Why generative AI adoption stalls across public service domains: an AMO comparison of Finnish wellbeing and municipal technical services

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Abstract

Purpose – This paper aims to examine how Finnish public employees' perceived barriers to generative AI adoption differ between regional wellbeing services and municipal technical services and identify which ability-motivation-opportunity (AMO) theory dimensions and items pose the greatest constraints.

Design/methodology/approach – Two web-based surveys were conducted in September 2025. The wellbeing services survey targeted a single regional organization ($n = 437$); the technical services survey covered land-use planning and construction supervision across 104 municipalities ($n = 218$). Respondents reporting no prior AI use ($n = 321$) rated 19 barrier items on a 0–3 scale.

Findings – Opportunity barriers were the highest-rated AMO dimension in the wellbeing services sample and were significantly more intense there than in the technical services sample; the absence of organizational guidelines, weak peer support, and limited encouragement from colleagues or supervisors accounted for the largest sectoral differences. The technical services barrier profile was more evenly distributed across AMO dimensions. Comparable motivation composites masked an item-level reversal: doubts about generative AI accuracy and reliability were significantly stronger in technical services, where they ranked as the highest-rated barrier.

Originality/value – The paper offers comparative, employee-level evidence on perceived barriers to generative AI adoption among public-sector non-users. The findings suggest a contextual reading of

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AMO in which the weight of each dimension may depend on the configuration of public service production. Item-level disaggregation adds a second layer to this reading, since composite comparisons concealed the reliability reversal observed in technical services. Public organizations may benefit from diagnosing employee-level barrier profiles before designing generative AI implementation strategies.

Keywords Generative AI, Public sector, AMO framework, Sectoral comparison, Finland, Civil servants

Paper type Research paper

Introduction

Public sector organizations are integrating artificial intelligence (AI) tools and features into administrative work, service production and decision-making (Mergel *et al.*, 2023; van Noordt *et al.*, 2025; Wirtz *et al.*, 2019). The pace and form of integration vary substantially across service domains. A healthcare professional engaging with a generative AI assistant operates under different regulatory and clinical constraints than a land-use planner using the same technology to draft a zoning report. Public administration scholarship has long documented that technologies, reforms, perceptions and managerial interventions land differently across domains of public service production (Bovens and Zouridis, 2002; Bullock *et al.*, 2020; Lipsky, 2010), yet comparative empirical evidence on how public employees across sectors perceive the obstacles to engaging with generative AI remains scarce (Alshahrani *et al.*, 2024; Mergel *et al.*, 2023). This study addresses this gap by comparing civil servants' perceived barriers to the adoption of generative AI across two domains of Finnish public service production.

By generative AI, we mean tools that produce text, image and video outputs from natural-language prompts (e.g. ChatGPT, Microsoft Copilot), as well as AI features embedded in software (Bright *et al.*, 2025; Pandey, 2026). Statistical models, automation and machine-learning decision-support systems or robotics fall outside this scope. Generative AI is currently the dominant form in Finnish public sector workplaces because it is widely accessible and, in many cases, requires limited technical infrastructure (Bright *et al.*, 2025; Pulkkinen, 2026).

Framing the analysis around barriers presupposes that generative AI adoption is sought in some contexts. We adopt this framing because Finnish public service production is under pressure from national AI strategies, the EU AI Act, and emerging organizational strategies to incorporate AI in their work (Liebig *et al.*, 2024; van Noordt *et al.*, 2025). The framing carries no assumption that adoption is desirable in every situation. The relevant question for public organizations concerns responsible and task-relevant incorporation, which makes the perceived constraints of employees who have not engaged with the technology a useful diagnostic. Adoption remains uneven; many public-sector AI initiatives are still at pilot or proof-of-concept stage, although documented exceptions exist across health, social services, taxation and procurement (Bright *et al.*, 2025; Madan and Ashok, 2023; Selten and Klievink, 2024).

The barriers public employees encounter in AI adoption are interconnected (Pulkkinen *et al.*, 2025a) and operate at multiple levels, spanning technological, individual, team, organizational, and environmental/institutional factors (Bullock *et al.*, 2020; Peeters, 2020). Skill deficits and attitudinal resistance coexist with resource scarcity, weak change management, competing strategic priorities, accountability demands and regulatory requirements (Ahn and Chen, 2022; Bannister and Connolly, 2020; Haesevoets *et al.*, 2025; Selten and Klievink, 2024; Wirtz *et al.*, 2019).

In the Nordic context, local and regional governments bear primary responsibility for public service delivery (Karlsson *et al.*, 2025; Lidman *et al.*, 2022). Existing AI research in these services concentrates on single domains, predominantly healthcare, education and central government (Sun and Medaglia, 2019; Zuiderwijk *et al.*, 2021). Research also tends to address organizational adoption decisions or the experiences of those already using AI, which leaves the perceptions of employees who have not engaged with the technology underexamined (Madan and Ashok, 2023). Comparative, employee-level evidence across service domains within a single administrative system is rarer still (Alshahrani *et al.*, 2024; Mergel *et al.*, 2023). Comparing care-oriented and expertise-oriented bureaucracies can reveal how the structural features of service domains relate to perceived barriers (Bovens and Zouridis, 2002; Lipsky, 2010).

Our research question is:

RQ. How do public employees' self-assessed AI adoption barriers differ between public wellbeing services (health and social care) and municipal technical services (land-use planning and construction supervision)?

We apply the ability-motivation-opportunity (AMO) framework (Appelbaum *et al.*, 2000; Blumberg and Pringle, 1982) as an analytical lens. Empirical data were collected through two web-based surveys in September 2025, and the analysis covers civil servants who reported not yet using AI tools or features in their work ($n = 321$). The two samples differ structurally. Wellbeing services data come from one regional organization and technical services data from 104 municipalities. This asymmetry mirrors how the two domains are organized in Finland.

The study makes two contributions. Theoretically, it extends the contextual reading of the AMO framework by examining how the weight of each dimension varied across two public service configurations within one country. Empirically, it offers comparative, employee-level evidence on perceived barriers to generative AI among non-users in two Nordic public service domains and identifies which dimensions and items were most constraining in each sample, information that can support managerial responses.

Background

The AMO framework

The AMO framework, which stems from organizational psychology and human resource management, holds that individual performance and behavior emerge as a function of three interdependent conditions. The individual must possess the relevant capability (ability), the inclination to act (motivation) and a supportive context that permits or enables the behavior (opportunity). The structure was first introduced by Blumberg and Pringle (1982), who identified opportunity as a neglected dimension in performance research, and was further developed in scholarship on high-performance work systems by Bailey (1993) and Appelbaum *et al.* (2000).

Ability covers the skills and cognitive capacities required to execute a task, together with the confidence to apply them. Motivation refers to the willingness and desire to engage in a behavior, whether grounded in expected benefits or in trust toward the object of that behavior. Opportunity captures the organizational and environmental conditions that enable or constrain action, including time, tools, guidance and social support.

The framework has structured research on employee behaviors such as knowledge sharing (Siemsen *et al.*, 2008) and, more recently, on AI adoption in public relations practice (Radwan *et al.*, 2026). The dimensions are interlinked, with their joint operation modeled through additive, multiplicative and constraining-factor logics (Bos-Nehles *et al.*, 2023;

Marin-Garcia and Tomas, 2016; Siemsen *et al.*, 2008). The relative salience of each dimension appears to vary across organizational settings, prompting calls for explicitly contextual applications (Bos-Nehles *et al.*, 2023). An employee's engagement with a new technology is shaped by capability, inclination and organizational and institutional conditions in combination (Peeters, 2020).

Placed alongside established technology adoption models, AMO answers a different question. The technology acceptance model and the Unified Theory of Acceptance and Use of Technology explain individual intention through perceived usefulness, ease of use, social influence and facilitating conditions (Davis, 1989; Venkatesh *et al.*, 2003). Both presuppose a specific technology the respondent knows well enough to evaluate. Our respondents are non-users who face a heterogeneous set of general-purpose tools and embedded AI features, many of whom have limited knowledge of which applications would suit their tasks. AMO poses a prior diagnostic question, namely whether the capability, inclination and enabling conditions for engagement exist.

The distinction from the technology-organization-environment (TOE) framework matters because several of our opportunity items concern organizational conditions. TOE locates the unit of analysis at the organization and explains adoption decisions made on its behalf (Tornatzky and Fleischer, 1990), a lens previously applied to systemic AI adoption challenges in Finnish health and social care (Pulkkinen *et al.*, 2025a). Opportunity in AMO refers to an individual employee's perception of organizational conditions. An organization may have guidelines its employees do not know about, or support structures that fail to reach the frontline; this gap between provision and experience is visible only at the employee level, where AMO operates and where the multi-level barriers documented in recent reviews can be disaggregated into theoretically grounded categories (Alshahrani *et al.*, 2024; Madan and Ashok, 2023).

Although the AMO framework stresses the interdependence of its dimensions, its classification carries explanatory weight of its own. In the constraining-factor logic, the weakest condition limits behavior (Bos-Nehles *et al.*, 2023; Siemsen *et al.*, 2008). A concentration of perceived barriers in one dimension points to the most salient candidate constraint and, for managers, a potential point of intervention. A civil servant who has not adopted generative AI may lack the capability to begin, see no reason to begin, or work in a setting that offers no occasion or permission to do so. This reading identifies possible constraining mechanisms without establishing causal effects.

Ability barriers in public sector generative AI adoption

Ability barriers center on employees' readiness to understand, learn and operate generative AI tools and embedded AI features. Many civil servants lack knowledge or prior experience with these tools, which is associated with low perceived self-efficacy (Ahmed *et al.*, 2023). Public organizations also struggle to recruit and retain staff with AI expertise, and AI literacy and data analytics competencies remain unevenly distributed across the workforce (Bannykh and Kostina, 2021; Mankevich *et al.*, 2023).

The subjective dimension matters analytically. Uncertainty about one's own competence operates as a barrier independently of objective skill levels, and negative prior experiences foster resistance (Bandura, 1997). Professional development opportunities and peer-based learning structures shape frontline workers' confidence in using new digital tools, particularly in social service settings (Bernhard and Wihlborg, 2022). Employees are often unaware of which AI applications are relevant to their tasks, and the complexity or poor usability of these tools poses further barriers, even when employees know the tools (Davis, 1989; Schedler *et al.*, 2019).

Ability barriers tend to be more pronounced in service domains with lower digital maturity. Finnish wellbeing services emerged from a 2023 reorganization and are still consolidating their digital infrastructures, governance practices and competence-building structures (Tynkkynen *et al.*, 2022), whereas municipal technical services have a longer history of working with spatial data, geographic information systems and digital permitting workflows (Pulkkinen *et al.*, 2025b). We therefore anticipate that ability barriers will be perceived as more constraining in wellbeing services.

Motivation barriers in public sector generative AI adoption

Motivational barriers concern the extent to which employees perceive the value of generative AI adoption and feel inclined to engage with it. Perceived usefulness is a central driver of technology uptake (Davis, 1989; Venkatesh *et al.*, 2003). When employees do not see concrete benefits for their daily tasks, their willingness to invest effort in learning a new tool can remain low. The benefits of AI tend to be diffuse or long-term in the public sector, such as gradual improvements in policy outcomes or reductions in administrative burden (Pandey, 2026). Peer attitudes and supervisor support also shape individual technology adoption decisions (Graf-Vlachy *et al.*, 2018).

Trust is an equally important motivational consideration and operates on multiple levels (Gefen *et al.*, 2003). Civil servants need to trust that AI-generated text, summaries or recommendations are accurate and reliable, and that using AI will not expose them to undue risks or blame. Public servants working where decisions about individuals' welfare or safety are at stake are particularly sensitive to questions of AI reliability and ethical legitimacy, and many remain skeptical of generative AI's readiness for complex tasks (Liebig *et al.*, 2024).

Ethical reservations often emerge when AI is perceived as operating in ways that cannot be publicly justified, potentially compromising principles of equity, accountability and human dignity. Anxieties about professional identity and the perceived devaluation of expertise constitute a further potential motivational inhibitor, especially when AI is framed as a decision-making surrogate (Ahmed *et al.*, 2023; Bullock *et al.*, 2020).

Sectoral patterns in motivation may be less straightforward than in ability. Healthcare-focused literature has emphasized trust, ethics and privacy concerns as central motivational barriers in care-oriented contexts (Apell and Eriksson, 2023; Sun and Medaglia, 2019). Yet professionals in expertise- and data-oriented domains, whose work has historically been structured around precise analytical outputs, also evaluate generative AI against demanding accuracy thresholds (Bullock *et al.*, 2020; Peeters, 2020). We therefore anticipate that the composition of motivational barriers will differ across sectors, although the overall intensity may be comparable.

Opportunity barriers in public sector generative AI adoption

Opportunity barriers reflect the organizational and institutional conditions that enable or constrain action. Even skilled and motivated employees may not use generative AI tools when their organization lacks adequate infrastructure, support structures and guidelines. Tight budgetary and staffing constraints make resource allocation to innovation initiatives difficult in public organizations (Gullmark, 2021). Time to learn and experiment with AI is frequently lacking (Ahmed *et al.*, 2023; Pulkkinen *et al.*, 2025a).

Technical IT support, peer networks and leadership behaviors that signal organizational endorsement function as enabling conditions for IT diffusion (Alshahrani *et al.*, 2025; Van der Voet *et al.*, 2016). Organizations also need to invest in data preparation and process re-engineering to open opportunities for AI use. In Nordic public organizations, collaborative innovation and organizational learning capacity are preconditions for technology-driven change, and municipalities vary widely in their capacity to provide such enabling conditions (Lidman *et al.*, 2022; Torfing, 2012).

The absence of formal organizational policies or guidelines may create ambiguity about accountability and acceptable use (Clarke, 2020; Eneman *et al.*, 2022). Recent case-based research on AI adoption in public-sector organizations confirms that leadership attention and structured communication are mechanisms for translating organizational endorsement into actual adoption (Alshahrani *et al.*, 2025). More broadly, regulatory demands and personal liability constrain experimentation with new technologies (Liebig *et al.*, 2024). The Nordic administrative model intensifies this tension through its combination of legalistic tradition and decentralized service delivery, where local discretion coexists with national regulatory frameworks (Ekendahl *et al.*, 2025; Kristensen, 2023). Errors in public service work carry serious consequences for clients and patients, creating an implicit barrier to the use of AI in high-stakes scenarios (Sun and Medaglia, 2019).

Opportunity barriers tend to be more pronounced in domains where organizational governance infrastructure for AI is still being established, and regulatory steering is dense. Wellbeing services in Finland operate under this configuration, with a strict regulatory regime governing health and social data (Apell and Eriksson, 2023; Tynkkynen *et al.*, 2022). We therefore anticipate that opportunity barriers will be perceived as more constraining in wellbeing services than in municipal technical services.

Sectoral variation and analytical expectations

Care-oriented bureaucracies, where street-level interactions with vulnerable clients and patients structure the work, differ from expertise- and data-oriented bureaucracies, where the production of analytical outputs and technical assessments dominates. These structural features shape the constraints and opportunities frontline workers encounter when new technologies are introduced (Alshahrani *et al.*, 2024; Bullock *et al.*, 2020; Mergel *et al.*, 2023). The comparison between Finnish wellbeing services and municipal technical services is therefore analytically generative. The two domains differ in client interactions, data intensity, regulatory steering, organizational maturity and digital infrastructure.

We have three analytical expectations. Ability barriers are anticipated to be more constraining in wellbeing services, and the same holds for opportunity barriers, where governance infrastructure is still consolidating. For motivation, the composition of barriers is expected to differ across sectors while overall intensity remains comparable. These expectations guide the interpretation of the empirical results without being formal hypotheses.

Research design and data

Research contexts

The study examines two domains of Finnish public service production, chosen to represent meaningfully different organizational contexts for civil servants' adoption of generative AI. Finland offers a productive empirical setting within the Nordic administrative tradition, given its advanced public-sector digitalization (European Commission, 2023), strong regional self-governance and the recent large-scale welfare reform that restructured responsibilities between local and regional governments.

Wellbeing services in Finland underwent significant reorganization following the 2023 welfare reform (Tynkkynen *et al.*, 2022), which transferred health, social and rescue services from municipalities to 21 newly established regional wellbeing services counties, the City of Helsinki and HUS Helsinki University Hospital. The reform represents one of the most extensive structural reorganizations in Nordic welfare administration in recent decades.

Municipal technical services, including land-use planning and construction supervision, have historically been among the earliest adopters of digital tools in Finnish local government, given the data-intensive nature of their work (Pulkkinen *et al.*, 2025b).

The two service domains differ in many ways. Wellbeing services involve sustained, direct contact with vulnerable populations and are governed by strict ethical, regulatory and data protection requirements. Municipal technical services are knowledge-intensive functions built around data-driven processes, including zoning, spatial planning, geographic information services, building permits and code enforcement. Technical departments typically employ between one and six professionals per municipality, with an estimated 3,000–4,000 practitioners nationwide. The two domains also represent different administrative tiers: wellbeing services counties embody regional governance, while technical services represent the local administration of autonomous municipal units that vary in population, financial resources and digital capacity.

Comparative design and its rationale

The comparison rests on two structurally different samples. Wellbeing services data come from a single regional wellbeing services organization, whereas technical services data were gathered from employees across 104 municipalities. The asymmetry reflects how the two domains are organized in Finland. Health and social care are produced by a small number of large regional organizations, the 21 wellbeing services counties, together with the City of Helsinki and HUS Helsinki University Hospital, while land-use planning and construction supervision are municipal functions dispersed across hundreds of local government organizations that vary in size, resources, staffing and digital readiness. Each sample therefore secures a different form of coverage. The wellbeing services sample provides access to a coherent regional organization employing thousands of professionals, although it cannot represent the wellbeing services field as a whole. The technical services sample prioritizes geographical breadth, drawing respondents from 104 municipalities nationwide. The chosen design favors field-level heterogeneity on the technical side and organizational coherence on the wellbeing side.

The comparison is exploratory and contextual in character. It contrasts two configurations of Finnish public service production in which sector, organization, administrative tier, geographical coverage, digital maturity and local managerial context vary by construction and cannot be separated with the present data. What the design can establish is whether perceived barrier profiles differ between the two configurations and where those differences concentrate. Which structural feature produces an observed difference remains beyond its reach, as does whether the wellbeing services pattern would replicate in other counties. The findings are accordingly read as exploratory barrier profiles observed in these samples.

Ethics

The study followed Finnish national research ethics guidelines (Finnish National Board on Research Integrity, 2019). For the wellbeing services organization, senior management and the research committee approved the research plan before data collection. For the technical services survey, organizational approval was not required because contact information was obtained exclusively from publicly accessible municipal websites under the Finnish Act on the Openness of Government Activities.

Participation in both surveys was voluntary and anonymous, with no monetary incentives, and respondents provided informed consent through a privacy statement before survey access. No identifying demographic information was collected, and data are stored securely within the EU region with access restricted to the research team.

Data collection

Empirical data were collected through two independent web-based surveys (Webropol) administered in September 2025. The wellbeing services survey targeted civil servants in a single regional wellbeing services county, with email invitations sent to all 4,226 employees, yielding 437 responses (a response rate of around 10%). The municipal technical services survey was conducted nationally, with individual email invitations sent to 2,646 civil servants working in land-use planning and construction supervision across all 292 mainland municipalities. The technical survey produced 218 responses from 104 municipalities, representing 36% of mainland municipalities and all 18 mainland regions of Finland, with an individual response rate of approximately 8%. Email addresses were collected from publicly accessible municipal websites.

Both surveys used a cross-sectional design with structured quantitative measures as the primary analytical instrument and additional open-ended qualitative questions analyzed elsewhere. Respondents first answered whether they had used AI tools or features in their work through the question:

Q1. Do you use, or have you used, AI applications in your work (e.g. ChatGPT, Copilot or AI features embedded in software)?

Those who reported prior use were directed to questions about usage patterns and experiences, while those who reported not using AI were presented with the 19-item barrier assessment, which is the focus of the present analysis. Respondents who selected the “do not know” option for the use question ($n = 15$) did not receive the barrier items and are not included in the analytical sample.

Measurement instrument and AMO mapping

The barrier assessment comprised 19 items shared across both surveys (see Appendix Table A1). Items were drawn from prior research introduced in the Background section. The assessment was introduced with the question:

Q2. To what extent do the following factors influence your decision not to use AI applications in your work?

Each item was rated on a four-point scale: 0 (no effect), 1 (slight effect), 2 (moderate effect), 3 (very strong effect), with an additional “do not know” response option.

The 19 items were mapped to the three AMO dimensions in accordance with published practice (Bos-Nehles *et al.*, 2023; Marin-Garcia and Tomas, 2016). To assess internal consistency of the AMO composites, Cronbach’s alpha was computed for each dimension on listwise complete cases: ability $\alpha = 0.60$ ($k = 4$, $n = 242$), motivation $\alpha = 0.80$ ($k = 6$, $n = 269$) and opportunity $\alpha = 0.85$ ($k = 9$, $n = 223$). Alpha for the full 19-item barrier instrument was 0.89 ($n = 211$). The motivation and opportunity composites meet conventional analytical thresholds. The ability composite falls below the 0.70 threshold, consistent with the small number of items (4) and the construct’s heterogeneity, which spans both objective skill gaps and subjective self-efficacy. The composites are not treated as latent measurement scales but as theoretically derived analytical aggregations of conceptually related items (Bos-Nehles *et al.*, 2023). The ability composite is retained as an analytical category, with item-level interpretation prioritized and the composite interpreted with caution.

Analytical approach

The analysis proceeded from descriptive characterization to inferential comparison. AMO composite scores were computed as the unweighted mean of the constituent items a respondent had rated, provided at least one item had a valid response. As an additional missing-data sensitivity check, composite comparisons were repeated by requiring valid responses to at least half of the items in each AMO dimension. The substantive pattern was unchanged (ability $p = 0.005$, motivation $p = 0.359$, opportunity $p < 0.001$). "Do not know" responses were treated as missing and excluded item-wise, producing variable effective sample sizes across barrier items.

Sectoral differences in AMO composite scores and individual items were assessed using Welch's independent-samples *t*-tests, which do not assume equal variances. Effect sizes were estimated using Hedges' g, with 95% confidence intervals reported for item-level comparisons. A significance level of $\alpha = 0.05$ was applied throughout. Item scores were dichotomized into low (0–1) and high (2–3) categories to compute the proportion rating each barrier as high in each sector.

Two robustness procedures addressed the risk of false positives and the ordinal character of the response scale. First, the Holm–Bonferroni procedure was applied to the 19 item-level comparisons; of the ten differences significant at uncorrected $\alpha = 0.05$, eight survived the correction. Second, because the four-point ratings are ordinal and the group sizes are unequal, all item-level and composite comparisons were re-estimated with Mann–Whitney U tests, which reproduced the parametric pattern. The same eight items remained significant under both procedures, and the composite-level conclusions were unchanged (opportunity $p < 0.001$, ability $p = 0.005$, motivation $p = 0.50$). Perceived difficulty of use (raw $p = 0.048$; non-parametric $p = 0.147$) and lack of IT support (raw $p = 0.023$; non-parametric $p = 0.022$, uncorrected only) did not meet both criteria. Findings that survive both checks are treated as the core results in what follows; the two weaker items are interpreted as tentative.

Results

Sample characteristics and generative AI use

Across the full survey sample ($N = 655$), generative AI use differed significantly by sector. Wellbeing services respondents reported lower use (43%) than technical services respondents (61%; $p < 0.001$).

The barrier analyses focus on respondents who reported not using AI in their work ($n = 321$; wellbeing services, $n = 236$; technical services, $n = 85$). Some background information is available on this analytical sample. Among those answering the question on position, supervisory or managerial roles were held by 7% of wellbeing services non-users and 24% of technical services non-users. Technical services non-users came from municipalities in all seven national population-size classes and from 16 of the 18 mainland regions. Age, length of work experience and other individual demographics were not collected. The decision protected the anonymity of respondents in technical departments that often employ fewer than six professionals per municipality.

In the combined sample, opportunity barriers registered the highest aggregate mean (M = 1.81), followed by motivation (M = 1.53) and ability (M = 1.46).

At the item level, the three highest-rated barriers were limited knowledge of available AI applications suitable for specific tasks, unclear concrete benefits in daily work, and inadequate training. The lowest-rated items were previous negative experiences with AI and fear of expertise devaluation.

Sectoral differences

In the results that follow, wellbeing services denotes the sample from a single regional organization and technical services the sample drawn from 104 municipalities. The overall mean of perceived barriers was higher in wellbeing services than in technical services (Table 1). Wellbeing services respondents reported significantly higher ability barriers and substantially higher opportunity barriers, while the motivation composite did not differ between sectors. Given the modest reliability of the ability composite ($\alpha = 0.60$), the ability difference is read primarily through its constituent items in Table 2. The opportunity dimension produced the largest sectoral gap.

The distribution of composite scores in Figure 1 shows the same composite-level pattern as Table 1.

Because supervisory or managerial roles were more common in the technical services sample (24% versus 7%), the composite comparisons were re-estimated among non-supervisory respondents only ($n = 275$). The pattern persisted. The opportunity gap was essentially unchanged ($g = 0.60$, $p < 0.001$), the ability difference remained significant though somewhat attenuated ($g = 0.34$, $p = 0.012$), the motivation composites stayed comparable, and doubts about accuracy and reliability remained higher in technical services ($g = -0.44$, $p = 0.003$).

Of the 19 individual barriers, ten differed significantly between the two sectors at the uncorrected level (Table 2). Eight of these constitute the core results, as they remained significant after Holm-Bonferroni correction and under non-parametric re-estimation. Perceived difficulty of use and perceived lack of IT support did not meet both criteria and are read as tentative. Nine of the ten differences favored higher ratings in wellbeing services. Doubts about AI accuracy and reliability formed the sole exception, the only barrier rated significantly higher in technical services.

Three of the four *ability* items differed significantly across sectors, all rated higher in wellbeing services. Competence uncertainty and limited knowledge of applications belong to the core results, whereas perceived difficulty of use remained tentative. Negative prior experiences did not differ and showed a higher rate of "do not know" responses, reflecting limited direct AI experience among non-users.

The *motivation* composite masked an item-level reversal. Doubts about AI accuracy and reliability stood out as the only one of the 19 items for which technical services scored significantly higher ($g = -0.56$). Other motivation items showed no significant sectoral variation; security and privacy concerns were nominally greater in technical services but did not reach significance ($p = 0.065$).

Table 1. AMO composite scores of perceived generative AI adoption barriers by sample on a 0–3 scale

AMO component	Wellbeing services M (SD) n	Technical services M (SD) n	t(df)	*p* (Two-sided)	Hedges' g
All 19 items	1.71 (0.64) $n = 235$	1.47 (0.57) $n = 85$	3.33 (167.8)	0.001	0.40
Ability (4 items)	1.53 (0.77) $n = 233$	1.26 (0.68) $n = 85$	3.01 (166.2)	0.003	0.36
Motivation (6 items)	1.51 (0.82) $n = 232$	1.57 (0.66) $n = 85$	−0.70 (182.9)	0.486	−0.08
Opportunity (9 items)	1.92 (0.70) $n = 234$	1.50 (0.71) $n = 85$	4.69 (145.9)	< 0.001	0.60

Note(s): Wellbeing services data are from one regional wellbeing services county; technical services data are from civil servants across 104 municipalities. Sectoral comparisons should be interpreted with this design asymmetry in mind

Source(s): Authors' own work

Table 2. Sectoral comparison of individual AI adoption barriers

Code	Barrier	Wellbeing services M (SD), n	Technical services M (SD), n	t(df) (Welch)	*p* (two-sided)	Hedges' g [95% CI]
Ability barriers						
A1 †	Competence uncertainty	1.72 (1.14), *n* = 232	1.20 (0.97), *n* = 84	3.87 (171.0)	< 0.001	0.46 [0.20, 0.71]
A2 †	Limited knowledge of apps	2.38 (0.89), *n* = 232	1.94 (1.05), *n* = 84	3.43 (129.0)	< 0.001	0.47 [0.22, 0.72]
A3	Perceived difficulty of use	1.22 (1.07), *n* = 206	0.94 (0.84), *n* = 51	2.00 (95.2)	0.048	0.27 [−0.04, 0.58]
A4	Negative prior experiences	0.44 (0.80), *n* = 202	0.55 (0.86), *n* = 66	−0.87 (104.4)	0.385	−0.13 [−0.41, 0.15]
Motivation barriers						
M1	Unclear concrete benefits	2.31 (0.93), *n* = 219	2.13 (0.99), *n* = 78	1.39 (129.0)	0.167	0.19 [−0.07, 0.45]
M2 †	Doubts about accuracy and reliability	1.54 (1.10), *n* = 218	2.13 (0.98), *n* = 82	−4.55 (162.5)	< 0.001	−0.56 [−0.82, −0.30]
M3	Security/privacy concerns	1.71 (1.16), *n* = 224	1.96 (1.02), *n* = 80	−1.86 (155.9)	0.065	−0.23 [−0.48, 0.03]
M4	Ethical concerns	1.65 (1.16), *n* = 224	1.73 (1.12), *n* = 75	−0.57 (131.0)	0.569	−0.08 [−0.34, 0.19]
M5	Concern that work tasks will change substantially due to AI	1.01 (1.07), *n* = 218	0.79 (0.95), *n* = 81	1.76 (160.4)	0.081	0.22 [−0.04, 0.47]
M6	Fear of expertise devaluation	0.75 (1.02), *n* = 220	0.61 (0.80), *n* = 79	1.25 (173.4)	0.213	0.15 [−0.11, 0.40]
Opportunity barriers						
O1	Insufficient time to learn	1.86 (1.09), *n* = 232	1.82 (1.03), *n* = 83	0.32 (153.1)	0.749	0.04 [−0.21, 0.29]
O2 †	Absence of guidelines/policies	2.15 (0.96), *n* = 224	1.38 (1.14), *n* = 79	5.40 (119.9)	< 0.001	0.76 [0.50, 1.02]
O3	Lack of suitable apps	2.06 (1.00), *n* = 214	1.84 (1.15), *n* = 67	1.44 (99.5)	0.153	0.22 [−0.06, 0.49]
O4 †	Inadequate training	2.36 (0.93), *n* = 231	1.78 (1.05), *n* = 83	4.43 (130.8)	< 0.001	0.60 [0.34, 0.85]
O5 †	Limited colleague/supervisor encouragement	1.55 (1.12), *n* = 218	0.81 (0.93), *n* = 77	5.71 (158.7)	< 0.001	0.69 [0.43, 0.96]
O6 †	Inadequate peer support	1.99 (1.02), *n* = 221	1.22 (1.00), *n* = 78	5.80 (136.7)	< 0.001	0.76 [0.49, 1.02]
O7 †	Materials not in digital format	1.61 (1.07), *n* = 199	1.12 (1.05), *n* = 59	3.16 (96.5)	0.002	0.46 [0.17, 0.75]
O8	Lack of IT support	1.69 (1.10), *n* = 205	1.33 (1.11), *n* = 69	2.30 (116.7)	0.023	0.32 [0.05, 0.59]
O9	Accountability uncertainty	1.76 (1.09), *n* = 222	1.86 (1.07), *n* = 73	−0.70 (124.2)	0.484	−0.09 [−0.36, 0.17]

Note(s): Welch's *t*-test was used throughout to accommodate unequal variances; *t*-values are reported to two decimal places, and degrees of freedom to one decimal place. Hedges' g is reported with 95% confidence intervals; n varies across items due to "do not know" responses being treated as missing. Items marked with † remained significant after Holm–Bonferroni correction and under Mann–Whitney U re-estimation; these constitute the core results. Sector labels denote the two sample configurations described in the Comparative design subsection
Source(s): Authors' own work

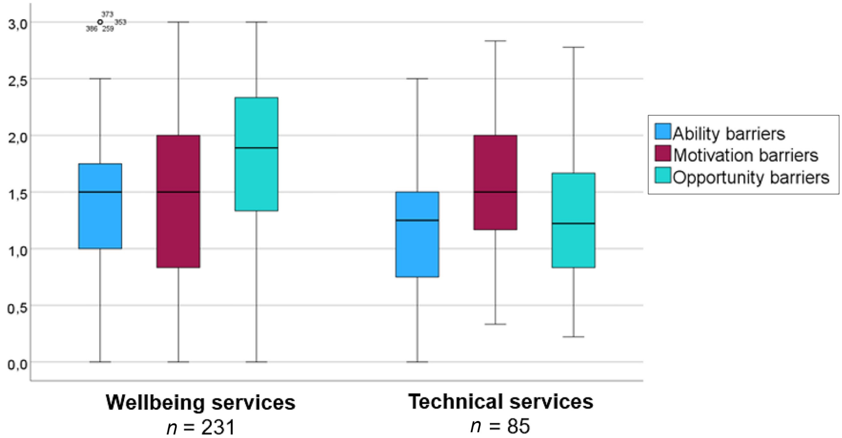

Figure 1. Perceived generative AI adoption barriers in public wellbeing and technical services in Finland (on a 0–3 scale), mapped to AMO theory dimensions. The figure includes respondents with a computable score on all three AMO composites. Wellbeing services data are from one regional organization; technical services data are from respondents across 104 municipalities

Source: Authors' own work

Six of the nine *opportunity* items differed significantly across sectors, all rated higher in wellbeing services. The largest effects concerned organizational guidelines and policies, peer support networks and colleague or supervisor encouragement. Inadequate training and non-digital data formats also belonged to the core results, whereas insufficient IT support reached significance only at the uncorrected level (Table 2).

Sector-specific barrier profiles

Table 3 ranks the 10 highest-rated barriers in each sector by the proportion of respondents rating each item as a moderate or strong barrier (scores 2 or 3 on a 0–3 scale). The two sector samples produced different profiles.

In wellbeing services, the top-ranked barriers were concentrated in the opportunity dimension, with two ability and two motivation items also among the top ten. Limited knowledge of applications and inadequate training ranked first and second, followed by unclear concrete benefits, the absence of guidelines and inadequate peer support.

The technical services profile was more heterogeneous across AMO dimensions. Doubts about AI accuracy and reliability ranked highest, followed by concerns about unclear concrete benefits and limited knowledge of applications. Trust-related concerns ranked highest in technical services, unlike in wellbeing services. The rest of the top 10 in technical services mixed opportunity barriers (insufficient time to learn, lack of suitable applications, inadequate training, accountability uncertainty) with motivation barriers (security and ethical concerns).

Discussion

Sectoral patterns in civil servants' perceived generative AI adoption barriers

Perceived barriers to generative AI adoption exhibited distinct profiles in the two samples. Opportunity barriers were the highest-rated dimension in wellbeing services and produced

Table 3. The ten highest-rated generative AI adoption barriers by sample

Rank	Wellbeing services	Technical services
	Barrier (% high barrier)	Barrier (% high barrier)
1	A: Limited knowledge of apps (84%)	M: Doubts about accuracy/reliability (76%)
2	O: Inadequate training (83%)	M: Unclear concrete benefits (73%)
3	M: Unclear concrete benefits (81%)	A: Limited knowledge of apps (67%)
4	O: Absence of guidelines/policies (76%)	O: Lack of suitable apps (64%)
5	O: Inadequate peer support (73%)	O: Insufficient time to learn (64%)
6	O: Lack of suitable apps (71%)	M: Security/privacy concerns (64%)
7	O: Insufficient time to learn (66%)	O: Inadequate training (61%)
8	O: Accountability uncertainty (61%)	O: Accountability uncertainty (60%)
9	A: Competence uncertainty (60%)	M: Ethical concerns (56%)
10	M: Security/privacy concerns (56%)	O: Lack of guidelines/policies (44%)

Note(s): High barrier denotes a rating of 2 (moderate effect) or 3 (very strong effect) on the 0–3 scale. Percentages indicate the share of respondents in each sector who rated the item 2 or 3; respondents selecting "do not know" are excluded from the denominator. Wellbeing services percentages describe one regional organization, and technical services percentages describe a sample drawn from 104 municipalities; the rankings characterize these sample configurations
Source(s): Authors' own work

the largest sectoral gap, whereas the technical services profile was distributed more evenly across the three dimensions. The largest effect sizes clustered around organizational support structures (guidelines, peer support and colleague or supervisor encouragement), conditions that appear interconnected. Without organizational endorsement through concrete policies and resource commitments, supervisors and peers may lack the prerequisites to provide structured support for adoption. The finding resonates with prior observations that organizational prerequisites for change frequently lag behind political ambitions in Nordic municipalities (Kristensen, 2023; Torfing, 2012). Dense statutory steering compounds this in wellbeing services, where the absence of explicit guidelines can be read as a missing mandate to use AI. Recent case evidence suggests leadership attention and structured communication as pivotal mechanisms for converting endorsement into adoption (Alshahrani *et al.*, 2025; Bannister and Connolly, 2020).

The motivation dimension produced the most analytically distinctive pattern. Composite-level similarity masked an item-level reversal. Doubts about AI accuracy and reliability were substantially stronger among technical services respondents and ranked as the top barrier in that sector. This reversal may be the most distinctive single finding of the study. Prior research has positioned trust and reliability concerns as central in care-oriented contexts (Apell and Eriksson, 2023; Sun and Medaglia, 2019). The present data suggest such concerns also surface in data-oriented domains, where analytical outputs carry implications for physical infrastructure, public safety and legally binding land-use decisions. One plausible interpretation is that domain expertise sharpens critical evaluation of AI outputs, although the present data cannot establish this mechanism. In wellbeing services, motivational concerns are dispersed across ethical reservations, unclear value propositions and privacy apprehensions, none of which match the technical-sector intensity around reliability.

Elevated ability barriers in wellbeing services were driven primarily by competence uncertainty and limited knowledge of available applications. The configuration differs from earlier healthcare research, which has emphasized privacy concerns and fears of professional replacement (Ramadan *et al.*, 2024). One plausible reading lies in the structural position of Finnish social care, which has historically lagged behind other service sectors in digitalization. Comparable patterns emerge in Sweden, where healthcare decision-makers were not always equipped to assess the potential impact of AI (Apell and Eriksson, 2023). Competence uncertainty concerns what employees believe they can accomplish, a confidence assessment shaped by mastery experience and social persuasion (Bandura, 1997). Co-occurring informational gaps and elevated competence uncertainty likely reinforce each other (Ahmed *et al.*, 2023).

Nine of the 19 barriers showed no significant sectoral variation, spanning all three AMO dimensions. Unclear concrete benefits ranked second-highest in the combined sample, indicating that the value proposition for AI in specific public service tasks remains insufficiently articulated. Insufficient time to learn, a lack of suitable applications and accountability uncertainty also emerged as shared barriers, suggesting that resource constraints and governance ambiguities are pervasive features of Finnish public-sector AI adoption (Eneman *et al.*, 2022; Haesevoets *et al.*, 2025).

Theoretical contributions

The main theoretical implication is that AMO barrier profiles appear to vary with the configuration of public service production in the context of generative AI adoption. The findings develop this claim at two levels.

At the dimension level, the results offer empirical support for the contextual reading advocated by Bos-Nehles *et al.* (2023). The descriptive ordering of AMO dimension means differed between the two samples, with opportunity barriers highest in the wellbeing services sample and a more even profile in the technical services sample. Earlier applications of AMO to knowledge sharing and AI adoption have largely examined how the framework operates within a given empirical context (Radwan *et al.*, 2026; Siemsen *et al.*, 2008). The present results suggest that the potency of each dimension may depend on the organizational configuration within which civil servants work (Bullock *et al.*, 2020).

The same context dependence extends below the dimension level. The motivation composites were comparable across the samples, yet a single item, doubts about AI accuracy and reliability, was rated significantly higher in technical services, whereas wellbeing services respondents rated every other significantly differing item higher. A composite-level reading would have classified motivation as sectorally uniform. Context thus appears to shape which items within a dimension become important. Future AMO research on technology adoption would accordingly benefit from examining within-dimension heterogeneity alongside composite comparisons.

Beyond AMO, the design adds employee-level comparative evidence to a literature dominated by single-domain studies (Alshahrani *et al.*, 2024; Madan and Ashok, 2023; Mergel *et al.*, 2023) and offers tentative grounding for the claim that technology utilization lands differently across domains of public service production (Bovens and Zouridis, 2002).

Practical implications for public sector organizations

The differences documented here suggest that generative AI adoption policy in public organizations should not be generic. Organizations may benefit from diagnosing their own employee-level barrier profiles before designing implementation initiatives, since local configurations of digital maturity and governance can produce variation that aggregate patterns do not capture.

How barrier ratings are read also matters. A high rating is not automatically a deficiency awaiting elimination; doubts about accuracy, accountability uncertainty and privacy concerns may function as legitimate safeguards against premature use in tasks where errors carry material or legal consequences (Bannister and Connolly, 2020;

Zuiderwijk *et al.*, 2021). The managerial task is to distinguish constraints that block informed engagement from professional caution worth preserving.

In wellbeing services, the core findings point to a lack of organizational permission and weak support structures. Senior management could establish explicit AI guidelines defining acceptable use, since their absence appeared to be read as a lack of mandate, and supervisors are well positioned to translate such guidelines into everyday encouragement. HR and training functions could develop role-based training, designate mentor users within units and create safe testing environments using non-client/patient data (Apell and Eriksson, 2023; Bernhard and Wihlborg, 2022). A workable sequence for managers would begin with a written policy on permitted uses and data handling. Role-based software and training anchored in everyday tasks could follow, together with the designation of a trained peer contact in each unit for low-threshold questions.

Technical services respondents rated doubts about AI accuracy and reliability as the top barrier, suggesting that responses in this domain might prioritize verification over awareness campaigns. National agencies and professional bodies for the built environment could develop verification standards and reliability assessment protocols for AI-assisted outputs in zoning, permitting and inspection work, while municipal managers could clarify how accountability for AI-assisted decisions is allocated. At the organizational level, a documented verification step, in which AI-assisted outputs are checked against source data before being entered into permit or planning documents, could translate these standards into daily practice. Transparent reporting of model performance, together with case evidence from comparable technical domains, may carry more weight with this professional group than enthusiasm-oriented communication (Bullock *et al.*, 2020).

Shared barriers, including unclear concrete benefits, uncertainty about accountability and the limited availability of suitable applications, point to limits on what any single organization can resolve alone. Software vendors could calibrate applications to public service task requirements, training providers could design sector-specific curricula and national agencies could clarify accountability frameworks and articulate task-level value propositions (Madan and Ashok, 2023; Schedler *et al.*, 2019). In Nordic multi-level governance, addressing these systemic constraints may require coordination across national, regional and organizational levels (Liebig *et al.*, 2024).

AI adoption also carries policy and societal weight. Verification practices and clear accountability arrangements protect the accuracy of decisions that directly affect residents, from care assessments to building permits. Visible, well-governed use of generative AI may support public trust in administration (Bannister and Connolly, 2020; Zuiderwijk *et al.*, 2021). Premature deployment without such safeguards could erode that trust in public service production.

Limitations and future research

The cross-sectional design precludes causal claims about the relationship between perceived barriers and actual adoption decisions. The analytical sample comprised respondents who reported no prior AI use, so the barriers identified represent non-adopters' perceptions; those who have already adopted AI may experience different profiles or have overcome the constraints documented here.

Sample structure is a further constraint. Wellbeing services data are drawn from a single regional organization; technical services data span 104 municipalities. Sector, organization, administrative tier and digital maturity covary in this design and cannot be separated analytically, so any observed difference admits several structural explanations. Idiosyncrasies within the single wellbeing organization may also influence the findings, since Finnish wellbeing services counties differ in size, population characteristics, resources, organizational maturity and digital infrastructure.

Response rates of approximately 10% and 8% raise concerns about non-response bias. Employees with stronger views on generative AI, whether curious or concerned, may have been more likely to respond, so the reported barrier levels reflect the responding samples and may deviate from population values in either direction. The sectoral contrasts would be distorted mainly if non-response differed between the two samples, a possibility these data cannot rule out. Supervisory status was available and differed between the samples (7% vs 24%); a sensitivity analysis restricted to non-supervisory respondents reproduced the main pattern. Age, work experience and professional background were not collected, a choice made to protect anonymity in small technical units. This prevents a detailed assessment of sample representativeness and of whether these characteristics condition the reported perceptions, and residual confounding by unmeasured role characteristics remains possible.

Self-report on a four-point scale is susceptible to social desirability and central-tendency biases. The wording targeted generative AI tools and embedded AI features, though some respondents may not have drawn sharp distinctions between generative AI and other forms of AI.

Item classification into AMO dimensions required interpretive judgment in several borderline cases, although the magnitude of the observed effects suggests that the dominant findings are robust. The ability composite's modest internal consistency ($\alpha = 0.60$) reflects the small number of items and the construct's heterogeneity, so item-level interpretation is prioritized for that dimension. "Do not know" response rates varied across items, reducing effective sample sizes most notably for items requiring direct AI experience. Treating these responses as missing may understate the phenomenon they express. The inability to assess a barrier can itself indicate limited awareness of the technology, a constraint conceptually adjacent to the ability dimension, and future instruments could accordingly treat "do not know" responses as substantive data.

Future research could address these limitations. Longitudinal designs would help characterize how perceptions of barriers change across adoption stages, and including AI adopters in comparative analyses would test whether the profiles documented here persist or shift after adoption. Broader sampling within wellbeing services would strengthen external validity; collecting background variables such as age, work experience and professional role, where unit sizes permit, would allow examination of their conditioning effects, and qualitative methods would deepen contextual understanding of the mechanisms underlying the patterns. Multi-country comparative studies would assess whether the sectoral patterns are specific to the Finnish institutional context or reflect more broadly generalizable features of Nordic and European public service AI adoption.

Conclusions

This exploratory comparative study identified distinct barrier profiles among public employees who had not adopted generative AI across two configurations of Finnish public service production. Opportunity barriers were the highest-rated dimension in the wellbeing services sample and substantially more intense there than in technical services. In wellbeing services, the core findings concerned the absence of organizational guidelines, inadequate peer support and limited encouragement from colleagues or supervisors. The motivation dimension contained an item-level reversal that composite measures obscured; doubts about AI accuracy and reliability ranked as the primary barrier in technical services.

These patterns are consistent with a configurational reading of AMO, in which the relative weight of the three dimensions may vary across public service configurations. Firm sector-level inference lies beyond the design, since sector, organization, administrative tier and digital maturity covary in the data; the profiles should be read as exploratory observations from one wellbeing services county and a heterogeneous municipal sample.

Within those limits, two observations appear robust enough to guide further work. Verification-related concerns surfaced most strongly in a data-oriented domain, suggesting that professional standards around AI verification may operate wherever decisions carry direct material consequences. Several barriers also persisted across both samples at levels that individual organizations seem unlikely to resolve alone, so environmental and institutional actors, including software vendors and national governance bodies, may play complementary roles. Replications across wellbeing services counties and in other countries, applying the 19-item classification developed here, would help establish whether these findings generalize.

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Appendix. Survey instrument for perceived barriers

Table A1. To what extent do the following factors influence your decision not to use AI applications in your work? 0 (no effect), 1 (slight effect), 2 (moderate effect) and 3 (very strong effect)

Code	Item (abbreviated)	AMO dimension	Classification rationale	Indicative sources
A1	Uncertainty about one's own competence	Ability	Self-efficacy beliefs operate as a capability barrier independently of objective skill	Bandura (1997); Ahmed *et al.* (2023)
A2	Limited knowledge of available applications	Ability	Awareness of task-relevant tools is an individual knowledge resource, a precondition for use	Schedler *et al.* (2019)
A3	Perceived difficulty of use	Ability	Perceived ease of use reflects the individual's capability to operate the tool	Davis (1989); Schedler *et al.* (2019)
A4	Previous negative experiences	Ability	Prior mastery experiences shape capability beliefs and learning readiness	Bandura (1997)
M1	Unclear concrete benefits	Motivation	Perceived usefulness drives the willingness to invest effort; the item measures perceived value, separate from whether suitable tools exist (O3)	Davis (1989); Pandey (2026)
M2	Doubts about accuracy and reliability	Motivation	Trust in output quality conditions the inclination to engage	Gefen *et al.* (2003); Liebig *et al.* (2024)
M3	Security and privacy concerns	Motivation	Perceived risk reduces willingness to act, even when use is possible	Sun and Medaglia (2019); Apell and Eriksson (2023)
M4	Ethical concerns	Motivation	Reservations about justifiability reduce the inclination to use AI in one's own tasks	Ahmed *et al.* (2023); Sun and Medaglia (2019)
M5	Concern about substantial task change	Motivation	Anticipated disruption to one's work weakens the desire to engage	Bullock *et al.* (2020)
M6	Fear of expertise devaluation	Motivation	Threats to professional identity act as a motivational inhibitor	Ahmed *et al.* (2023); Bullock *et al.* (2020)
O1	Insufficient time to learn	Opportunity	Time allocation is an organizational resource decision outside the individual's control	Ahmed *et al.* (2023); Gullmark (2021)
O2	Absence of organizational guidelines	Opportunity	Formal policies constitute an institutional permission structure	Clarke (2020); Eneman *et al.* (2022)
O3	Lack of suitable applications in the organization	Opportunity	Tool provision is an organizational resource condition; the item concerns availability, separate from the individual's awareness of tools (A2)	Gullmark (2021); Madan and Ashok (2023)

(*continued*)

Table A1. Continued

Code	Item (abbreviated)	AMO dimension	Classification rationale	Indicative sources
O4	Inadequate training	Opportunity	Training provision is an organizational support structure; the resulting skill, in contrast to the provision, belongs to ability	Bernhard and Wihlborg (2022); Bannykh and Kostina (2021)
O5	Limited colleague or supervisor encouragement	Opportunity	Social endorsement in the work environment enables or withholds occasions for use	Graf-Vlachy *et al.* (2018); Van der Voet *et al.* (2016)
O6	Inadequate peer support	Opportunity	Peer-based support structures are an organizational learning condition	Bernhard and Wihlborg (2022); Lidman *et al.* (2022)
O7	Materials not in digital format	Opportunity	Data infrastructure is an organizational precondition for the use of AI	Madan and Ashok (2023); Sun and Medaglia (2019)
O8	Lack of technical IT support	Opportunity	Technical support functions are enabling conditions provided by the organization	Alshahrani *et al.* (2025); Van der Voet *et al.* (2016)
O9	Uncertainty about accountability	Opportunity	Accountability allocation is a governance condition set by the institutional environment, beyond the reach of individual disposition	Bannister and Connolly (2020); Liebig *et al.* (2024)

Note. The classification follows published AMO practice, in which opportunity denotes the work environment as perceived by the employee (Bos-Nehles *et al.*, 2023; Marin-Garcia and Tomas, 2016). For borderline items, the rationale column states the distinction applied
Source(s): Authors' own work

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