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Navigating the Automation–Augmentation Paradox: A Case Study of Artificial Intelligence Integration in Public Management Functions

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Abstract:

The application and utilization of Artificial Intelligence (AI) have increased recently in all organizations, including those in the public sector. From an organizational perspective, AI utilization should generate both economic and social gains. In this context, it is necessary to address the automation-augmentation paradox. Namely, this paradox stems from the question of whether AI replaces humans in performing tasks (i.e., automation) or whether the application of AI necessitates an increase in AI-human interactions (i.e., augmentation). The starting point of the research is the POSDCORB framework, which delineates the core functions of a manager and offers a classical perspective on their administrative responsibilities. AI shall increasingly transform the POSDCORB framework by streamlining management functions and enhancing decision-making accuracy. The main research question is what can be automated using AI for management functions, and what requires augmentation between AI and humans for these functions? To assess AI's impact on POSDCORB managerial functions in public sector organizations, the study uses both qualitative and

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quantitative data sources, enhancing validity through data triangulation. The research findings indicate that AI's impact varies across management functions, with public managers particularly preferring augmentation for strategic planning tasks, coordination, reporting, and potential dynamic financial adjustments. Finally, public managers' report ongoing tension due to a tendency to switch between automation and augmentation as tasks evolve.

Keywords:
artificial intelligence, automation-augmentation paradox, management functions, principal-agent theory, technology acceptance frameworks

1. Introduction

The application and utilisation of AI have increased recently in all organisations, including the public sector. From the organisational perspective, AI utilisation should generate both economic and social gains. In this context, it is necessary to address the automation-augmentation paradox (Raisch & Krakowski, 2021). Namely, this paradox stems from the question of whether AI replaces humans in performing tasks (i.e., automation) or whether the application of AI necessitates an increase in AI-human interactions (i.e., augmentation). Early research posited AI as a solution for the crisis in strategic planning, suggesting that machines could assist decision-making at all organizational levels (Orsini, 1986). This approach promised increased managerial efficiency by delegating routine tasks to AI (Geisler, 1986). More recently, AI's role in management has expanded, advocating for a partnership where AI handles administrative tasks, allowing managers to apply human judgment and decision-making skills (Kolbjørnsrud et al., 2016). This collaboration emphasizes the augmentation of human abilities rather than outright automation. The COVID-19 pandemic has accelerated this integration, with AI being crucial for foresight and organizational agility (Shafiabady et al., 2023).

The question of AI's relevance in public management is less explored. Although there has been a considerable growth in the volume of literature concerned with the utilization and application of AI in the public sector (Madan & Ashok, 2023; Sousa et al., 2019), the scoping literature review revealed there is a lack of empirical studies on AI's practical applications in the public sector, particularly in supporting and enhancing the distinct managerial functions in the public sector (Pevcin & Debelak, 2025). The scoping research explored the discourse on AI's role and relevance within public sector management, revealing four critical themes in the literature: adoption and implementation challenges, governance and ethical considerations, policy and strategic development, and impact assessment and application challenges. Hence, there is an evident lack of studies analysing the role of artificial intelligence in managerial functions within the public sector, and this study aims to address this gap.

The starting point of the research is the POSDCORB framework (Gulick & Urwick, 1937), which delineates the core functions of a manager and offers a classical perspective on the administrative responsibilities of managers. Thus, the POSDCORB framework in management theory delineates the core functions of the (top) manager. The POSDCORB acronym stands for Planning, Organizing, Staffing, Directing, Coordinating, Reporting, and Budgeting, encapsulating the essential tasks that managers undertake to achieve organizational goals. AI shall increasingly transform the POSDCORB framework by streamlining management functions and enhancing decision-making accuracy (Chaturvedi et al., 2025). To understand the mechanisms through which the automation–augmentation paradox manifests in managerial functions, principal–agent theory provides a compelling explanatory lens, as this theory conceptualizes the relationship between principals (e.g., elected officials or citizens) and agents (e.g., public managers) in terms of goal alignment, information asymmetry, and monitoring costs. This theory emphasizes the complex relationships among principals and agents, especially in the public sector (György, 2012), which are further exacerbated by informational asymmetry (Lane, 2013).

The main research question is what can be automated using AI for management functions, and what necessitates augmentation between AI and humans for these functions. To induce subrogation within the main research question, the study would like to portray evidence on factors that foster utilization of AI among public managers; on the relevance of AI for performing specific top management functions; and the role and importance of AI in either increasing or decreasing principal-agent problems, where we specifically focus on the context of the public sector. The motivation for the research derives from the identified consensus that management literature needs to better address the practical use of AI in organizations (Raisch & Krakowski, 2021), as well as from the identified specifics regarding the public sector, where the introduction of AI has yet to be matched by research into its managerial implications (Sousa et al., 2019). In fact, by adopting a more general perspective, it has been acknowledged that there is a lack of literature and studies on the effects of digital transformation on public management (Urs et al., 2024). This study aims to provide additional insights into this domain.

To assess AI's impact on POSDCORB managerial functions in public sector organizations and the magnitude of principal-agent issues, the study uses both qualitative and quantitative data sources, enhancing validity through data triangulation. In this context, relevant technology acceptance frameworks (TOE and UTAUT) are used, supplemented with the Analytic Hierarchy Process (AHP) method and semi-structured phased interviews.

2. Theoretical framework and literature review

The automation-augmentation paradox suggests that both perspectives on AI in management are inherently limited, shaped by context and task demands rather than being universally beneficial or detrimental. Derrida's (1998) deconstruction theory highlights the tendency to construct binary oppositions, such as automation and augmentation, in ways that privilege one side while marginalizing the other. This dichotomy often oversimplifies the dynamic complexities of AI's role in managerial tasks (Derrida, 1998).

Applying AI to managerial tasks typically begins with a choice between automation and augmentation. For structured, routine tasks—such as processing invoices—organizations often opt for automation by encoding specific rules and relationships into algorithms, which enables managers to delegate such tasks to machines (Gillespie, 2014; Russell et al., 2010). However, most managerial tasks are more complex, involving ambiguous conditions and requiring nuanced judgment. Here, augmentation becomes necessary, allowing managers to work interactively with AI, using their expertise to complement the system's capabilities (Brynjolfsson & Mitchell, 2017; Holzinger, 2016). Unlike rule-based automation, augmentation relies heavily on the tacit knowledge of domain experts, who must remain "in the loop" to refine problem-solving processes collaboratively with AI (Holzinger, 2016).

This iterative, co-evolutionary process involves managers and machines learning from each other to build and adjust rules and models over time. In supervised learning, managers provide labeled training data that guides the AI in developing predictive rules, while unsupervised learning allows the machine to identify patterns independently (Jordan & Mitchell, 2015). Managers then leverage their domain expertise to interpret outputs, correct biases, and mitigate overfitting risks that could compromise decision-making (Russell et al., 2010). Over time, augmentation can facilitate a transition to automation. Once robust models are developed through collaborative learning, they can be automated to handle routine tasks, freeing managers to focus on higher-level responsibilities (Langley & Simon, 1995). Thus, the relationship between automation and augmentation is cyclical and interdependent: organizations may initially choose one approach based on task complexity. However, they may later shift, creating a continuous interplay that reflects the paradox's inherent tension (Smith & Lewis, 2011).

Moreover, the POSDCORB framework in management theory, which delineates the core functions of a manager, was conceptualized by Gulick and Urwick in 1937. The acronym stands for Planning, Organizing, Staffing, Directing, Coordinating, Reporting, and Budgeting, encapsulating the essential tasks that managers undertake to achieve organizational goals. According to Gulick and Urwick (1937), planning involves setting objectives and deciding on the steps necessary to achieve them. Organizing entails establishing a formal structure of authority and responsibility. Staffing covers the recruitment, selection, and training of employees, while directing ensures that tasks are completed through leadership and communication. Coordinating ensures the harmonious functioning of various activities, and reporting involves keeping stakeholders informed about the organization's progress. Finally, budgeting involves the allocation of financial resources. POSDCORB has been foundational in management studies, offering a classical perspective on the administrative responsibilities of managers.

Furthermore, AI is increasingly transforming the POSDCORB framework by streamlining management functions and enhancing decision-making accuracy:

- In the planning phase, AI can utilize big data analytics and machine learning to forecast trends and optimize strategic decisions, enabling managers to predict market dynamics and respond proactively (Agrawal et al., 2018).
- AI's impact on organizing is evident in the deployment of automated systems for resource allocation and workflow management, ensuring tasks are performed efficiently and in line with organizational goals (Haefner et al., 2021).
- In terms of staffing, AI is transforming recruitment and talent management through advanced algorithms that improve candidate screening and reduce bias, thus facilitating more objective hiring processes (Tambe et al., 2019).
- For directing, AI-powered tools enhance communication and provide real-time decision support, allowing managers to lead teams with increased precision and less administrative burden (Jarrahi, 2018).
- In coordinating, AI can integrate various organizational systems, fostering better synchronization and communication between departments, which is crucial for operational agility (Brock & Von Wangenheim, 2019).
- AI also reshapes reporting by automating data collection and analysis, allowing for real-time tracking of key performance indicators (KPIs), which supports more informed managerial decisions (Davenport & Ronanki, 2018).
- Finally, in budgeting, AI aids in financial forecasting, optimizes expenditure planning, and enhances fraud detection, ensuring more accurate and efficient resource allocation (Batarseh & Yang, 2020). These advances demonstrate that AI is not only improving the efficiency of POSDCORB functions but also reshaping management practices for greater adaptability in the digital age.

To understand the mechanisms through which the automation–augmentation paradox manifests in managerial functions, Principal–Agent Theory provides a compelling explanatory lens. Initially developed in the context of contract economics and institutional analysis (Jensen & Meckling, 1976), this theory conceptualizes the relationship between principals (e.g., elected officials or citizens) and agents (e.g., public managers) in terms of goal alignment, information asymmetry, and monitoring costs. AI can function both as a monitoring tool and a strategic resource in this principal–agent relationship. On the one hand, AI systems reduce information asymmetry by increasing transparency and enabling real-time monitoring of managerial performance (Cordella & Willcocks, 2012). On the other hand, over-reliance on automation may constrain managerial discretion, undermining the adaptive capacity and nuanced judgment required in public administration (Bannister & Connolly, 2014). The choice between automation and augmentation can thus be interpreted as a response to shifting dynamics within the principal–agent framework. Automation may be favored when goal clarity and measurability are high, and when principals demand control and standardization. In contrast, augmentation is more likely when managerial discretion is necessary to interpret soft data, reconcile competing stakeholder interests, or innovate under conditions of uncertainty (Koivula et al., 2024). Hence, the automation–augmentation paradox is not merely a technological issue but also an institutional one, reflecting deeper tensions in how authority, accountability, and expertise are distributed within public organizations.

The principal-agent framework has been proposed because it is an interesting paradigm for the analysis of incentives in contracting in general. The practice of public administration can actually be conceptualized from a principal-agent approach, particularly if the starting point is the goal difference between principals and agents (Lane, 2020; Van Thiel & Smullen, 2021). Thus, we have the context of relationships with informational asymmetries regarding the agents' backgrounds and limited ability to observe their activities. Specifically, public administration functioning is conditioned by policy refinement, which is done during the implementation process and routinely held as the responsibility of agents (Gauld, 2007).

We utilize this approach because we are mainly concerned with the potential conflicts of interest and variation in goals between principals and agents, which affect the incentives of agents to utilize and reveal AI. Namely, the literature suggests that the principal-agent framework is particularly relevant for analyzing the utilization of artificial intelligence, as it highlights potential conflicts of interest and information asymmetry between the principal and the agent. The above can lead to unintended consequences or suboptimal outcomes, raising challenges particularly related to developing tools for incentive design and monitoring, and ultimately affecting both principals' and agents' responsibilities (Guggenberger et al., 2023; Kolt, 2025; Yoo & Giannetti, 2024). Put differently, this should correspond to the so-called value-alignment problem, which is closely related to the regulation of AI systems and the development of procedures for human oversight of AI decision-making systems (Hadfield-Menell, 2021).

We recognize that other theoretical approaches could form the foundations of our study, e.g., the management change approach (By, 2005; Chowdhury & Chandra Shil, 2022). The principal-agent framework and management change approach are actually interconnected, yet follow different procedural and process logic. We decided to omit the foundations of the management change approach because it is much broader than the purposes and methodology of our research. Our research does not focus on the holistic processes of organizational transformation, nor do we anticipate or scrutinize the broader organizational shifts and transitions. Additionally, we do not consider potential strategies and processes for adapting an organization to new circumstances.

3. Methodology, research design and data

We employed a mixed-methods approach, combining quantitative and qualitative analyses to examine the automation–augmentation paradox among public managers in Slovenia. Sequential mixed methods is a research design that integrates quantitative and qualitative approaches sequentially, enabling researchers first to identify broad patterns and relationships through quantitative analysis and then elaborate on these findings with in-depth qualitative inquiry. As noted by Venkatesh et al. (2013) this approach facilitates a more comprehensive understanding of complex phenomena by combining the precision of numerical data with the rich, contextual insights gained from qualitative methods.

Table 1:

Research design

LEVEL	CONSTRUCT	DATA COLLECTION	METHOD
Individual Level	TOE (Mikalef et al., 2023) UTAUT (Zuiderwijk et al., 2015) Principal-Agent Problem (Cable & DeRue, 2002; Deci & Ryan, 1994; Gagné et al., 2010; Mayer et al., 1995; Podsakoff et al., 2009)	Semi-structured Interview Focus Group	Quantitative and Qualitative
Organizational Level			

Source: Authors' own, 2025

By testing the constructs at different levels of analysis, the research will undergo multilevel analysis, allowing us to develop a more in-depth and complex understanding of the phenomena (Klein & Kozlowski, 2000). According to Hox et al. (2010), multilevel research can help researchers investigate the impact of contextual factors (e.g., organizational, group, individual) on the outcome of interest, which is particularly important in management research where the impact of context on individual behavior is often of interest. According to Klein and Kozlowski (2000), investigating cross-level effects is particularly important in management research, where understanding the interplay between individual and contextual factors is critical. Finally, multilevel analysis can improve the fit of the statistical model by accounting for the clustering of individuals within higher-level units, resulting in more accurate estimates of the effects of interest and more precise predictions (Snijders & Bosker, 2012).

3.1. Sample description and selection process

The quantitative component of the study involved a total of ten public managers from Slovenian public sector organizations, all of whom participated in a structured focus group using the AHP method. Rather than using a standard survey design, the AHP questionnaire was employed as input for a guided group discussion. This approach facilitated collective discussion, clarification of priorities, and the aggregation of expert managerial judgments. Given the low diffusion of AI technologies in the Slovenian public sector and the homogeneity of managerial roles, a sample of ten decision-making units is considered analytically robust for deriving meaningful weights and priorities in multi-criteria decision analysis (Ossadnik et al., 2016; Saaty, 1990).

The qualitative component involved twenty public managers from Slovenian public sector organizations, divided into two groups of ten. Public managers from organizations without AI implementation were interviewed through semi-structured interviews in May 2024, while those from organizations with AI implementation participated in a focus group discussion in April 2025. Notably, the same group of ten public managers who participated in the quantitative focus group also comprised the AI-implementing group in the qualitative study.

All participants held mid- to senior-level managerial positions in departments such as finance, urban development, social services, and general administration. They were responsible for one or more of the POSDCORB functions (Gulick & Urwick, 1937), making them suitable informants for assessing the managerial implications of AI. The selection followed a purposive sampling strategy, coordinated with senior leadership who were first informed about the study's objectives and methodology. Their agreement facilitated internal communication and access to relevant staff. Public managers were invited to participate based on predefined inclusion criteria: holding a management role, being involved in administrative or strategic functions, and having responsibilities related to technological development or innovation. This structure enabled an in-depth comparison of managerial discretion, control, and accountability —core constructs in Principal–Agent Theory (Eisenhardt, 1989) —between AI-adopting and non-adopting contexts within the public sector.

3.2. Quantitative research design

The quantitative component focuses on measuring organizational and individual readiness for AI implementation. To structure this assessment, the study draws on the Technology–Organization–Environment (TOE) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT), as both provide validated constructs for identifying the factors that influence technological readiness and adoption in organizational contexts. The TOE framework captures external and internal conditions — including technological infrastructure, institutional capacity, and environmental pressures — while UTAUT focuses on individual perceptions, such as performance expectancy, effort expectancy, social influence, and facilitating conditions.

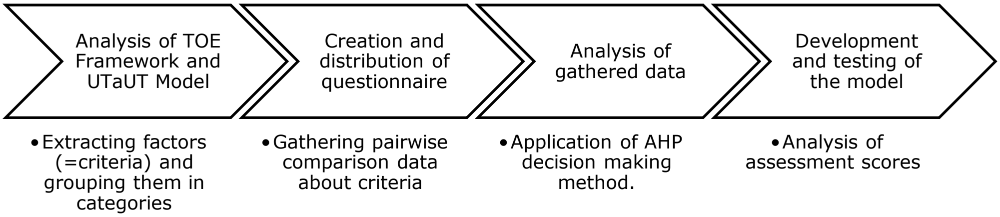
To determine the relative importance of the factors identified within these frameworks, the study applies the Analytic Hierarchy Process (AHP) (Saaty, 1990). According to previous research, AHP is a widely used method for group decision-making (Janković & Popović, 2019). It offers several advantages, as it allows the aggregation of individual judgments or priorities using geometric or arithmetic means

(Huang et al., 2009; Ossadnik et al., 2016).

First, a decision model for assessing AI readiness was developed as a hierarchical, tree-like structure that embeds thirteen criteria into four categories: technology, organization, environment, and individual readiness.

Figure 1:

Steps to create and test proposed decision model



Source: Authors' own, 2025

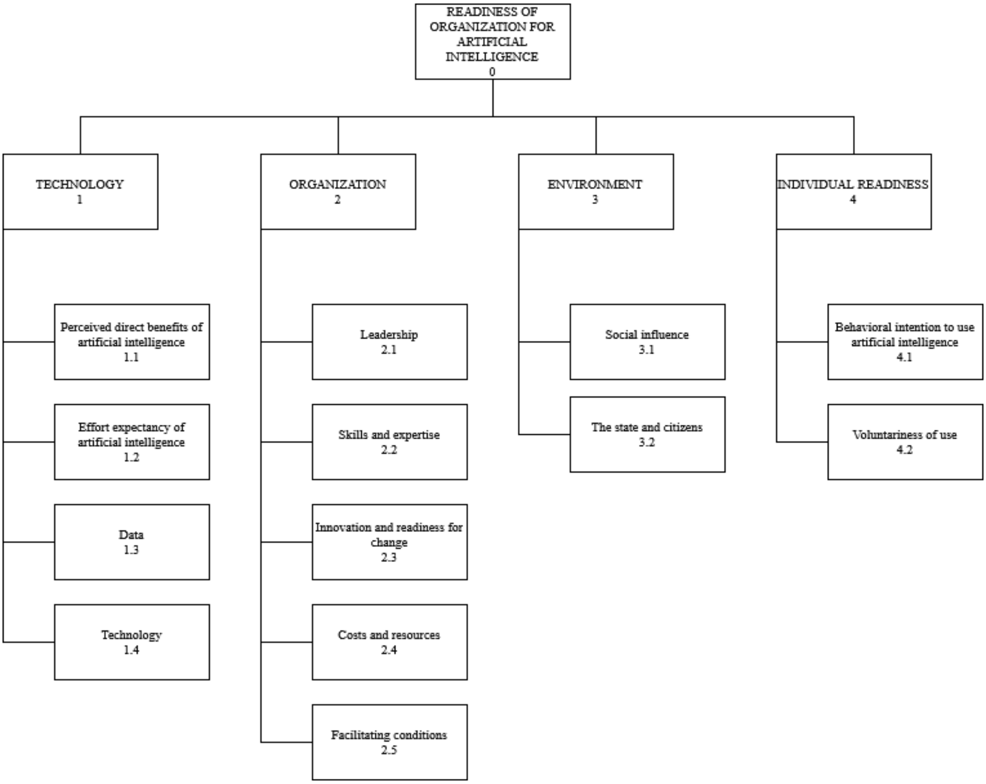
Secondly, a structured AHP questionnaire was created and used as input for a focus group session with public managers from four Slovenian public sector organizations. Within this focus group, participants were asked to conduct pairwise comparisons between criteria within each category, as well as between the four categories themselves. The comparisons were based on a standard AHP scale from one to nine: where one indicated equal importance, three indicated moderate preference, five signified strong importance, seven indicated very strong importance, and nine reflected extreme importance of one element over another. These pairwise comparisons allowed managers to express the relative priorities of each criterion based on their professional judgment and experience. This approach ensured that the assessment of AI readiness was not only grounded in established theoretical frameworks but also refined through collective reasoning and expert deliberation, enhancing the analytical robustness of the findings.

Third, we applied AHP to our group decision problem. The quantitative data were analyzed using AHP to determine the weight of various factors influencing organizational readiness for artificial intelligence. Their responses were translated into pairwise comparison matrices. Based on these pairwise comparison matrices, the final weights were calculated using the geometric mean method. As well, we calculated the consistency index (CI) and consistency ratio (CR) to check whether the collected pairwise comparisons are consistent.

Finally, we developed our model (Figure 2), tested it on synthetic cases, and calculated the overall score for the organization.

Figure 2:

Hierarchical decision model



Source: Authors' own, 2025

3.3. Qualitative research design

The qualitative research involved two distinct groups of public managers from Slovenian public sector organizations, using different data collection methods. The first group, consisting of public managers from organizations without AI implementation, participated in semi-structured interviews conducted in May 2024. The second group, composed of public managers from organizations where AI had already been implemented in several key departments, participated in a focus group held in April 2025. This comparative before-and-after design enabled a focused examination of managerial expectations and experiences across different stages of AI integration.

All interviews and the focus group discussion were structured around the POSDCORB framework, allowing for consistent discussion of the core managerial functions. Managers were asked to reflect on how specific tasks—such as planning, reporting, and budgeting—were carried out prior to the adoption of AI and how these tasks had changed following implementation. Particular attention was paid to perceived shifts in autonomy, control by superiors, and the degree of task standardization. The interviews and the focus group were designed to investigate key aspects of the principal–agent relationship in the context of AI integration. In the pre-implementation phase, managers described their expectations about how AI would influence their decision-making authority, oversight from superiors, and alignment with organizational goals. In the post-implementation phase, managers reflected on actual changes to their roles, including whether they felt more closely monitored, whether certain decisions had become more automated, and whether AI tools supported or limited their professional judgment. The comparison between the two groups provided insight into how AI adoption affects task execution, accountability, and perceived discretion across organizational functions. Interview transcripts were thematically coded to identify patterns of change that signal either increased automation or more substantial reliance on human input. These findings were interpreted using the principal–agent lens to assess how AI reshapes managerial agency and controls within a public sector context.

4. Results

4.1. Quantitative research results

Based on expert contributions evaluated using the Analytic Hierarchy Process (AHP), the assessment of AI readiness across public sector managerial functions shows clear priorities in the four main categories. Individual readiness was rated as the most influential category (36.65%), followed by organization (28.38%), technology (18.55%) and environment (16.43%). This distribution reflects the experts' emphasis on people-centric factors, such as employee voluntarism and behavioral intent, which are critical to AI adoption. The low consistency ratio (CR = 0.024) confirms the reliability of these aggregated assessments.

Within the technology category, data (35.36%) emerged as the highest priority criterion, followed by technology infrastructure (26.20%), effort expectation (22.37%), and perceived direct benefit (16.07%). This ranking indicates that basic technical resources and ease of use are considered more important at this stage than the expected benefits of AI adoption.

In the organization category, skills and expertise (27.32%) and innovation and readiness for change (22.38%) were weighted most heavily. In contrast, facilitating conditions (13.51%) and costs and resources received comparatively less importance, highlighting a focus on organizational capabilities and adaptability over structural or financial conditions.

While the environment category was the least important overall, it showed an apparent internal disparity: social influence (71.04%) was prioritized well ahead of state and citizens' factors (28.96%), highlighting the greater influence of internal social pressures compared to external mandates or citizen demands.

Within individual readiness, voluntariness of use (68.16%) was rated significantly higher than behavioral intention to use AI (31.84%), highlighting the critical role of employee autonomy in the adoption of AI in the public sector. The perfect consistency index (CI = 0) for both the Environment and Individual Readiness categories reflects a strong consensus among the experts.

Taken together, these results suggest that AI readiness in the public sector is primarily driven by individual and organizational factors rather than purely technological or environmental factors. The above highlights the importance of developing employee skills, fostering innovation readiness, and voluntary engagement as key components of successful AI integration.

Table 1:

AI readiness weights and consistency indicators

Category	Criterion	Weight (%)
Technology	Data	35.36
Technology	Technology Infrastructure	26.20
Technology	Effort Expectancy	22.37
Technology	Perceived Direct Benefits	16.07
Organization	Skills and Expertise	27.32
Organization	Innovation and Readiness for Change	22.38
Organization	Costs and Resources	19.80
Organization	Leadership	17.00
Organization	Facilitating Conditions	13.51
Environment	Social Influence	71.04
Environment	State and Citizens	28.96
Individual Readiness	Voluntariness of Use	68.16
Individual Readiness	Behavioral Intention to Use AI	31.84

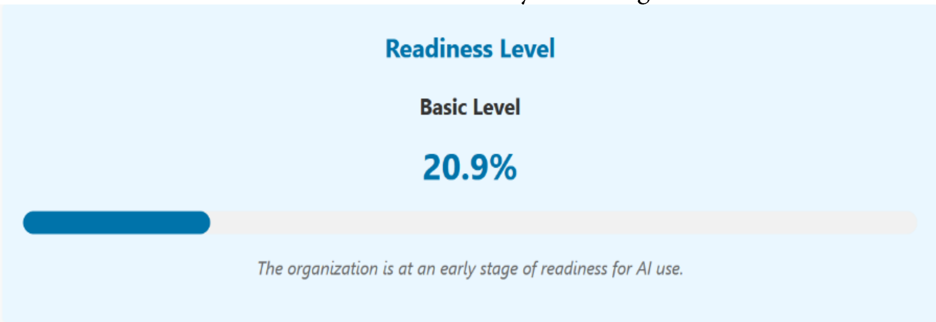
Source: Authors' own, 2025

The proposed decision model is acceptable because it clearly differentiates the alternatives, with apparent point gaps that justify classifying them into meaningful ranking groups or classes. Our synthetic organizations were ranked in three out of five groups, with two synthetic organizations narrowly missing the best group (less than 2%) and the worst group (less than 1%). The proposed decision model is robust. Minor changes do not affect the class boundaries, and the final ranking is consistent with the preferences of public managers. Synthetic organizations that received a high score in the Individual Readiness category received a higher score, which was consistent with the model's preferences.

The decision support system provides two key visual outputs to guide decision makers. The first visual presents the overall assessment result, indicating the organization's current readiness level and identifying the corresponding stage of AI readiness. It offers a clear, high-level overview of where the organization stands in its adoption journey (see Figure 3).

Figure 3:

Current readiness level of synthetic organization 8.

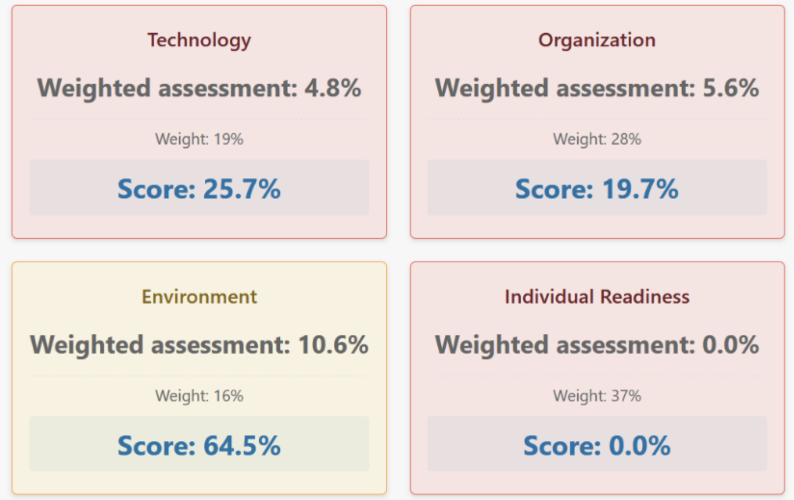


Source: Authors' own, 2025

The second visual breaks down the assessment by category, showing the organization's performance in each of the four categories. It also illustrates how each category's score contributes to the overall readiness score through weighted aggregation. While the displayed weights are rounded to whole numbers for clarity, the actual calculations use precise, unrounded weight values that were gathered in the previous step of research to ensure accuracy (see Figure 4).

Figure 4:

Synthetic organization 8 performance in all four categories



Source: Authors' own, 2025

Based on the assessment results, the system also generated tailored recommendations to support the organization in addressing specific gaps and improving its AI readiness (see figure 5).

Figure 5:

Tailored recommendation for synthetic organization

Source: Authors' own, 2025

4.2. Qualitative research results

This section presents the results of the qualitative study, based on semi-structured interviews and a focus group with public managers from the No AI-implemented and AI-implemented groups within the Slovenian public sector. The findings are structured around the POSDCORB framework and interpreted through the lens of Principal–Agent Theory. The table below provides an overview of the demographic and professional characteristics of the ten public managers interviewed in May 2024 as part of the No-AI-implemented group.

Table 2:
Sample characteristics of public managers (No AI-Implemented, May 2024)

Participant	Gender	Age	Department / Functional Area	Years in Managerial Role
Manager A (Pre)	Male	60	Finance and Budgeting	21
Manager B (Pre)	Female	41	Investment Projects	14
Manager C (Pre)	Male	51	Public Procurement	17
Manager D (Pre)	Male	45	Legal and Administrative Affairs	24
Manager E (Pre)	Male	54	Social Affairs	14
Manager F (Pre)	Female	60	Public Infrastructure	23
Manager G (Pre)	Male	40	Environmental Services	10
Manager H (Pre)	Male	51	Project Management	13
Manager I (Pre)	Male	51	Internal Audit and Risk Management	11
Manager J (Pre)	Female	54	Director of Municipal Administration	10

Source: Authors' own, 2025

The participants' ages ranged from 42 to 60 years (M = 52.40, SD = 5.87). They had substantial experience in managerial roles, with tenures ranging from 10 to 24 years (M = 17.00, SD = 4.64).

The table below presents the sample characteristics of ten public managers who participated in a focus group in April 2025, as part of the AI-implemented group, after AI had been deployed within the same public sector organization.

Table 3:
Sample characteristics of public managers (AI-Implemented, April 2025)

Participant	Gender	Age	Department / Functional Area	Years in Managerial Role
Manager A (Post)	Male	58	Mayor	13
Manager B (Post)	Female	55	Director of Municipal Administration	11
Manager C (Post)	Male	54	Administration, Reception, and Archive	23
Manager D (Post)	Male	54	Social Affairs	15
Manager E (Post)	Female	58	General Administrative Services	15
Manager F (Post)	Male	60	Finance and Budgeting	22
Manager G (Post)	Female	59	Investment Projects	13
Manager H (Post)	Female	42	Investment Projects	15
Manager I (Post)	Female	44	Economic Public Infrastructure	22

Manager J (Post)	Male	58	Spatial Planning (External Consultant)	24

Source: Authors' own, 2025

The participants' ages ranged from 42 to 60 years (M = 53.30, SD = 5.98), reflecting a mature group with established roles in municipal governance. Their tenure in managerial positions ranged from 11 to 24 years (M = 17.00, SD = 4.64), indicating extensive professional experience in public administration and leadership.

Table 4:

Findings and interpretations from the No AI-Implemented Group

POSDCORB Function	Relevant Quotation	Summary of Findings from the No AI-Implemented Group	Principal–Agent Interpretation
Planning	"AI could help prepare more accurate financial forecasts, but I worry it will just be another way for superiors to control us."	Anticipated support for forecasting and alignment, with concerns about increased oversight.	Potential for enhanced principal oversight through predictive analytics may reduce agent discretion.
Organizing	"Standardized processes might save time, but they often miss the context that only I can understand from my experience."	Expected streamlining of workflows, but concern over loss of adaptability.	Standardized workflows could limit agents' flexibility to exercise context-based judgment.
Staffing	"I don't use AI—neither individually nor organizationally—for staffing. I don't trust it with something as sensitive and interpersonal as hiring."	Welcomed objectivity in recruitment, but feared loss of contextual judgment.	AI seen as a way to align evaluation processes with principal expectations, but risks agent disempowerment.
Directing	"If everyone gets guidance from a system, do they still see me as a leader?"	Mixed views on AI assisting vs. diminishing leadership authority.	AI may shift perceived authority from agent-led to system-driven leadership, raising legitimacy concerns.
Coordinating	"We often solve issues with a quick call—I'm not sure AI can replace that informal know-how."	Expected improved data sharing, with concerns about loss of informal coordination.	Formalized coordination could reduce information asymmetry but weaken informal trust-based practices.
Reporting	"I don't use AI—neither individually nor organizationally—for staffing. I don't trust it with something as sensitive and interpersonal as hiring."	Anticipated support in performance tracking, but increased exposure to scrutiny.	Increased transparency supports monitoring but heightens principal control over agents.
Budgeting	"If a mistake happens in an AI-generated budget—am I still the one accountable?"	Optimism about improved forecasting, but concerns over accountability for AI-driven outputs.	Data-driven budgeting may improve accountability but also create new asymmetries in understanding financial decisions.

Source: Authors' own, 2025

Moreover, alongside the analysis of managerial perceptions, the study also examined the availability and planning of AI-related training and education. Interviews with the No AI-implemented group revealed that by May 2024, no structured educational activities —such as workshops, seminars, webinars, or tailored training programs on artificial intelligence or generative AI —had been organized for public sector staff. Nonetheless, there was a growing recognition among managers of the need for such initiatives to support a future transition toward AI-enabled management practices.

Table 5:

Findings and interpretations from the AI-Implemented Group

POSDCORB Function	Relevant Quotation	Summary of Findings from the AI-Implemented Group	Principal–Agent Interpretation
Planning	"I use it to improve sentence structure, not for actual decision-making."	Used mostly for text formatting; limited impact on strategic decisions.	Minimal AI use limits both support and control; agent autonomy remains high but underutilized.
Organizing	"We haven't implemented AI tools collectively yet—it's more of an individual initiative."	No change reported; routines remained manual and based on personal judgment.	No perceived shift in oversight or discretion; traditional agent control persists.
Staffing	"I like help from AI in recruitment—like CV screening—but the final say must always stay with me."	AI not used; decision-making remains human-centered with resistance to change.	Agent-led decisions dominate due to low trust in AI; potential for principal-agent misalignment remains.
Directing	"Sometimes I ask AI tools for ideas, but I always double-check the logic myself."	Concerns about reduced original thinking, though some used AI for idea generation.	AI use for idea generation does not undermine authority, but concern persists about future loss of agent initiative.
Coordinating	"So far, coordination remains manual. Any AI tools—if used—are accessed individually, but there's no shared platform or policy."	No systematic use of AI tools for interdepartmental coordination.	No AI-enabled visibility or integration; agents retain discretion, but coordination remains fragmented.
Reporting	"AI gives me a good first draft, but the final report still reflects my decisions."	AI used for drafting and formatting reports; managers retained final control.	AI increases visibility of reports without challenging agent control; supports minimal oversight.
Budgeting	"We haven't implemented AI in budgeting due to data protection risks. Any experimentation, like testing ChatGPT, has been informal and individual, not embedded into our systems."	AI not integrated with financial tools; low adoption due to legal and technical concerns.	Lack of AI integration maintains agent control but exposes gaps in principal monitoring and compliance systems.

Source: Authors' own, 2025

Managers expressed a preference for future training to be organized in collaboration with specialized private consultants, professional associations, or potentially under the auspices of national ministries. However, insights from the municipal director revealed that the most effective format to date has been cooperation with local government associations such as the Association of Municipalities and Towns of Slovenia (SOS) and the Union of Municipalities of Slovenia (ZOS), which occasionally collaborate with ministries—though not yet in the field of artificial intelligence. While no structured AI-specific education had yet been initiated within the municipality, several employees who showed personal interest had independently attended various lectures and seminars. The municipality generally refrains from organizing tailor-made educational programs solely for its own staff. Instead, it opts to participate in shared offerings coordinated at the national level, particularly through SOS, which is currently searching for a new training provider due to discontinuation with the existing partner. The director emphasized the importance of tailoring educational formats to the varying levels of AI familiarity among staff. On the one hand, some employees are AI novices and would benefit from general awareness-raising sessions.

On the other hand, occasional users are seeking more advanced, in-depth content. To address these needs, the director proposed a model similar to Excel training courses, featuring tiered workshops like "AI Use for Municipalities – Basic Level" and "AI Use for Municipalities – Advanced Level." Online delivery formats were particularly favored, allowing participants to test tools interactively during the session. While the municipality receives many training offers, preference is given to programs specifically adapted to municipal work. Moreover, motivated employees are encouraged to stay informed about AI-related developments and share relevant opportunities with colleagues. The municipality is especially interested in practical applications of AI across various domains—including finance, spatial planning, social services, and executive management.

Furthermore, the table below compares findings from the no AI-implemented and AI-implemented groups, highlighting shifts in task execution and perceived managerial control, and offering interpretations grounded in Principal–Agent Theory.

Table 6:

Comparison of POSDCORB-related findings and principal–agent dynamics

POSDCORB Function	No AI-implemented	AI-implemented	Principal–Agent Comparison
Planning	Anticipated support for forecasting and alignment, with concerns about increased oversight.	Used mostly for text formatting; limited impact on strategic decisions.	Potential for enhanced principal oversight through predictive analytics may reduce agent discretion. / Minimal AI use limits both support and control; agent autonomy remains high but underutilized.
Organizing	Expected streamlining of workflows, but concern over loss of adaptability.	No change reported; routines remained manual and based on personal judgment.	Standardized workflows could limit agents' flexibility to exercise context-based judgment. / No perceived shift in oversight or discretion; traditional agent control persists.
Staffing	Welcomed objectivity in recruitment, but feared loss of contextual judgment.	AI not used; decision-making remains human-centered with resistance to change.	AI is seen as a way to align evaluation processes with principal expectations, but risks agent disempowerment. / Agent-led decisions dominate due to low trust in AI; potential for principal-agent misalignment remains.

Directing	Mixed views on AI assisting vs. diminishing leadership authority.	Concerns about reduced original thinking, though some used AI for idea generation.	AI may shift perceived authority from agent-led to system-driven leadership, raising legitimacy concerns. / AI use for idea generation does not undermine authority, but concern persists about future loss of agent initiative.
Coordinating	Expected improved data sharing, with concerns about loss of informal coordination.	No systematic use of AI tools for interdepartmental coordination.	Formalized coordination could reduce information asymmetry, but weaken informal trust-based practices. / No AI-enabled visibility or integration; agents retain discretion but coordination remains fragmented.
Reporting	Anticipated support in performance tracking, but increased exposure to scrutiny.	AI used for drafting and formatting reports; managers retained final control.	Increased transparency supports monitoring but heightens principal control over agents. / AI increases visibility of reports without challenging agent control; supports minimal oversight.
Budgeting	Optimism about improved forecasting, but concerns over accountability for AI-driven outputs.	AI not integrated with financial tools; low adoption due to legal and technical concerns.	Data-driven budgeting may improve accountability but also create new asymmetries in understanding financial decisions. / Lack of AI integration maintains agent control but exposes gaps in principal monitoring and compliance systems.

Source: Authors' own, 2025

5. Discussion

As far as we know, this is the first study to integrate the TOE and UTAUT frameworks to assess readiness for AI adoption in the public sector. While the TOE framework captures systemic factors that influence technology adoption, it does not address individual-level factors that are essential in a context such as the public sector, where employee behavior plays a crucial role. UTAUT, on the other hand, focuses precisely on these individual acceptance variables. Their integration, therefore, provides a more comprehensive assessment of readiness. The results of the AHP in the combined model reveal that the most important category for AI utilization is individual readiness, followed by organization, then technology, and finally, the environment. In the technology category, data is the most important criterion, followed by technology. The effort expectancy of AI is in third place, and the least important criterion is the perceived direct benefits of AI. In the organization category, the most important criterion is skills and expertise, followed by innovation and readiness for change, then costs and resources, leadership, and finally, facilitating conditions. In the environment category, social influence is much more important than the state and its citizens. In the individual readiness category, voluntariness is much more important than the behavioral intention to use AI.

In addition, the post-implementation evaluation of AI use in local government can be systematically interpreted through the lens of the proposed AHP-based decision model. The model prioritizes the main categories – Individual Readiness (36.65%), Organization (28.38%), Technology (18.55%), and Environment (16.43%) – with multiple criteria, each of which helps explain specific implementation patterns.

Individual readiness and organization together account for more than 65 % of the total weight, suggesting that systemic and behavioral factors are closely linked. The above would be overlooked if either TOE or UTAUT were applied in isolation. This integration offers a novel theoretical approach to modeling readiness and fills an important gap in the literature on AI adoption, where structural and individual factors are often treated separately. It provides a basis for future frameworks that consider the multi-level nature of technological change in the public sector.

Each POSDCORB function is associated with a subset of relevant criteria that shed light on the observed level of AI integration:

- In the case of planning, the relevant criteria include voluntariness of use and behavioral intention to use AI, which reflect individual readiness. Technological aspects are captured through the perceived direct benefits of AI, while organizational factors encompass leadership and the availability of costs and resources. Planning, being inherently strategic and dependent on leadership initiative, currently exhibits limited AI integration. This is primarily due to the perception of AI as a voluntary rather than essential tool, as evidenced by the high global weighting of voluntariness. Additionally, the relatively low value assigned to AI's direct benefits suggests that it is not broadly recognized as a strategic enabler. Organizational constraints, such as a lack of leadership initiative and insufficient resources, further hinder AI adoption in this function.
- Organizing is shaped by criteria such as the behavioral intention to use AI (individual readiness), the availability of data (technological factor), and organizational elements like skills, expertise, and readiness for change. This function depends heavily on structured data flows, technological infrastructure, and competent personnel. Nonetheless, the ongoing reliance on manual processes and subjective judgment signals a weak behavioral intent to adopt AI. This situation is exacerbated by limited data infrastructure and a lack of organizational readiness, indicating that both technological and organizational barriers constrain broader AI integration, despite the moderate potential for automation in this area.
- The function of staffing is governed by the voluntariness of use, which indicates individual readiness, along with organizational characteristics such as innovation readiness and expertise, and the influence of environmental factors, notably social influence. Staffing remains predominantly human-centric and resistant to automation. Employees are not obligated to engage with AI in HR decision-making. This voluntariness, combined with weak organizational readiness for change and limited external or internal pressure, reinforces the continuation of traditional, discretionary practices. The absence of compelling social or institutional drivers diminishes momentum toward transformation in this domain.
- In the directing function, the key criteria are behavioral intention to use AI

(individual readiness), perceived direct benefits (technology), and leadership (organization). While AI is occasionally used for idea generation, signaling a certain degree of openness among employees, the moderate global weight assigned to behavioral intention suggests that adoption remains inconsistent. The perceived lack of strategic value and limited leadership support further suppressed the expansion of AI usage. Persistent concerns about the loss of creativity and human initiative also reduce willingness to integrate AI in leadership and guidance tasks systematically.

- Coordinating relies on technological factors such as data integration, organizational factors like skills and innovation readiness, individual voluntariness, and environmental influences, including social influence. Despite the importance of shared platforms and interdepartmental collaboration, AI is rarely utilized systematically to facilitate coordination. The absence of robust AI tools, coupled with fragmented organizational structures, impedes effective integration. The high degree of voluntariness allows individuals to disengage from AI use, and weak social influence fails to generate the necessary alignment pressure. As a result, coordination processes remain siloed and inconsistent.
- For the function of reporting, the relevant criteria include behavioral intention to use AI (individual readiness), data (technology), and leadership (organization). Reporting tasks, particularly those related to formatting and tracking, present low-risk opportunities for AI integration. The moderate global importance attributed to the behavioral intention to use AI facilitates incremental automation, while structured data systems further support such initiatives. Leadership generally accepts AI involvement in reporting, as long as it does not encroach on strategic authority or decision-making.
- Lastly, budgeting is evaluated through technological readiness, costs and resources (organization), social influence (environment), and voluntariness of use (individual readiness). Among all POSDCORB functions, budgeting exhibits the lowest level of AI adoption. The above is due to a combination of legal and technical obstacles. Although technology is moderately weighted globally, it is insufficient to overcome the perceived legal risks or legacy system constraints. Limited organizational resources and the absence of significant social or institutional encouragement further deter AI investment in budgeting. The predominance of voluntariness once again enables staff to opt out of automation in this sensitive yet essential function.

Moreover, the integration of the AHP and the qualitative component in this study provides strong triangulation that supports the researchers' initial assumptions about the dynamics of AI adoption in public management. Specifically, the study hypothesized that AI would be selectively integrated into managerial functions based on perceived readiness, strategic value, and contextual constraints, and that augmentation—rather than full automation—would be the prevailing mode of engagement. The AHP results confirmed that individual readiness, particularly voluntariness and behavioral intention to use AI, is the most influential factor in determining whether and how AI is implemented. This prioritization was mirrored in the qualitative interviews, where managers consistently emphasized personal attitudes, discretion, and trust as decisive in their willingness to adopt AI tools. Conversely, for functions such as planning and budgeting—assumed initially to benefit from AI support—low levels of actual integration were observed. These findings aligned with lower perceived benefits and organizational barriers identified in the AHP analysis, as well as minimal leadership initiative and resource availability. The methodological convergence thus reinforces the assumption that successful AI adoption is not solely a matter of technological infrastructure. However, it is highly contingent on individual agency, organizational culture, and legal context. Furthermore, the consistent preference for augmentation over automation—particularly in discretion-heavy tasks—validates the theoretical framing of the automation–augmentation paradox as a dynamic rather than binary phenomenon. In sum, the interplay of AHP and qualitative insights confirms that AI adoption among public managers remains cautious, nuanced, and context-sensitive, with augmentation emerging as the more viable and accepted pathway in the current stage of digital transformation in the public sector.

The study provides valuable empirical and theoretical insights into how the integration of AI into public management reshapes managerial functions and alters principal–agent dynamics. Drawing on the POSDCORB framework, the findings reveal that AI's influence is uneven across managerial domains, with its utility most evident in functions like reporting and planning, and least in staffing and budgeting. These patterns align with the nature of tasks embedded in each function and their susceptibility to either standardization or discretion. From the perspective of principal–agent theory, AI has the potential to reduce information asymmetry and monitoring costs, two core dimensions of agency problems, by introducing tools that enhance transparency, real-time reporting, and predictive analytics. The above is particularly visible in the reporting function, where AI was used to assist in drafting documents and formatting outputs, thereby making managerial performance more legible to principals without entirely displacing managerial discretion. Similarly, in planning, although AI was primarily used for low-level formatting rather than strategic foresight, there is potential for enhanced principal oversight through data-driven forecasting. However, these theoretical benefits are mediated by strong institutional and individual-level constraints. In more sensitive or discretionary functions such as budgeting and staffing, AI implementation was minimal due to concerns over legal accountability, lack of trust in algorithmic judgment, and fear of losing human agency.

These findings point to a critical mechanism: while AI can be designed to improve control and alignment in principal–agent relationships, its actual adoption depends on whether agents perceive such technologies as supportive or threatening to their professional judgment and legitimacy. Where AI use is voluntary and unstandardized, managers retain significant discretion, and potential gains in accountability remain unrealized. The interviews of the AI-implemented group further underscore that AI, in its current form, does not fundamentally shift the balance of power in the principal–agent relationship, but may serve as an auxiliary tool in low-risk domains. Interestingly, this becomes relevant when contrasting public and private sector managers, where for the former, autonomy (i.e., freedom from political interference) has been increasingly stressed by the New Public Management revolution, but tends to be in practice comparatively much more limited (Bezes & Jeannot, 2018; Entwistle, 2021). Overall, the study suggests that AI acts as a conditional governance enhancer, and its ability to mitigate agency problems is strongest where tasks are rule-based and measurable, and weakest where human interpretation, normative judgment, and political sensitivity are involved. Thus, the introduction of AI into public management functions reinforces the idea that technological tools cannot be abstracted from the institutional and relational contexts in which they operate. Effective use of AI in public governance, therefore, requires not just technological capability, but also organizational will, legal clarity, and trust between principals and agents.

6. Conclusion

The paper addresses the lack of empirical literature in management science on the effect of AI utilization on managerial functions, as well as on the magnitude and dimensions of the principal-agent problem. Thus, our study contributes to the research on the utilization of AI in public sector organizations, specifically focusing on management functions. The practical value of the research relates to empirical testing of (amended) paradox theory, which suggests that organizations often encounter competing, yet interdependent demands - such as the need for both stability and change, short-term and long-term goals, and control and flexibility. Specifically, AI introduces its own set of paradoxes into managerial work, as managers must balance between human intuition and AI-driven data analytics, centralized control and decentralized automation, and short-term operational efficiency versus long-term strategic innovation. In addition, we focus on testing the specifics related to performing management functions in the public sector. We acknowledge certain specifics in this context, such as the fact that setting goals by public sector managers may take more time and input, as their goals may focus on the feelings and perceptions of the public rather than facts and data alone. They should bear in mind the necessity to pursue public interest, and they have accountability to a larger set of stakeholders, which ultimately alters the nature of their management functions.

From a theoretical perspective, our study contributes to refining the automation–augmentation paradox by demonstrating that AI rarely replaces managerial work but rather reshapes it through subtle and context-specific augmentation. Furthermore, the study extends principal–agent theory by revealing that AI can both mitigate and reinforce asymmetries in information and control, depending on the function and institutional setting. The dual use of inductive and deductive reasoning allowed us to observe empirical patterns emerging from decision-making processes, which we then grounded in established theoretical frameworks, thus enriching the explanatory power of both.

The study makes a practical contribution by providing a structured and actionable decision support model for assessing readiness for AI in the public sector. By integrating Technology-Organization-Environment and the Unified Theory of Acceptance and Use of Technology, we capture both the systemic and individual determinants of technology acceptance. These factors have often been neglected in previous research. We used the Analytic Hierarchy Process (AHP) for the study. The results of the AHP show that individual readiness is the most important factor, followed by organizational, technological and environmental aspects.

For the context of management functions, the results suggest that utilization of AI is particularly preferred for planning, coordinating, reporting and budgeting functions, if we follow the POSDCORB framework. However, it should be of limited relevance when supporting the staffing function. However, while AI utilization may help reduce principal-agent issues related to planning and coordinating by increasing perceived control over agents, this does not apply to the budgeting function. Finally, regarding the (top) management functions, the results of the endeavor suggest that the prevalence is more of an augmentation dimension than an automation dimension within the paradox description, at least when scrutinizing evidence from the public management perspective.

Several limitations should be acknowledged. First, the experimental testing was conducted on a relatively small and context-specific sample of public managers in Slovenia, which may limit the generalizability of the findings to broader or more heterogeneous populations. While the size was adequate for the AHP and group decision-making process, future research should expand the sample size and diversity. Second, the study focused exclusively on managerial perceptions, thus omitting other relevant perspectives such as those of citizens, elected officials, or IT personnel. Third, we observed hints of individual-level concealment behavior – i.e., selective or informal use of AI tools – which may reflect underlying tensions in perceived autonomy and accountability, and which future research should investigate further.

To conclude, this article provides novel empirical and theoretical insights into how AI affects core public management functions, revealing that augmentation, rather than automation, prevails in most managerial tasks, especially where discretion and stakeholder complexity are high future research should also explore the evolution of AI utilization across different phases of implementation and compare how institutional logics, organizational cultures, or policy mandates influence the balance between augmentation and automation.

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References

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press.

Bannister, F., & Connolly, R. (2014). ICT, public values and transformative government: A framework and programme for research. Government Information Quarterly, 31(1), 119–128. https://doi.org/10.1016/j.giq.2013.06.002

Batarseh, F., & Yang, R. (Eds.). (2020). Data democracy: At the nexus of artificial intelligence, software development, and knowledge engineering (1st ed.). Academic Press.

Bezes, P., & Jeannot, G. (2018). Autonomy and managerial reforms in Europe: Let or make public managers manage? Public Administration, 96(1), 3–22. https://doi.org/10.1111/padm.12361

Brock, J. K.-U., & Von Wangenheim, F. (2019). Demystifying AI: What Digital Transformation Leaders Can Teach You about Realistic Artificial Intelligence. California Management Review, 61(4), 110–134. https://doi.org/10.1177/1536504219865226

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. Science, 358(6370), 1530–1534. https://doi.org/10.1126/science.aap8062

By, R. T. (2005). Organisational change management: A critical review. Journal of Change Management, 5(4), 369–380. https://doi.org/10.1080/14697010500359250

Cable, D. M., & DeRue, D. S. (2002). The convergent and discriminant validity of subjective fit perceptions. Journal of Applied Psychology, 87(5), 875–884. https://doi.org/10.1037/0021-9010.87.5.875

Chaturvedi, A., Yadav, N., & Dasgupta, M. (2025). Tech-Driven Transformation: Unravelling the Role of Artificial Intelligence in Shaping Strategic Decision-

Making. International Journal of Human–Computer Interaction, 41(19), 12305–12324. https://doi.org/10.1080/10447318.2025.2456534

Chowdhury, A., & Chandra Shil, N. (2022). Understanding change management in organizational context: Revisiting literature. Management and Entrepreneurship: Trends of Development, 1(19), 28–43. https://doi.org/10.26661/2522-1566/2022-1/19-03

Cordella, A., & Willcocks, L. (2012). Government policy, public value and IT outsourcing: The strategic case of ASPIRE. The Journal of Strategic Information Systems, 21(4), 295–307. https://doi.org/10.1016/j.jsis.2012.10.007

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the Real World. Harvard Business Review, 96(1), 108–116.

Deci, E. L., & Ryan, R. M. (1994). Promoting Self-determined Education. Scandinavian Journal of Educational Research, 38(1), 3–14. https://doi.org/10.1080/0031383940380101

Derrida, J. (1998). Of grammatology (Corrected ed). Johns Hopkins University Press.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. The Academy of Management Review, 14(1), 57–74. https://doi.org/10.2307/258191

Entwistle, T. (2021). Public Management. Routledge. https://doi.org/10.4324/9780429331046

Gagné, M., Forest, J., Gilbert, M.-H., Aubé, C., Morin, E., & Malorni, A. (2010). The Motivation at Work Scale: Validation Evidence in Two Languages. Educational and Psychological Measurement, 70(4), 628–646. https://doi.org/10.1177/0013164409355698

Gauld, R. (2007). PRINCIPAL-AGENT THEORY AND ORGANISATIONAL CHANGE: Lessons from New Zealand Health Information Management. Policy Studies, 28(1), 17–34. https://doi.org/10.1080/01442870601121395

Geisler, E. (1986). Artificial management and the artificial manager. Business Horizons, 29(4), 17–21. https://doi.org/10.1016/0007-6813(86)90018-2

Gillespie, T. (2014). The Relevance of Algorithms. In T. Gillespie, P. J. Boczkowski, & K. A. Foot (Eds.), Media Technologies (pp. 167–194). The MIT Press. https://doi.org/10.7551/mitpress/9780262525374.003.0009

Guggenberger, T., Lämmermann, L., Urbach, N., Walter, A., & Hofmann, P. (2023). Task delegation from AI to humans: A principal-agent perspective. ICIS 2023 Proceedings. https://aisel.aisnet.org/icis2023/hti/hti/13

Gulick, L. H., & Urwick, L. (1937). Papers on the science of administration. Institute of Public Administration. https://dn720003.ca.archive.org/0/items/papersonscienceo00guli/papersonscienceo00guli.pdf

György, A. (2012). Public Sector's Principal-Agent Theory in a Global World. Politeja, 20/3, 101–108.

Hadfield-Menell, D. (2021). The Principal-Agent Alignment Problem in Artificial Intelligence (Technical Report No. UCB/EECS-2021-207; p. 166). University of California. https://www2.eecs.berkeley.edu/Pubs/TechRpts/2021/EECS-2021-207.pdf

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda☆. Technological Forecasting and Social Change, 162, 120392. https://doi.org/10.1016/j.techfore.2020.120392

Holzinger, A. (2016). Interactive machine learning for health informatics: When do we need the human-in-the-loop? Brain Informatics, 3(2), 119–131. https://doi.org/10.1007/s40708-016-0042-6

Hox, J., Moerbeek, M., & Van De Schoot, R. (2010). Multilevel Analysis (0 ed.). Routledge. https://doi.org/10.4324/9780203852279

Huang, Y., Liao, J., & Lin, Z. (2009). A study on aggregation of group decisions. Systems Research and Behavioral Science, 26(4), 445–454. https://doi.org/10.1002/sres.941

Janković, A., & Popović, M. (2019). Methods for assigning weights to decision makers in group AHP decision-making. Decision Making: Applications in Management and Engineering, 2(1), 147–165. https://doi.org/10.31181/dmame1901147j

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Klein, K. J., & Kozlowski, S. W. J. (2000). From Micro to Meso: Critical Steps in Conceptualizing and Conducting Multilevel Research. Organizational Research Methods, 3(3), 211–236. https://doi.org/10.1177/109442810033001

Koivula, K., Shamsuzzoha, A., & Shamsuzzaman, M. (2024). Application of artificial intelligence as a knowledge creation instrument in tax procedures. Engineering Applications of Artificial Intelligence, 133, 108417. https://doi.org/10.1016/j.engappai.2024.108417

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2016). How Artificial Intelligence Will Redefine Management. Harvard Business Review, 2(1). https://hbr.org/2016/11/how-artificial-intelligence-will-redefine-management

Kolt, N. (2025). Governing AI Agents. Notre Dame Law Review, 101, 1–48. https://doi.org/10.2139/ssrn.4772956

Lane, J.-E. (2013). The Principal-Agent Approach to Politics: Policy Implementation and Public Policy-Making. Open Journal of Political Science, 03(02), 85–89. https://doi.org/10.4236/ojps.2013.32012

Lane, J.-E. (2020). The Principal–Agent Approach and Public Administration. In J.-E. Lane, Oxford Research Encyclopedia of Politics. Oxford University Press. https://doi.org/10.1093/acrefore/9780190228637.013.1462

Langley, P., & Simon, H. A. (1995). Applications of machine learning and rule induction. Communications of the ACM, 38(11), 54–64. https://doi.org/10.1145/219717.219768

Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. Government Information Quarterly, 40(1), 101774. https://doi.org/10.1016/j.giq.2022.101774

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. The Academy of Management Review, 20(3), 709. https://doi.org/10.2307/258792

Mikalef, P., Islam, N., Parida, V., Singh, H., & Altwaijry, N. (2023). Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. Journal of Business Research, 164, 113998. https://doi.org/10.1016/j.jbusres.2023.113998

Orsini, J.-F. (1986). Artificial intelligence: A way through the strategic planning crisis? Long Range Planning, 19(4), 71–77. https://doi.org/10.1016/0024-6301(86)90273-6

Ossadnik, W., Schinke, S., & Kaspar, R. H. (2016). Group Aggregation Techniques for Analytic Hierarchy Process and Analytic Network Process: A Comparative Analysis. Group Decision and Negotiation, 25(2), 421–457. https://doi.org/10.1007/s10726-015-9448-4

Pevcin, P., & Debelak, K. (2025). Artificial Intelligence and Public Management: A Systematic Literature Review of the Prevailing Directions of Research. In S. Drezgić, V. Buterin, N. D. Samaržija, A. A. Blecich, & B. Fajdetić (Eds.), Artificial Intelligence and Productivity: Challenges and Opportunities (pp. 145–158). University of Rijeka, Faculty of Economics and Business. https://www.efri.uniri.hr/upload/319.%20sjednica/To%C4%8Dka_3.1._2.pdf

Podsakoff, N. P., Whiting, S. W., Podsakoff, P. M., & Blume, B. D. (2009). Individual- and organizational-level consequences of organizational citizenship behaviors: A meta-analysis. Journal of Applied Psychology, 94(1), 122–141. https://doi.org/10.1037/a0013079

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. Academy of Management Review, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Russell, S. J., Norvig, P., & Davis, E. (2010). Artificial intelligence: A modern approach (3rd ed). Prentice Hall.

Saaty, T. L. (1990). An Exposition of the AHP in Reply to the Paper "Remarks on the Analytic Hierarchy Process." Management Science, 36(3), 259–268. https://doi.org/10.1287/mnsc.36.3.259

Shafiabady, N., Hadjinicolaou, N., Din, F. U., Bhandari, B., Wu, R. M. X., & Vakilian, J. (2023). Using Artificial Intelligence (AI) to predict organizational agility. PLOS ONE, 18(5), e0283066. https://doi.org/10.1371/journal.pone.0283066

Smith, W. K., & Lewis, M. W. (2011). Toward a Theory of Paradox: A Dynamic equilibrium Model of Organizing. Academy of Management Review, 36(2), 381–403. https://doi.org/10.5465/amr.2009.0223

Snijders, T. A. B., & Bosker, R. J. (2012). Multilevel analysis: An introduction to basic and advanced multilevel modeling (2. ed). SAGE.

Sousa, W. G. D., Melo, E. R. P. D., Bermejo, P. H. D. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. Government Information Quarterly, 36(4), 101392. https://doi.org/10.1016/j.giq.2019.07.004

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910

Urs, N., Roja, A., & Nisioi, I. (2024). Digital Transformation in Organizational Management: A Bibliometric Analysis. NISPAcee Journal of Public

Administration and Policy, 17(1), 198–227. https://doi.org/10.2478/nispa-2024-0009

Van Thiel, S., & Smullen, A. (2021). Principals and Agents, or Principals and Stewards? Australian Arms Length Agencies' Perceptions of Arm's Length Government Instruments. Public Performance & Management Review, 44(4), 758–784. https://doi.org/10.1080/15309576.2021.1881803

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the Qualitative–Quantitative Divide: Guidelines for Conducting Mixed Methods Research in Information Systems1. MIS Quarterly, 37(1), 21–54. https://doi.org/10.25300/MISQ/2013/37.1.02

Yoo, D.-H., & Giannetti, C. (2024). A Principal-Agent Model for Ethical AI: Optimal Contracts and Incentives for Ethical Alignment. Discussion Papers, Article 2024/313. https://www.ec.unipi.it/documents/Ricerca/papers/2024-313.pdf

Zuiderwijk, A., Janssen, M., & Dwivedi, Y. K. (2015). Acceptance and use predictors of open data technologies: Drawing upon the unified theory of acceptance and use of technology. Government Information Quarterly, 32(4), 429–440. https://doi.org/10.1016/j.giq.2015.09.005