

Artificial intelligence in public procurement: a multilevel dynamic capabilities perspective

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Abstract

Purpose – This study explores how artificial intelligence (AI) adoption in public procurement emerges through dynamic capabilities across individual and organisational levels.

Design/methodology/approach – A qualitative study was conducted with 20 professionals from 13 Finnish public organisations engaged in AI-related procurement initiatives. Using the Gioia methodology, interviews and supplementary documents were analysed to identify enablers, barriers and transformation mechanisms.

Findings – The findings show that dynamic capabilities – sensing, seizing and transforming – are distributed across levels and shaped by bottom-up and top-down mechanisms. Individual experimentation feeds organisational learning, while leadership and governance structures enable or constrain scaling. Most organisations remain in the early phases, with transformation hampered by silos, vendor lock-in and weak orchestration.

Originality/value – The study advances dynamic capabilities theory by demonstrating its multilevel nature in the public sector. It provides actionable insights into aligning individual initiatives with organisational structures to achieve sustainable, AI-enabled procurement transformation.

Keywords Public procurement, Artificial intelligence, Dynamic capabilities, Multi-level analysis

Paper type Research article

1. Introduction

Public procurement provides a critical setting to study organisational adaptation to technological change, as it combines strict legal frameworks with significant economic and societal impacts. Even incremental improvements in transparency or automation can yield substantial public value; however, successful transformation depends on more than structural reform alone. Dynamic capabilities theory highlights the role of sensing, seizing and reconfiguring in adaptation (Teece, 2007), but less is known about how these processes unfold through the interaction of organisational structures and individual practices (Helfat and Martin, 2014; Salvato and Vassolo, 2018).

Artificial intelligence (AI), as a general-purpose technology exemplifies this challenge, since its adoption requires both organisational reconfiguration and the skills and adaptive behaviours of procurement professionals (Crafts, 2021). This dual dependence positions procurement as both an enabler and a bottleneck for AI-enabled transformation. However, prior research has rarely examined why public organisations stall at the pilot stage despite favourable conditions or how individual experimentation and organisational mechanisms align to support reconfiguration. Addressing this gap and responding to the call by Madan and Ashok (2023), this article investigates AI adoption in Finnish public procurement to show how employees' adaptive behaviours interact with organisational structures to shape dynamic capabilities across levels.

Public procurement thus emerges as a critical arena for examining how AI-enabled transformations are realised in practice. Representing over 16% of the European Union's



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Gross Domestic Product ([European Court of Auditors, 2023](#)), procurement is more than an administrative routine: it is a strategic lever for delivering efficiency, transparency and broader public value ([Malacina et al., 2022](#)). However, its potential is often constrained by fragmented processes, risk-averse cultures and limited room for experimentation ([Uyarra et al., 2014](#)). These conditions amplify the challenges of embedding AI, where organisational reconfiguration must be matched by individual-level skills and adaptive behaviours. While private-sector experiences showcase AI's potential in areas such as spend analysis, supplier evaluation, and contract automation ([Hallikas et al., 2021](#); [Harju et al., 2023](#)), public-sector uptake has been uneven. Pilot initiatives are widespread across Europe, but structural barriers, accountability requirements and insufficient capability development have slowed scaling ([European Commission, Joint Research Centre, 2021](#)). Addressing these limitations requires cultivating dynamic capabilities that bridge organisational structures and individual expertise, enabling procurement to move from isolated experiments towards sustained, AI-driven transformation.

Finland provides an ideal context for examining AI adoption in public procurement. It is recognised as a forerunner in public-sector innovation and procurement policy ([European Commission, 2021](#)) and ranks ninth globally on the 2024 AI Readiness Index, reflecting strong institutional capacity and digital infrastructure ([Oxford Insights, 2024](#)). Since the launch of the national “AI Finland” strategy in 2017, significant investments have created favourable structural conditions, yet large-scale transformation remains limited. This paradox makes Finland a valuable setting to investigate how AI adoption in organisational level can move beyond pilots towards sustained practice transformation, offering both managerial insight and theoretical contributions.

Current research on AI in public procurement relies heavily on anticipated benefits rather than actual operational experiences, as relatively few agencies currently use AI technologies in operational settings. Consequently, a deeper understanding of the practical challenges in implementing AI is urgently required. Because existing studies frequently employ static frameworks that obscure the practical organisational challenges of implementation ([Neumann et al., 2024](#)), this study conceptualises AI adoption as a dynamic, trial-and-error process of capability development. Furthermore, successful AI utilisation necessitates examining internal and external AI competencies and investigating the collaboration between various stakeholders, an area where comprehensive research remains notably absent ([Andersson et al., 2025](#)). These misalignments between structures and agency hinder reconfiguration and underscore the need for dynamic capabilities that integrate strategic foresight with operational learning. Such capability building in public organisations is conditioned by legal institutional design, particularly through governance and organisational design routines that shape authority, accountability, coordination and adaptability ([Spanó et al., 2024](#)). This study therefore positions AI adoption in public procurement as a capability development challenge that must be analysed through the interaction between agency and these legally embedded organisational arrangements.

This study employs a qualitative design, drawing on multiple data sources to capture both organisational processes and the perspectives of procurement and development professionals. Focusing on leading organisations with active AI projects, it examines how dynamic capabilities are activated, constrained and recombined in practice. The article proceeds as follows: [Section 2](#) reviews the literature on public procurement, AI in the public sector and dynamic capabilities; [Section 3](#) outlines the research design; [Section 4](#) presents the findings, including a dynamic capabilities model of AI adoption and barriers to scaling; [Section 5](#) discusses the theoretical and managerial implications; and [Section 6](#) concludes with key insights and future research directions.

2. Literature review

2.1 Conceptualising artificial intelligence and dynamic capabilities in AI transformation

For the purposes of this study, AI is defined in accordance with the [OECD \(2024\)](#), which characterises an AI system as “a machine-based system that, for explicit or implicit objectives,

infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments". This definition is intentionally broad, reflecting the general-purpose nature of AI and encompassing both generative AI systems and more established techniques such as machine learning and robotic process automation.

Dynamic capabilities refer to an organisation's ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments (Teece, 2007). Originally developed for the private sector to analyse how firms sustain competitive advantage under conditions of technological and market change, the concept has since been extended beyond its original corporate setting. In the strategic management literature, the dynamic capabilities framework has increasingly been applied to public sector contexts, particularly in studies of digital transformation where organisations face simultaneous demands for efficiency, innovation and accountability. In these settings, dynamic capabilities are understood less as mechanisms for competitive advantage and more as organisational capacities to adapt governance structures, develop new practices and respond to evolving policy, technological and societal pressures (Kattel and Mazzucato, 2018; Piening, 2013). The dynamic capabilities perspective is especially suited to AI adoption, as it captures not only the technological dimension but also the organisational learning and adaptation processes required for sustainable transformation.

In public procurement, dynamic capabilities can be understood as the ability to sense opportunities for digital innovation, seize them through resource mobilisation and strategic alignment, and transform established routines to embed new practices. Recent studies refine these processes into identifiable microfoundations, such as strategic foresight, innovation management and cross-functional collaboration (Herold *et al.*, 2023), as well as continuous capability orchestration to address evolving technical, managerial and relational gaps (Xu and Pero, 2023). Unlike static adoption models, this perspective views AI integration as an iterative process of learning-by-doing, collaborative problem-solving and ongoing adaptation, where success depends not only on favourable initial conditions but also on the sustained reconfiguration of resources, knowledge and relationships over time. Importantly, public-sector distinctiveness suggests that capability building is mediated by legal-institutional conditions, as legal and institutional designs shape organisational routines (e.g. governance, budget and finance, and public procurement and partnerships) that frame the development and sustainability of dynamic capabilities (Spanó *et al.*, 2024). However, existing applications of the dynamic capabilities lens often remain generic, theorising capabilities at an organisational level without unpacking how they are constructed and reinforced through individual action. This highlights the need for a multilevel perspective that links individual agency with institutional transformation processes.

2.2 Individual perspectives on developing AI

Conventional IT adoption models typically portray technology uptake as a linear transformation shaped by technological, organisational and environmental conditions. In the public sector, these models explain adoption in terms of efficiency gains or improved citizen services, yet they often overlook the role of individual users, treating them as passive recipients of predetermined processes. AI, particularly generative AI (GenAI), complicates this view. Its general-purpose nature, implementation complexity and dependence on cultural change and cross-unit collaboration mean that adoption is not a discrete event but an ongoing journey of experimentation, feedback loops and continual adjustment (Neumann *et al.*, 2024). For individual professionals, this requires not only technical training but also the willingness to test, adapt, and integrate AI tools into established routines under conditions of uncertainty. From a dynamic capabilities perspective, such adaptive capacity rests on microfoundations, understood as the individual skills, decision-making practices and cognitive frames that underpin organisational learning (Chen *et al.*, 2023). Especially, in public organisations these

microfoundations are conditioned by human resources rules that govern recruitment and career structures, incentives and professional development, and reskilling mechanisms, shaping whether individuals can credibly sense, seize and transform their work practices around AI over time (Spanó *et al.*, 2024). Eisenhardt and Martin (2000) stress the importance of examining these practices to understand how capabilities are built and sustained, while Teece (2007) conceptualises microfoundations as the skills, norms and routines that enable adaptation. Subsequent work shows that dynamic capabilities manifest differently across levels and contexts (Chirumalla *et al.*, 2023; Schilke *et al.*, 2018), which underscores the value of analysing how public procurement professionals sense, experiment and seize the opportunities presented by AI.

Importantly, AI differs from earlier digital innovations, such as cloud computing, customer relationship management systems, and algorithmic analytics, because it enables individuals to derive personal value and work more autonomously without requiring immediate, organisation-wide uptake. Recent evidence shows that individuals who gain personal benefits from AI are significantly more likely to drive wider organisational success (Ransbotham *et al.*, 2021). This suggests that individual-level engagement is not peripheral but foundational to collective transformation. Realising AI's transformative potential thus requires a closer examination of how individual-level factors – such as skills, motivation and experimentation – interact with organisational structures and strategic objectives. These interactions shape an organisation's progress through the dynamic capability cycle of sensing, seizing and transforming, with specific enablers and barriers influencing the development of these capabilities. However, prior research has not systematically explored how these dynamics operate across individual and organisational levels in public-sector contexts, highlighting the need for the multilevel perspective proposed in this article.

2.3 Public organisational perspectives on developing AI

AI has already become a central driver of digital transformation in public administration (Chandra and Feng, 2025). Traditional applications, including algorithmic decision-making, predictive analytics and robotic process automation, have reshaped operations by automating routine tasks and strengthening data-driven decision-making (Van Noordt and Misuraca, 2022). However, these developments have also raised important challenges concerning trustworthiness, transparency and accountability in algorithmic systems (Alon-Barkat and Busuioc, 2023). These tensions raise difficult questions about how decision-making responsibilities should be distributed between humans and AI systems and how to safeguard fairness and legitimacy in public services (Bullock, 2019). Such challenges make clear that the organisational capabilities required for AI adoption cannot be reduced to technical expertise alone – they also involve governance arrangements, ethical oversight and the ability to reconcile innovation with democratic accountability.

Prior research has identified several organisational barriers to AI adoption in the public sector, ranging from inadequate digital infrastructure and persistent skills gaps to complex ethical and legal uncertainties (Neumann *et al.*, 2024; Rjab *et al.*, 2023). Addressing these challenges requires not only investments in technology but also strong dynamic capabilities at the organisational level. Successful deployment depends on strategic leadership, an innovation-supportive culture and robust data governance practices (Hong *et al.*, 2022). At the same time, comprehensive regulatory frameworks are needed to mitigate risks and ensure the ethical application of AI in public administration (Mügge, 2023). Organisational design is central in this process because it balances bureaucratic stability with the flexibility to reconfigure routines, while also clarifying responsibility and the boundaries of delegated decision authority needed to enable cross functional AI collaboration (Spanó *et al.*, 2024). In summary, public-sector AI adoption is a dynamic-capability challenge: organisations must keep sensing opportunities, seize them by aligning strategy and mobilising resources, and then reconfigure structures and processes to sustain effectiveness and legitimacy.

2.4 Artificial intelligence and public procurement

Public procurement is increasingly recognised as a strategic instrument for advancing policy objectives. Once seen as a transactional activity, it now functions as a governance tool that can stimulate innovation, promote sustainability and embed public values (Uyarra and Flanagan, 2010). Innovative procurement practices diverge fundamentally from routine, compliance-driven processes, requiring different forms of organisational sensing, seizing and reconfiguring (Loijas *et al.*, 2024). AI adds new opportunities in public sector by enhancing citizen interaction, personalising services and supporting creativity in administrative processes (Mergel *et al.*, 2023), but realising this potential requires careful attention to human-machine interaction and governance for ethical use (Choi and Park, 2023). Unlike earlier systems, GenAI can be adopted directly by individuals, shifting adoption dynamics from being organisation-led to involving strong individual agency. This makes the interplay between the individual and organisational levels critical, yet systematic studies of how such dual-level dynamics shape AI adoption in public procurement remain scarce. The alignment between individual initiatives and organisational structures in AI-driven procurement remains insufficiently examined.

Comparisons with the private sector highlight both opportunities and limitations in the public domain. Private companies are already leveraging AI to support product and service innovation, accelerate development through rapid prototyping and optimise supply chain management. Applications include demand forecasting, outsourcing decisions and improvements in scheduling, routing, cost control and transportation efficiency. In industries such as e-commerce and manufacturing, leading firms use GenAI to increase visibility and responsiveness in highly dynamic markets (Modgil *et al.*, 2025). AI technologies are beginning to influence procurement across sectors and are increasingly recognised for their potential to reduce manual workloads, enhance supplier evaluation, detect anomalies and strengthen contract management and risk assessment (Guida *et al.*, 2023).

Although AI demonstrates substantial potential to enhance efficiency, operational capabilities and sustainability within public procurement, actual implementation remains highly limited and in its infancy due to profound barriers, including stringent IT security requirements, resource deficits, legal constraints and siloed organisational structures (Andersson *et al.*, 2025). Given that contemporary studies frequently rely on static implementation frameworks, a critical question emerges: how can future models adequately capture the practical challenges of AI adoption and the dynamic, trial-and-error nature of capability development within the public sector? For the public sector, these applications represent not only opportunities for efficiency but also a broader capability challenge: the ability to align individual experimentation with organisational systems and governance frameworks to ensure that AI adoption contributes to both operational performance and public value creation.

3. Research approach

This study applies a qualitative, interpretive research design to explore the dynamics of AI adoption in public procurement organisations. It draws on qualitative data from semi-structured interviews with public organisations operating under Finnish public procurement law. Finland provides a compelling empirical setting: as a digitally advanced country, it combines high levels of public-sector digitalisation with a strong policy orientation towards AI-driven innovation. Case organisations included state-level agencies, large cities, wellbeing services counties and publicly owned companies – all operating under public procurement legislation. Organisations were selected purposively to ensure that AI had been piloted or deployed in procurement-related activities, enabling us to capture relevant and varied experiences. The interviewed organisations were early adopters selected to capture variations in organisational size, procurement maturities and stages of AI adoption. This snowball

sampling strategy ensured exposure to a diverse set of experiences while allowing for analytical generalisation rather than statistical inference.

This study utilised the Gioia methodology's structured approach to inductive concept development, progressing from first-order informant terms to second-order theoretical themes and aggregate dimensions (Gioia *et al.*, 2012). The ultimate aim was not the static elaboration of constructs; instead, the analysis was processual in orientation – it sought to capture the unfolding of dynamic processes associated with AI adoption in public procurement. The dynamic capabilities framework (sensing, seizing and transforming) served as a sensitising device; however, the analysis aimed to refine this framework by tracing how transitions between capability states are socially constructed and enacted over time. Accordingly, the data analysis proceeded in two steps. First, interview accounts were systematically coded using a Gioia-type data structure that gave voice to organisational actors. Second, this static representation was transformed into a process model that highlighted temporality, sequences and transitions in capability development. This hybrid approach thus combined the transparency of Gioia-inspired coding with a processual lens, enabling the study to demonstrate both its empirical grounding and organisational adaptation under technological change.

Data collection was primarily based on semi-structured interviews, supplemented by documentary materials, such as organisational websites, internal presentations and AI-related tender documentation. In total, 20 individuals were interviewed across 13 organisations between January and March 2025. The interviewees included procurement managers, developers and digitalisation specialists, each reflecting their organisation's perspective on AI adoption. The interviews lasted for approximately 60 min, were recorded with participant consent and were transcribed verbatim. The interview protocol covered themes such as awareness and perceptions of AI, implementation experiences, barriers and enablers, comparisons with private-sector practices and anticipated future developments. Table 1 summarises the case organisations, interviewees and illustrative areas of AI focus.

As noted above, snowball sampling was employed to identify AI frontrunners within the public sector. These actors represented a range of organisational types; however, despite their structural and operational differences, the interview data indicate that they were broadly comparable in terms of both the stages of AI adoption and the challenges encountered during implementation. This snowball sampling strategy ensured exposure to a diverse set of experiences, while supporting analytical generalisation rather than statistical inference.

Data analysis followed a thematic strategy guided by abductive reasoning, combining theory-driven and inductive coding. Initial codes were informed by the dynamic capabilities framework – particularly sensing, seizing and transforming (Teece, 2007) – and then refined iteratively through the open coding of text segments, axial coding into broader categories, cross-case pattern matching and model development. The outcome was a dynamic capabilities model and an implementation typology grounded in empirical regularities. Credibility was strengthened through peer debriefing within the research team, member checking with selected respondents and triangulation with supplementary data. Together, these steps ensured robustness and enhanced the validity of insights into how AI adoption in public procurement unfolds across both the individual and organisational levels.

4. Findings

4.1 *Interplay of individual and organisational capabilities in AI adoption*

This section presents the empirical findings from 20 semi-structured interviews across 13 public organisations, complemented by supporting documents from the Internet. The analysis is structured around the dynamic capabilities framework and reported in three subsections: (1) the enabling factors of AI-related capabilities at both the individual and

Table 1. Overview of organisations and interviewees

Organisation type	Number of organisations	Number of interviewees	Roles	AI focus areas in procurement
State-level and regional public agency	5	8	Procurement specialists, procurement managers, AI specialists, directors	- AI strategy and needs mapping - Matching invoices with contracts in BI reporting solutions - Low-threshold pilots and employee-driven initiatives - AI-assisted translations and summaries - Procurement guidelines automation - Predictive analytics for service needs
Large city	5	8	Directors, procurement directors and managers, procurement specialists, AI specialists	- Supplier evaluation tools - AI pilots in procurement calendars, contract and tender analysis - AI-assisted tendering for small-scale procurements
Publicly owned company	3	4	Procurement specialists, AI specialists	- Reporting automation - AI-assisted contract and bid drafting, contract translations, summaries - AI-assisted risk assessments - Automation of tender evaluation (DPS) - Reference price discovery tools - AI applications supporting circular economy - AI agent pilots
Total	13	20		

Source(s): Authors' own work

organisational levels, divided into sensing, seizing and transforming phases; (2) the barriers hindering capability development in these same phases and (3) a dynamic capabilities model of AI adoption in public procurement. Central to this analysis is the examination of interaction mechanisms between levels: bottom-up mechanisms, where individual initiatives influence organisational learning, and top-down mechanisms, where organisational structures and strategies shape individual agency. [Figure 1](#) generalises these key findings by mapping the dynamic capability categories (sensing, seizing and transforming) across the individual and organisational levels, while also highlighting the flows of influence between them.

The data reveal that dynamic capabilities in AI adoption operate as a layered and distributed system, cutting across roles and organisational boundaries. Sensing, seizing and transforming are not confined to top management or centralised strategy units but frequently originate from individual procurement professionals experimenting with AI tools and transferring insights upward through bottom-up mechanisms. Conversely, organisational decisions, leadership support and procurement structures create top-down conditions that can either enable or constrain individual experimentation and adoption. Most organisations are currently positioned in the sensing or early seizing phase, with only a few moving towards sustained

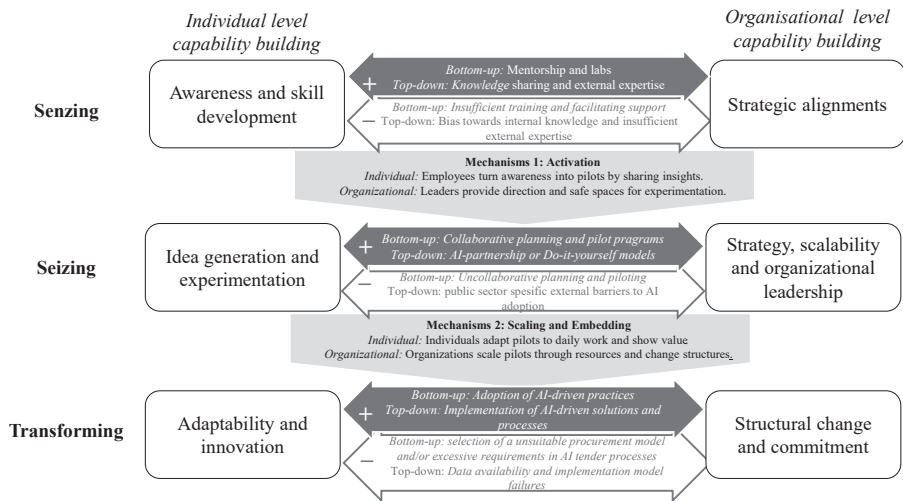


Figure 1. Transformation mechanism between dynamic capability categories. Source: Authors' own work

production use in procurement processes. Good AI practices and solutions in public procurement are largely embedded within existing supplier contracts or accessed through licence for off-the-shelf AI solutions rather than procured via competitive tendering.

Across the procurement lifecycle, different dynamic capabilities manifest through distinct configurations of AI use. In the pre-tendering phase, particularly in market scanning, problem framing and tender design, AI adoption is primarily driven by individual-level capabilities and the use of general-purpose language models. In contrast, later stages of the procurement process, including tender analysis, contract management and procure-to-pay-processes, rely more heavily on organisational data and system integration. These applications require greater investment, cross-functional coordination and transformation efforts, reflecting a shift from individual experimentation towards institutionally embedded capability development.

Using the dynamic capabilities framework as an analytical lens, the findings show that organisations were typically engaged in different phases of capability development simultaneously, although the dominant activities varied across organisational contexts.

Some organisations primarily focused on sensing activities such as market scanning, or identifying potential use cases. Others had progressed to seizing capabilities by launching pilot projects and experimenting with AI tools in procurement-related tasks. However, only a small number of organisations showed early signs of transforming capabilities, where AI initiatives began to move beyond experimentation towards more institutionalised organisational arrangements. Taken together, these findings suggest that AI adoption in public procurement remains emergent and experimental, shaped not only by the presence of individual and organisational capabilities but also by the quality of the interaction mechanisms that connect them.

Illustrating the organisation's sensing capabilities in the context of emerging technologies, a representative of a large municipality describes their approach to early-stage AI exploration: "As we scan the horizon to understand the true potential of AI for our city, exploration is key. Early adopters and innovative units are the ones conducting those first experiments. At this stage, it's about them having the courage to try something completely new, while others watch and follow behind, picking the good solutions and practices. Experimenting isn't always smooth sailing, but it's great that there are people willing to give it a try".

Many organisations had progressed from sensing activities to seizing capabilities, where identified AI opportunities were translated into experimentation and pilot implementation. In

several organisations, experimentation was organised through proof-of-concept projects designed to test potential applications in a controlled environment. As interviewees from a state agency explained: “Last year we started building the foundation for AI work together with a technology partner. The idea was to create an operating model and environment where we can test things safely. Now many proof-of-concept projects are starting, and we collect ideas from users and turn them into pilots. The real challenge is embedding AI into everyday operational processes and that’s the real challenge”.

One interviewee from a public owned company explained how they have progressed beyond experimentation towards more institutionalised AI development: “Strong leadership support and positive organization culture have been essential in advancing AI in our organisation. We started by mapping potential use cases and running small experiments to understand where AI could support procurement processes. Based on these pilots, we are now preparing an innovation partnership procurement to develop an AI-based solution, supported by external funding”.

4.2 Enabling factors of dynamic capabilities of AI at the individual and organisational levels

The enabling factors for AI adoption in public procurement reflected a multilayered system of dynamic capabilities operating across the individual, organisational and interactional levels, as summarised in [Table 2](#). These factors were not isolated but interdependent, with bottom-up and top-down mechanisms connecting individual initiatives to organisational structures. Across the dataset, management support emerged as the most frequently cited enabler, being mentioned in every capability phase. While this demonstrates the importance of leadership, the specific microfoundations differed across sensing, seizing and transforming. The interplay of these dimensions appears to explain why some organisations progress towards broader AI transformation while others remain confined to experimentation.

At the individual level, three recurring enablers were identified: awareness and skills development, idea generation and experimentation, and adaptability and innovation. In the sensing phase, individuals built competence through training, education, mentoring and small-scale testing, often recognising AI’s potential through personal curiosity. In the seizing phase, individuals contributed by brainstorming AI opportunities, experimenting with solutions and taking calculated risks in pilot projects. By the transforming phase, adaptability and innovation became critical, with employees leveraging general language models, fostering creativity and embracing continuous learning. Adaptability refers to the ability to reconfigure procurement practices in response to technological change, while innovation encompasses both process innovation and outcome innovation related to AI-enabled solutions. These behaviours underline that dynamic capabilities are rooted in distributed agency, not just formalised organisational strategies.

At the organisational level, the enablers related to strategic alignment, leadership commitment and the institutionalisation of AI practices. In the sensing phase, organisations supported awareness building through management backing, market scanning and proof-of-concept pilots. Seizing was enabled by strategies for scalability, leadership action and the accessibility of data to facilitate cross-functional integration. In the transforming phase, maturity was characterised by structural change and commitment: dynamic organisational cultures, formal change management processes and systematic feedback loops allowed AI to be embedded into everyday operations. Importantly, these enablers demonstrate that organisational capability is not limited to technical investments but depends equally on governance structures and cultural readiness.

Interaction mechanisms – both bottom-up and top-down – proved decisive in linking individual initiatives with organisational structures. Bottom-up processes, such as mentoring programmes, collaborative pilot planning and the adoption of AI-driven practices, created pathways for individual experimentation to influence organisational learning. Top-down

Table 2. Enabling factors and dynamic capabilities of AI at the individual and organisational levels

Dynamic capability category	Individual level	Interaction mechanism	Organisational level
<i>Sensing</i>	<i>Awareness and skills development</i>	<i>Bottom-up: Mentorship and labs</i>	<i>Strategic alignments</i>
<i>Second-order themes</i>	+ Individuals recognise the potential of AI through personal interest	+ Mentoring programmes to develop individual AI competencies to foster skills development	+ Management support
<i>First-order informant terms</i>	+ AI-related skills through training, education, and small-scale testing	+ General innovation labs where individuals can experiment with AI technologies	+ Continuous market and supplier scanning to find relevant AI solutions and practices
		+ Active and encouraging communication about pilots	+ Organisational small-scale proofs of concept
		+ Sector-specific collaborative platforms for sharing good practices	+ Integrating AI awareness into strategic vision
		<i>Top-down: Knowledge sharing and external expertise</i>	+ The combination of digitalisation and project management provides a solid basis for AI adoption
		+ Knowledge dissemination through workshops and external consultants	+ Clear and AI-positive organisational policies on data protection and AI security
		+ Encouraging proactive identification of AI opportunities	+ Positive societal pressure
		+ Strategic partnership consultancy model for sensing activities	+ Reform of the Administrative Act to use automation in the public sector
		+ Peer support among public actors	
		+ Free access to easy-to-use and continuously improving general AI tools	
		+ Example set by leaders	

(continued)

Table 2. Continued

Dynamic capability category	Individual level	Interaction mechanism	Organisational level
<i>Seizing</i> <i>Second-order themes</i> First-order informant terms	<i>Idea generation and experimentation</i> + Encouraging individuals to brainstorm AI opportunities together + Empowering individuals to experiment with AI solutions and take calculated risks	<i>Bottom-up: Collaborative planning and pilot programmes</i> + Development-oriented personnel + Integration of individual contributions into strategic planning + Creating cross-functional teams to integrate individual insights into evaluating AI initiatives + Facilitating small-scale AI pilot projects to test feasibility and gather data for larger implementation + Organisational platform for horizontal knowledge sharing and collaboration <i>Top-down: AI partnership or do-it-yourself models</i> + Large-language-model (LLM)-centric partnership model relying on a single language model + Open and modular multi-vendor partnership model + Organisationally tailored and secure do-it-yourself AI model based on open or closed language models	<i>Strategy, scalability and organisational leadership</i> + Strategy + Management support + Experimentation culture + Implementation and prioritisation principles of AI initiatives and resource allocation + Accessibility of data and continuous improvement of data quality + Leadership action plan focusing on organisational AI adoption

(continued)

Table 2. Continued

Dynamic capability category	Individual level	Interaction mechanism	Organisational level
<i>Trans-forming</i>	<i>Adaptability and innovation</i>	<i>Bottom-up: Adoption of AI-driven practices</i>	<i>Structural change and commitment</i>
<i>Second-order themes</i>	+ Wide exploitation of general language models and tools at the individual level	+ Adoption of new AI-driven practices with general AI tools	+ Management support
<i>First-order informant terms</i>	+ Encouraging a mindset of continuous learning and flexibility among employees	+ Adoption of individual sector-specific AI solutions for targeted needs	+ Modifying organisational structures and processes to better integrate AI capabilities
	+ Fostering a culture that values creativity and innovative thinking	<i>Top-down: Implementation of new AI-driven solutions and processes</i>	+ Dynamic resource reallocation to AI initiatives
		+ Successful tendering of AI solutions/ partnerships to enable further implementation	+ Commitment to AI by embedding it into organisational culture and practices
		+ Successful implementation of AI projects and/or AI updates to existing solutions	+ Regular feedback systems to align individual AI capabilities with organisational goals
		+ Implementation of change management practices	+ Establishing processes to scale successful AI pilots across the organisation
		+ Implementing a mechanism to regularly collect feedback and ROI in AI projects	+ Organisation's procurement maturity

Source(s): Authors' own work

mechanisms included knowledge sharing, strategic consultancy, leadership-driven AI partnership models and the structured implementation of new AI solutions. The most effective organisations combined both directions of influence: individuals were encouraged to test and share insights, while leaders institutionalised successful practices into broader strategies. This reciprocal dynamic illustrates that sensing, seizing and transforming do not develop in isolation but through the continuous circulation of knowledge, commitment and resources across levels.

4.3 Barriers to dynamic capabilities and AI at the individual and organisational levels

The barriers to AI adoption in public procurement manifested across the individual, organisational and interactional levels, cutting through the sensing, seizing and transforming phases of dynamic capabilities. As summarised in [Table 3](#), these barriers were not isolated but were mutually reinforcing, often compounding one another across levels. While technical challenges remained relevant, the findings show that the main constraints were organisational and social: a lack of skills, limited experimentation, unclear strategies and restrictive governance frameworks. This suggests that AI adoption difficulties stem less from the technology itself and more from the misalignment of dynamic capabilities across levels of action.

At the individual level, barriers were dominated by uncertainty, lack of expertise and low confidence in AI tools. In the sensing stage, employees expressed scepticism about AI's reliability and reported fear of potential errors, leading to a reluctance in recognising or proposing new opportunities. In the seizing stage, skill deficits, combined with concerns over job continuity, constrained the willingness to experiment with pilots. Finally, in the transforming stage, the absence of established practices or guidance left procurement professionals without clear reference points, resulting in limited initiative to embed AI into daily processes. Together, these findings highlight how weak individual-level foundations prevent organisations from mobilising the distributed agency required for capability development.

At the organisational level, barriers were characterised by strategic ambiguity, resource constraints and rigid structures. During the sensing phase, a lack of managerial competence, unclear strategic direction and restrictive procurement rules weakened organisations' readiness to engage with AI. In the seizing phase, the absence of coherent strategies, limited experimentation cultures and restrictive interpretations of privacy and security regulations prevented pilots from scaling. In the transforming phase, hierarchical structures, inflexible organisational processes and insufficient long-term commitment were evident, hampering the institutionalisation of AI. These findings underscore that without clear strategies, committed leadership and adaptive structures, organisational barriers overshadow technical feasibility and stall transformation.

Interactional mechanisms further reinforced these challenges. Bottom-up processes were hindered by insufficient training, a lack of inclusive pilot projects and overly burdensome specification requirements in procurement. This not only created confusion and slowed experimentation but also discouraged individuals from engaging in AI initiatives. Top-down barriers included regulatory-induced caution, limited use of external expertise and failures in implementing supportive infrastructure, such as machine-readable interfaces or robust data governance. Such shortcomings disrupted communication between levels, leaving individual initiatives unsupported and organisational ambitions unrealised. The result was a fragmented system in which barriers at one level cascade across others, preventing sensing from turning into seizing and seizing into sustained transformation.

4.4 Transformation mechanisms between dynamic capability categories

The analysis of organisational maturity in AI adoption reveals that the public procurement organisations tended to cluster around early sensing and seizing activities, with only one case reaching the first stage of transformation. This distribution highlights both the progress and the

Table 3. Barriers to dynamic capabilities and AI at the individual and organisational levels

Dynamic capability category	Individual level	Interaction mechanism	Organisational level
<i>Sensing</i> Second-order themes First-order informant terms	<i>Uncertainty: A lack of skills and confidence</i> - Uncertainty and concern about potential errors related to AI use - Staff's low competence and scepticism - A lack of AI expertise or motivation in the organisation	<i>Bottom-up: Insufficient training and facilitating support causing confusion</i> - Insufficient training and guidance in the organisation - Inconsistent use of AI, causing confusion and security risks <i>Top-down: Bias towards internal knowledge stocks and lack of external expertise</i> - Caution and regulatory-induced slowness - Resources focused on pre-studies, not on actual experimentation - Uncertainty and insufficient knowledge about regulation and application - Limited use of external AI experts, partly due to their insufficient understanding of the public sector's needs	<i>Lack of strategic alignment and resource allocation</i> - Low managerial competence and critical attitude - Overly high expectations of technology that is still in development - Organisational unclarity about the short- and long-term benefits of AI and potential use cases - Organisational restrictions on the use of open tools - Low legal expertise and scepticism
<i>Seizing</i> Second-order themes First-order informant terms	<i>Lack of idea generation and experimentation</i> - Lack of AI expertise and skills - Fear of job continuity due to AI automation - Black box feature of GenAI excludes innovativeness and experimentation	<i>Bottom-up: Uncollaborative planning and pilot programmes</i> - Non-inclusive pilot projects that exclude end-user involvement - Non-inclusive planning of potential pilot cases <i>Top-down: Public sector-specific external barriers to AI adoption</i> - A shortage of AI professionals in the market - A lack of tailored and ready-made solutions for the public sector in the market - Limited support for local languages in AI language models - Privacy and security restrictions regarding internal and confidential data	<i>Lack of strategy, scalability, and organisational leadership</i> - The lack of a strategy, vision or action plan for AI and data - The lack of an experimentation culture - Internal overregulation may restrict innovation in the piloting phase - Without strategic alignment and proper expectation management, pilots risk remaining isolated and unscalable - A lack of support for privacy and security issues in the public sector

(continued)

Table 3. Continued

Dynamic capability category	Individual level	Interaction mechanism	Organisational level
<i>Trans-forming</i> <i>Second-order themes</i> First-order informant terms	<i>Lack of practical guidance and practices</i> - A lack of established good practices for successful transformation - A lack of practical guidance for public procurement experts in tendering AI solutions	<i>Bottom-up: Selection of an unsuitable procurement model and/or excessive requirements in AI tender processes</i> - Broad involvement in specification work can lead to excessive requirements in the tendering process - A failed AI tender process can discourage future actions <i>Top-down: Data availability, accessibility, and implementation model failures</i> - A lack of machine-readable interfaces in existing systems - Bureaucracy and regulation may limit data access and analytics - Privacy and IT restrictions slow down transformation processes - Barriers and regulations restricting free movement of data between the public sector and external actors - Undervaluation and uncertainty of data quality and processing - A partnership model centred around a single LLM or provider or do-it-yourself model may prove insufficient in transformation	<i>Challenges in change management and long-term commitment</i> - Hierarchical organisational culture challenges - Inflexible organisational structures and processes for integrating AI capabilities into transformation - Challenges in planning and resourcing the post-pilot investment, maintenance and development phases - AI infrastructure limitations in handling larger datasets
Source(s): Authors' own work			

limitations of current practices: while many organisations actively scan markets, test small-scale pilots and explore partnerships, few succeed in scaling or embedding AI solutions into their core processes. The findings suggest that the main challenge lies not in recognising opportunities or launching experiments but in building the mechanisms that enable progression between the capability phases of sensing, seizing and transforming. These progression points – which we call transformation mechanisms – determine whether organisations remain stuck in experimentation or advance towards systemic change. Importantly, these mechanisms represent more than procedural steps; they embody the ability of organisations to align individual initiative, leadership support and structural conditions to drive innovation forward. Understanding these mechanisms therefore provides a lens for explaining uneven maturity levels across organisations.

The first transformation mechanism, “from sensing to seizing”, hinges on the ability to convert awareness and market scanning into structured pilot activities. In less mature organisations, sensing occurs either as isolated individual curiosity or as passive observation of technological developments, often without organisational interaction or commitment. More advanced organisations engage in active market scanning and internal discussions yet still struggle to progress without clear leadership direction and secure data practices. In the present study, successful transitions from sensing to seizing were found where individual awareness was channelled into collaborative planning, supported by leadership commitment and combined with external expertise. In these cases, sensing became actionable, leading to pilot projects and initial experimentation. However, even at this stage, concerns over data safety, a lack of organisational interaction, and a dependency on external vendors slowed the pace of progression. The findings suggest that without mechanisms to institutionalise individual knowledge and market insights, sensing risks remains a fragmented and underutilised capability. Moving effectively into seizing therefore requires the deliberate orchestration of organisational dialogue, prioritisation and risk management. We classify this transformation mechanism as an activation that operates at both the individual and organisational levels: employees turn awareness into pilots by sharing insights, while leaders provide direction and safe spaces for experimentation.

The second transformation mechanism, “from seizing to transforming”, depends on the organisation’s capacity to scale pilots into embedded practices. In this study, at the seizing stage, organisations experimented with isolated pilots or adopted partnership models, but scaling often stalled due to organisational silos, vendor lock-in and fragmented strategies. Only one organisation had advanced to the transformation stage by embedding AI into a single procurement process. However, broader integration – whether through multi-process adoption or network-level collaboration with external stakeholders – remained absent. The findings therefore point to a systemic gap: organisations can sense and seize opportunities but lack the governance, leadership and resource orchestration to transform. In summary, while the maturity pathway shows promise in the early stages, it reveals a persistent inability to progress beyond pilots. This underscores the need for deliberate transformation mechanisms – strategic orchestration, the diversification of partnerships and investment in organisational change management – that bridge the gap between experimentation and sustainable AI-enabled procurement practices. Without these, pilots risk remaining symbolic demonstrations rather than pathways to institutionalised capability. True transformation requires reframing AI not as a set of tools but as a long-term strategic shift in how public organisations and their procurement processes are organised and governed. We classify this transformation mechanism as scaling and embedding, which unfolds at both the individual and organisational levels: individuals adapt pilots to their daily work and demonstrate value, while organisations allocate resources and adjust structures to scale pilots into embedded practices.

5. Discussion

Taken together, the findings demonstrate that AI adoption in public procurement is shaped by a dynamic tension between enabling factors and barriers that operate across the individual,

organisational and interactional levels. Enablers thrive when individual experimentation is supported by organisational commitment and reinforced through reciprocal interaction mechanisms, allowing sensing, seizing and transforming to progress in concert. Conversely, barriers emerge when these levels are misaligned: individuals lack confidence and skills, organisations fail to provide strategic clarity or resources, and interaction mechanisms are weakened by poor communication, restrictive regulations, or burdensome procedures. From a dynamic capabilities perspective, the contrast between enablers and barriers underscores that AI adoption is not a linear process but a contested, multilevel capability challenge. This tension provides the foundation for the discussion that follows, where we situate these findings within existing theory and explore their implications for understanding public procurement as a domain of AI-enabled transformation.

While the dynamic capabilities framework provides a useful lens for interpreting AI adoption, its original formulation is rooted in firm-level adaptation under competitive pressures. In contrast, public procurement operates within a fundamentally different selection environment, where adaptation is shaped less by market competition and more by legal mandates, accountability requirements and political authorisation. This distinction calls for a more explicit public-sector translation of dynamic capabilities. Recent work by [Spanó *et al.* \(2024\)](#) provides a useful extension by linking dynamic capabilities to legal–institutional design and to concrete organisational routines. Rather than treating sensing, seizing and transforming as abstract organisational capacities, they conceptualise these as sets of lower-order capabilities embedded in public-sector practices, such as strategic foresight, structured decision-making, stakeholder coordination and resource orchestration.

Importantly, [Spanó *et al.* \(2024\)](#) identify five groups of institutionalised routines – governance, organisational design, budget and finance, procurement and partnerships, and human resources – as key mediators of dynamic capability development. Our empirical findings provide support for this categorisation. The barriers identified in this study, such as organisational silos, vendor lock-in, regulatory rigidity and skills shortages, can be interpreted as dysfunctions within these institutional domains. Conversely, enabling factors – such as leadership support, experimentation spaces and collaborative partnerships – reflect the presence of supportive institutional arrangements that nurture capability development, thereby highlighting the need for managing the dynamic tension between enabling and constraining factors.

Our findings resonate strongly with this view. For instance, sensing in public procurement is not limited to identifying technological opportunities, but also involves navigating political feasibility and regulatory constraints, as reflected in organisations’ cautious approach to experimentation and data use. Seizing similarly extends beyond resource mobilisation to the structuring of procurement models and partnership arrangements, where decisions are shaped by legal rules, risk-avoidance norms and vendor dependencies. Finally, transforming capabilities in our data – particularly the difficulty of scaling pilots – are closely tied to institutionalised routines related to post-pilot budgeting, procurement procedures and human resource development.

This shifts the analytical focus from capability possession to capability conditioning. Taken together, these insights suggest that dynamic capabilities in public procurement are not only multilevel, as demonstrated in this study, but also institutionally constituted. That is, they are embedded in and shaped by legal rules, governance structures and administrative routines that both enable and constrain organisational adaptation.

Building on this institutional perspective, our findings further reinforce that dynamic capabilities are distributed across individual and organisational levels, but their development depends on how effectively these levels are aligned within existing institutional structures. Examining the enablers and constraints to AI adoption through the lens of dynamic capabilities opens a new way to see how organisations face distinct opportunities and challenges at each stage of sensing, seizing and transforming. Context-specific institutional factors appear to shape the pace, direction and sustainability of adoption efforts. These factors remain partly

organisation-specific and path-dependent. Overall, AI adoption maturity in the examined organisations was characterised by promising sensing and seizing capabilities but an underdeveloped transformation capacity. The inability to transition from pilot projects to organisation-wide adoption was rooted in a combination of structural barriers, such as silos and leadership gaps, and resource-based constraints, including limited resources and vendor lock-in. Overcoming these constraints requires a deliberate shift towards the strategic orchestration of AI initiatives, the diversification of technology partnerships and investment in organisational change management to bridge the gap between experimentation and sustained transformation. Piloting AI solutions requires neither the same level of advanced data infrastructure nor the extent of procurement procedures and strategic commitment from senior leadership that are necessary for process transformation through the delivery of production-level AI applications.

AI adoption maturity can be understood as a multidimensional process that evolves both across phases of capability development and through interactions between the individual and organisational levels. [Figure 1](#) illustrates this along two dimensions of change: interaction between individual- and organisational-level capabilities and progression across three phases – sensing, seizing and transforming. On the individual side, employees develop awareness, generate ideas and adapt practices, while on the organisational side, leadership provides alignment, resources and structural commitment. The interaction between these levels is critical, as individual experimentation feeds into organisational strategy and, in turn, organisational support enables further individual learning. Across the phases, sensing focuses on awareness and skill development, seizing emphasises idea generation and experimentation, and transforming involves embedding AI into broader structures through adaptability and innovation. Together, these dimensions show that maturity is not a linear technology adoption process but a co-evolution between levels over time. This framing highlights that successful AI adoption requires both cross-level alignment and sequential progression across phases to move from isolated pilots towards systemic transformation.

In summary, the discussion illuminates how dynamic capabilities for AI in public procurement are constructed, enacted and constrained within real-world environments. It highlights the importance of aligning individual initiatives with organisational structures and adapting sensing, seizing and transformation practices to the logic of AI-driven change. These insights set the stage for future directions and implications.

6. Conclusion

This study examined the adoption of AI in Finnish public procurement through a multilevel dynamic capabilities lens. The findings show that successful adoption depends on recursive interactions between individual initiatives and organisational structures, extending dynamic capabilities theory by illustrating how sensing, seizing and transforming capabilities unfold in public sector contexts ([Piening, 2013](#); [Teece, 2007](#)). The results highlight AI's dual role: while it offers significant potential to improve efficiency, transparency and public value, progress remains limited, as many organisations are confined to pilots and early initiatives. Advancing towards systemic transformation requires addressing governance and capability barriers and fostering hybrid approaches that combine experimentation with strategic governance, scalable partnerships and continuous capability building. Realising benefits beyond pilots further depends on interoperable data infrastructures and cross-functional data governance that enable analytics to scale across procurement processes ([Handfield et al., 2019](#)).

Our findings extend the literature on dynamic capabilities in the public sector in three main ways. First, we show that capability development is not confined to the organisational level but requires simultaneous microfoundations at the individual level. While prior studies of public sector AI adoption emphasise structural enablers such as data governance, regulation and leadership support ([Alon-Barkat and Busuioc, 2023](#); [Neumann et al., 2024](#)), they rarely investigate how these enablers interact with individual-level practices. By demonstrating how

individual sensing and experimentation can feed into organisational development or, conversely, how the absence of individual initiative can hamper reconfiguration, we provide evidence that dynamic capabilities are genuinely multilevel phenomena, extending Teece's (2007) framework to include the distributed agency of professionals within organisations. Second, we highlight how the interaction between the individual and organisational levels acts both as a driver and a barrier to capability development, thereby addressing the research gap identified by Schilke *et al.* (2018) and clarifying how bottom-up and top-down mechanisms jointly shape capability evolution in regulated procurement contexts. Third, we identify transition mechanisms between maturity stages, showing how recursive interactions across levels influence the progression from sensing and seizing to transformation. In doing so, our study complements recent work on the meaningful use of AI in the public sector (Andersson *et al.*, 2025), which emphasises the alignment of institutional logics with professional practices and supports Schilke *et al.*'s (2018) view that dynamic capabilities are not exercised in linear or purely rational ways but are guided by heuristics that shape judgement and routines.

This study contributes to public-sector dynamic capabilities research (Spanó *et al.*, 2024) by showing that capability development in public procurement is not only multilevel but also embedded in legal–institutional structures. Sensing, seizing and transforming are shaped by routines related to governance, organisational design, budgeting, procurement and human resources, where barriers such as vendor lock-in, regulatory rigidity and skills shortages reflect institutional constraints rather than purely operational challenges. This extends the dynamic capabilities framework beyond its firm-centric origins by highlighting that sustainable AI adoption depends on the alignment between organisational capabilities and the legal–institutional environment shaping both individual and organisational action.

Our findings empirically substantiate this claim in the procurement domain: organisations that rely exclusively on top-down initiatives struggle to move beyond pilots, while those that foster bottom-up experimentation – combined with strategic orchestration – are more likely to embed AI into procurement processes. This interplay refines the concept of dynamic capabilities in public administration by showing that sustainable AI adoption emerges only when organisational structures, governance frameworks and professional practices co-evolve. In doing so, we advance a more nuanced account of capability building under the conditions of legal constraint, democratic accountability and public value creation. Overall, the study demonstrates that the transformative role of AI in public procurement hinges on the ability of public organisations to integrate individual experimentation with organisational leadership, thereby evolving procurement from a transactional function into a platform for AI-enabled value creation.

As a qualitative study, the findings are context-specific and not statistically generalisable, although they may be transferable to other public-sector settings. Future research should investigate the longitudinal dynamics of AI adoption, undertake cross-national comparisons and examine performance implications. In particular, longitudinal studies could explore how heuristics shape transitions between capability stages. Our results indicate that such heuristics – such as rules of thumb concerning decision-making, risk, compliance or resource allocation – may be pivotal in determining when organisations move from sensing to seizing, and subsequently from seizing to transforming. Further longitudinal and comparative work would thus be valuable for tracing the evolution of these heuristics alongside capability development and for assessing their influence on the scaling of AI-enabled innovations.

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