragmented information environments, inconsistent documentation practices, and low trust in analytics constrain the transformation of data into actionable knowledge. Resistance associated with these tensions reveals efficiently problematic systemic misalignment and guides subsequent action to remedy the challenges (Engin et al., 2025; Mills & Sætra, 2025; Ramadan et al., 2024). Consistent with emerging perspectives on strategic renewal in digitally transforming organizations (Warner & Wäger, 2019), our study indicates that data readiness and cultural readiness must co-evolve for AI to support innovative, adaptive governance.

Second, our study extends the dynamic capabilities view toward ethical, institutional, and socio-technical domains. Following the logic of the dynamic capabilities view that explicates the roles of sensing, seizing, and transforming (Teece, 2017; 2018), our findings show that sensing without shared interpretation and trust remains insufficient and align with recent work suggesting that AI augments analytical capabilities while human actors remain central in interpreting environmental signals and guiding strategic responses (Agyapong Siaw & Ali, 2024). In particular, by introducing the AI-Human Capability Loop, adaptability is conceptualized as a relational and evolving capability emerging from recursive interaction between cognitive understanding, collaborative confidence, and ethical adaptability, which emphasizes its interactional nature (Schilke et al., 2017).

In addition to extending the discussion on dynamic capabilities, the suggested framework also highlights a fundamental tension between the logic of AI systems and the requirements of public governance (Kashyap et al., 2021). While algorithmic systems prioritize efficiency, consistency, and optimization, public decision processes especially in healthcare require contextual judgment, ethical reflection, and accountability. This reflects a broader paradox in digital transformation, where increased data availability does not automatically translate into improved decision capacity (Vial, 2019; Warner & Wäger, 2019). The AI-Human Capability Loop addresses this tension by positioning AI as an extension of human cognitive capacity rather than its replacement.

In terms of practical implications, the findings highlight the need for public sector organizations, particularly in healthcare governance, to move beyond tool-centric approaches in AI implementation. Governance structures should ensure that human reflection becomes an institutionalized component of AI-supported decision processes. This can include practices such as strengthening data literacy, enabling transparent interpretation of analytics, and formalizing cross-functional processes for dialogue, sensemaking, and ethical deliberation. Without such structures, AI risks reinforcing existing silos rather than enabling systemic learning and adaptive coordination. The implications of these findings can be synthesized as an integrated capability structure that connects leadership, trust, and institutional alignment in enabling adaptive governance (see Figure 2).

This study has several limitations that serve as stepping stones for future research. The abductive, qualitative research design prioritizes conceptual development over causal explanation, limiting the ability to establish generalizable relationships. Generating similar constraints, the empirical material is derived from a single case context (Yin, 2014). The empirical examination also captures an organization under change, meaning that not all remedies to AI adoption challenges are fully employed and tested yet. Future research should therefore explore how AI-human synergy evolves over time and across diverse institutional contexts. Longitudinal research designs enable deeper insight into how cognitive understanding, collaborative confidence, and ethical adaptability co-develop and interact, particularly in relation to shifts in governance structures and technological infrastructures. Building on the conceptual foundations introduced in this study, future studies can hopefully develop operational measures for assessing AI-human synergy.

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