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A Dual-Level Model of AI Readiness in the Public Sector: Merging Organizational and Individual Factors Using TOE and UTAUT

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Abstract

Artificial intelligence (AI) is increasingly transforming the public sector, although the willingness of organizations to adopt such technologies varies widely. Existing models, such as the technology–organization–environment (TOE) model, highlight systemic drivers and barriers but overlook the individual-level factors that are also critical to successful adoption. To address this gap, we propose a decision model that combines the TOE model with the unified theory of acceptance and use of technology (UTAUT) and combines the dimensions of technology, organization, environment, and individual readiness. The model was developed using the Analytic Hierarchy Process (AHP) and supports group decision-making by combining the pairwise comparison matrices of multiple experts into a consolidated priority structure. Specifically, many expert judgments were used to create a group matrix for the four main categories and four additional group matrices for the criteria within each category. This structured approach allows for a systematic assessment of whether a public sector organization is ready for AI adoption. The results show the importance of both systemic factors (such as data, technology, innovation, and readiness for change) and individual factors (such as social influence and voluntariness of use). The final model provides a comprehensive and practical decision-making tool for public sector organizations to assess readiness, identify gaps, and guide the strategic adoption of AI.

Keywords: unified theory of acceptance and use of technology (UTAUT); technology–organization–environment (TOE); Analytic Hierarchy Process (AHP); group decision-making

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1. Introduction

Over the past four decades, AI has moved from a laboratory curiosity to a general-purpose technology that is reshaping how organizations plan, decide, and deliver value. Early debates in management science framed AI as a tool for relieving managers of data-intensive routines so they could concentrate on strategy [1,2]. More recent scholarship argues that the real promise lies in augmentation: humans and machines collaborating so that algorithms execute repetitive analytics while managers apply judgment, negotiate trade-offs, and engage stakeholders [3,4]. In the public sector, this promise is even more compelling because governments must balance efficiency gains with fairness, transparency, and accountability. COVID-19 put that tension in sharp relief: agencies that had already embedded AI in forecasting, triage, or service-delivery systems were faster

at pivoting policies and reallocating resources [5,6]. Yet comparative studies show that public organizations lag behind private firms in systematic AI deployment, owing to legal constraints, fragmented data, and limited change-management capacity [7]. Moreover, it has been acknowledged that much less has been written on various organizational and socio-technological challenges of public organizations in general in comparison to private ones [8,9].

AI adoption in government is shaped by normative commitments that have no direct analog in business. Mandates for due process, equal treatment, and public scrutiny restrict the use of opaque "black-box" models and raise the stakes of algorithmic error [10,11]. At the organizational level, risk-averse cultures, budget cycles, and political oversight slow down experimentation, while at the macro level, governments face mounting pressure to modernize frontline services and regulatory enforcement [12,13]. From the public management perspective, a hierarchical way of delivering services prevails and joint decision-making in the form of collaborative governance is promoted [8]. Conceptual ambiguity adds another hurdle: commentators routinely invoke AI as a catch-all label for everything from rules-based process automation to self-learning generative models, making it hard to compare cases or design targeted interventions. What is labeled as public management is itself an evolving, interdisciplinary construct that blends economics, administration, data science, and law; its boundaries and success criteria are still contested. These factors create a dual knowledge gap: we lack both a clear vocabulary for "AI readiness" in public administration and a diagnostic instrument that accounts for institutional, technological, and behavioral dimensions.

To close this gap, we propose a dual-level model of AI readiness that combines the technology–organization–environment (TOE) framework [14] with the unified theory of acceptance and use of technology (UTAUT; [15]). TOE captures systemic enablers such as IT infrastructure, organizational culture, and regulatory climate, while UTAUT explains how perceived usefulness, effort expectancy, and social influence drive individual uptake. Merging these lenses allows us to diagnose whether structural conditions and human attitudes are aligned for successful AI adoption. Because readiness involves multiple, partly qualitative criteria, we operationalize the model with the Analytic Hierarchy Process (AHP), a well-established multi-criteria decision-making (MCDM) technique that derives consistent priority weights from pairwise expert judgments [16]. Prior work has validated AHP in public-sector technology selection, including digital government dashboards and blockchain-enabled procurement [17–19]. We extend that line of research by applying AHP to an integrated TOE–UTAUT hierarchy and testing it with municipal decision-makers.

The resulting model advances scholarship and practice simultaneously: it bridges the digital–government, public–management, and technology–acceptance literature through an empirically prioritized hybrid framework, and it equips managers with a transparent tool for spotting capability gaps and allocating resources to data, infrastructure, or training. Municipal governments—often resource-constrained yet under strong pressure to digitalize—stand to benefit most from this evidence-based roadmap. Ultimately, this study supports responsible, citizen-centered, and accountable AI integration in public administration.

The following research questions guide this paper:

- RQ1: How can a comprehensive multi-criteria decision-making model be developed to assess organizational readiness to adopt AI in public administration?
- RQ2: What technological, organizational, environmental, and individual factors influence this readiness?
- RQ3: How can these factors be structured and weighted to support strategic decision-making in the public sector?

- RQ4: How does the integration of TOE and UTAUT frameworks enhance the robustness and relevance of AI readiness assessments?

The remainder of the paper is organized as follows: Section 2 surveys the literature on public-sector AI adoption and MCDM applications; Section 3 details the TOE, UTAUT, and AHP foundations and describes the research design; Section 4 applies the proposed model in a two-round expert evaluation across Slovenian municipalities; Section 5 presents and discusses the results; and Section 6 concludes with managerial implications and future research avenues.

2. The Literature Review

The integration of AI into public-sector operations is a fast-moving research frontier because of AI's promise to boost efficiency, effectiveness, and public value. Explaining why some agencies adopt AI while others resist, therefore, requires models that capture both general technology predispositions and system-specific perceptions (see Table 1). Early studies relied on the Technology Acceptance Model (TAM; [20]), which explained roughly 37% of variance in behavioral intention through perceived usefulness and perceived ease of use. Subsequent versions progressively addressed TAM's limitations: TAM2 added social influence and cognitive instrumental processes, lifting explanatory power; TAM3 introduced antecedents of ease/usefulness (e.g., computer self-efficacy), raising the variance explained to about 40–53% [21,22]. In parallel, the Technology Readiness Index (TRI; [23]) captured an individual's general predisposition toward new technologies; its latest form, TRI 2.0, condensed the original 36 items to 16 while retaining the two enablers (optimism and innovativeness) and two inhibitors (discomfort and insecurity) that segment citizens and employees into readiness profiles [24]. Bridging these two approaches, the Technology Readiness and Acceptance Model (TRAM; [25]) integrates TRI and TAM to explain how readiness beliefs shape perceptions of usefulness and ease of use, offering a more holistic view of user acceptance of emerging technologies like AI.

The most comprehensive stream emerged with the unified theory of acceptance and use of technology (UTAUT; [15]), which integrates eight predecessor models and, with its moderators (age, gender, experience, and voluntariness), can account for up to 70% of intention variance—substantially higher than any single TAM iteration. Its consumer-oriented extension, UTAUT2, broadened the lens beyond organizational settings by adding hedonic motivation, price value, and habit [26]. Comparative reviews show distinct strengths: the TAM family excels at diagnosing perceptions of a specific system during organizational rollouts; TRI 2.0 is useful for segmenting general technology predispositions in citizen or employee populations; and UTAUT/UTAUT2 provides the highest predictive validity when contextual moderators are salient.

Building on these insights, our study adopts UTAUT, rather than TAM3 or TRI 2.0, as the individual-level layer of a dual-level readiness model because (i) UTAUT offers the greatest explanatory power, (ii) its moderator set aligns with public-sector heterogeneity (e.g., tenure-based voluntariness), and (iii) its constructs map cleanly onto the organizational and environmental factors captured by the technology–organization–environment (TOE) framework. By nesting UTAUT within TOE and operationalizing their combined constructs through the Analytic Hierarchy Process, we provide a multi-criteria decision model that can diagnose whether a public agency is structurally and behaviorally prepared for AI adoption.

Table 1. AI adaptation models.

Model Name and Version	Authors	Year	Key Constructs
TAM (Original)	[20]	1989	Perceived usefulness (PU) Perceived ease of use (PEOU)
TAM2	[21]	2000	PU + PEOU Subjective norm Image Job relevance Output quality Result demonstrability Moderators: experience, voluntariness
TAM3	[22]	2008	TAM2 constructs Antecedents of PEOU: computer self-efficacy, anxiety, playfulness Anchors and adjustments for PEOU/PU
TRI (Original)	[23]	2000	Optimism Innovativeness Discomfort Insecurity
TRI 2.0	[24]	2015	Optimism Innovativeness Discomfort Insecurity (streamlined to 16 items)
UTAUT (Original)	[15]	2003	Performance expectancy Effort expectancy Social influence Facilitating conditions Moderators: age/gender/experience
UTAUT2	[26]	2012	UTAUT constructs Hedonic motivation Price value Habit
TRAM	[25]	2005	TRI dimensions TAM constructs

Moreover, for the literature review, we used papers from the Web of Science, which we found using the search parameters "AI acceptance" AND "public sector" AND ("TOE framework" OR "UTAUT model") AND "decision models". As mentioned in [27], the Web of Science is widely regarded as the world's leading platform for retrieving the scientific literature and citation-based analysis. We chose Web of Science because its strengths lie in its broad coverage of the scholarly literature, robust citation analysis tools, and ability to track the impact of research without sacrificing historical coverage and focus on traditional science disciplines. In addition, Web of Science may be better suited for searching and analyzing Open Access resources at the publication level [28].

The search initially yielded 100 records. We added an additional record identified from a different source. Based on an assessment of full-text relevance, five papers were selected for final inclusion. The remaining 96 records were excluded based on relevance, conceptual orientation, and methodological suitability (see Figure 1).

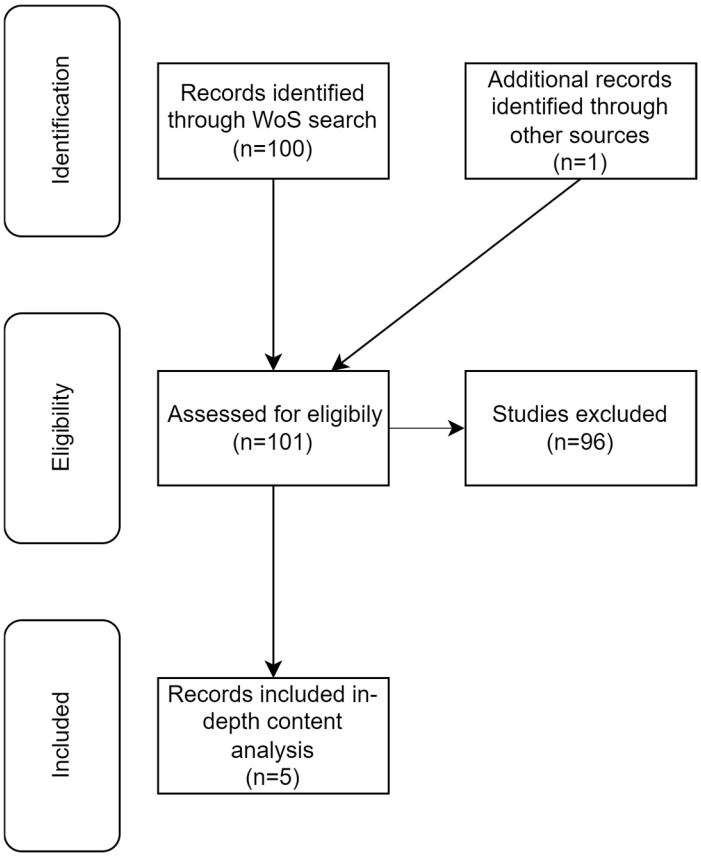


Figure 1. PRISMA diagram presenting the selection of included studies.

The five studies examined various aspects of AI adoption and acceptance of AI in governmental and organizational contexts.

Specifically, they address the following:

(1) The impact of AI-enabled services on citizen satisfaction in government agencies [19];
(2) The factors that influence the trust and perceived usefulness of AI-based HR tools among professionals [29];
(3) Citizens' acceptance of AI in the delivery of public services [30];
(4) The perception and willingness of government employees to support the use of AI technologies [17];
(5) The determinants of the acceptance of AI technologies by employees within organizations [31].

These studies include a range of stakeholders—including citizens, public sector employees, and HR professionals—and overall provide valuable insight into the challenges and opportunities associated with the adoption of AI in the public sector.

While these studies provide a broad understanding of stakeholder perspectives, they focus largely on individual acceptance and attitudes and do not provide a comprehensive framework for assessing organizational readiness to adopt AI. This highlights the need for an integrated multi-criteria decision-making model that considers both organizational and individual factors, as proposed in our study.

As can be seen from the literature, none of the studies examined explicitly uses a decision-making model to assess the readiness for artificial intelligence. The existing research focuses primarily on individual perceptions, citizen acceptance, or the impact of AI adoption rather than the organizational determinants that influence readiness for AI implementation—especially in the public sector.

The identified research gap is the lack of a comprehensive and structured framework for assessing AI readiness at the organizational level. No study uses multi-criteria decision-making (MCDM) methods to assess and weigh the relative importance of different readiness criteria. While some papers refer to theoretical models such as UTAUT or TOE, they often do so in isolation. The lack of integration between these frameworks limits the explanatory and predictive power of existing models.

To address this gap, this study proposes a hybrid decision model that combines the technology–organization–environment (TOE) framework with the unified theory of acceptance and use of technology (UTAUT). This approach enables the inclusion of both systemic organizational factors and individual readiness variables. In addition, the model incorporates MCDM techniques—in particular, the Analytic Hierarchy Process (AHP)—to derive weightings for each criterion, thus supporting evidence-based, transparent, and context-sensitive assessments of organizational readiness to adopt AI in public administration.

AHP was selected as the central decision-making method for this study because it has proven to be effective in addressing complex, multi-criteria decision problems and can systematically quantify the judgments of experts. This approach is particularly well-suited for modeling organizational readiness to adopt AI, where different factors—technological, organizational, environmental, and individual dimensions—need to be prioritized within a hierarchical structure. AHP facilitates the decomposition of the decision problem, supports the consistency check of expert contributions, and enables the aggregation of multiple expert judgments into a coherent group decision. The application of AHP has been proven in previous research on technology adoption, digital transformation, and strategic planning in the public sector, which underlines its suitability for this context. For example, it has been used to evaluate the quality of AI-generated digital educational resources using the combined Delphi method and AHP [32], to prioritize corruption-prone stages in public procurement for blockchain integration [33], and to identify critical success factors for BIM implementation [34]. Furthermore, studies such as ceramic antenna manufacturing [35] demonstrate the use of AHP within the TOE framework, similar to the hybrid approach adopted in our study. Another study, such as chatbot adoption intention in the public sector [36], highlights a real-world gap where user-level perspectives could be added. Building on this established methodology, our study contributes to a novel application of AHP to assess the organizational readiness to adopt AI in the public sector while integrating the TOE and UTAUT frameworks to capture both systemic and individual determinants. Integrating both TOE and UTAUT frameworks is a viable methodology for assessing different technological, organizational, environmental, and individual factors influencing the adoption of a new technology [37,38].

3. Methodology

3.1. Research Design

This study adopts a multi-level, empirical approach to assess AI readiness in public sector organizations, with a specific focus on Slovenian municipalities. The unit of analysis includes both the organizational level (municipal administration) and the individual level (municipal managers), in alignment with the dual-level conceptual framework proposed in this paper. This structure enables the integration of individual perceptions (as captured through the AHP-based questionnaire) into a broader organizational readiness assessment.

The research unfolded in two sequential rounds, each designed to support instrument refinement, data consistency, and model robustness. In Round 1, a small municipality served as a pilot site, where 10 managers completed the online survey on 1 April 2025. In addition to providing data, respondents were asked to offer feedback on questionnaire

clarity and logic, which informed the final design. This round served to test the usability and reliability of the AHP decision model in a real-world administrative context.

In Round 2, the refined instrument was distributed to four additional municipalities—ranging from small to medium size—with 19 completed responses collected between 3 April and 11 June 2025. The selection of municipalities was purposive, ensuring variability in the population size (from <10,000 to >40,000 residents), digital maturity, and AI exposure. The data collection was conducted via the 1 ka platform, using email invitations. Respondents evaluated AI readiness criteria using pairwise comparisons on a 1–9 scale, based on the AHP methodology. On average, completion time was approximately 20 min.

Sample: descriptive statistics (see Table 2).

Table 2. Descriptive statistics.

Indicator	Value
Average Age	46.9
Min Age	25.0
Max Age	65.0
Average Total Tenure (years)	21.4
Min Total Tenure	3.0
Max Total Tenure	35.0
Female (%)	62.5
Male (%)	31.2
Non-disclosed Gender (%)	3.1
University Degree (%)	56.2
Master's Degree (%)	31.2
Secondary or Lower (%)	9.4
Leadership Role (%)	21.9
High ICT Skills (%)	21.9
Good ICT Skills (%)	62.5
Average ICT Skills (%)	12.5

The dataset included 29 respondents from Slovenian municipalities. The average respondent age was 46.9 years, ranging from 25 to 65 years. The average total work experience (tenure) was 21.4 years, with values ranging from 3 to 35 years. The sample comprised 62.1% women, 31.0% men, and 6.9% of respondents who did not disclose their gender. In terms of educational attainment, 51.7% held a university degree, 34.5% held a master's degree or specialization, and 13.8% had a secondary or vocational degree. Only 20.7% of participants held a leadership role. Regarding self-assessed digital competencies, 20.7% rated their ICT skills as very high, 62.1% as good, and 13.8% as average. These descriptive characteristics indicate a relatively experienced, predominantly female, and well-educated sample with moderate leadership responsibilities and strong digital readiness—an important factor for AI adoption readiness assessments.

To ensure analytical rigor, we implemented several quality controls. Consistency ratios (CR) were calculated for each participant and for the aggregated matrices, with only responses meeting the threshold of CR < 0.10 included in the analysis. Priority weights for each AI-readiness criterion were derived using the eigenvector method, and geometric mean aggregation was used to synthesize group-level judgments. A sensitivity analysis was

conducted by perturbing local weights ±10% and computing the impact on global priorities. Kendall's W was also calculated to assess the level of agreement across municipalities.

The validity and reliability of the instrument were addressed through multiple strategies: (1) content validity was verified through expert review by two digital government scholars and one senior municipal CIO; (2) construct reliability was confirmed with a Cronbach's α of 0.91 in the pilot round; and (3) internal consistency was strong, with group-level CR values of 0.024 (Round 1) and 0.004 (Round 2). To assess non-response bias, we compared early and late responders using *t*-tests on key priority weights, finding no significant differences ($p > 0.10$).

This study complied with all relevant ethical standards: participation was voluntary, informed consent was obtained, and all data were stored on an encrypted university server in line with GDPR regulations. By structuring the research in two iterative phases and ensuring methodological transparency, this study builds a robust and replicable empirical foundation for understanding and supporting AI adoption in the public sector.

3.2. Method

Firstly, to determine the relative importance of the factors identified within these frameworks, this study applies the Analytic Hierarchy Process (AHP) [39]. According to previous research, the AHP is well-suited to be used in group decision problems and conflict resolution. The creator of AHP argues that pairwise comparisons are essential for measuring intangible factors and deriving relative scales [39,40]. However, the AHP has faced criticism for potentially producing arbitrary rankings [41]. Despite this, AHP is a widely used method for group decision-making [42], offering several advantages as it allows for the aggregation of individual judgments or priorities using geometric or arithmetic means [43,44]. AHP can prioritize elements, establish key measures, and provide more accurate judgments in business decisions [45]. The method incorporates consistency tests to improve response quality [45]. Various approaches exist for assigning weights to decision-makers, including the geometric mean method (GMM) and eigenvector method [42,46], which will be used in our case.

3.3. Proposed Model

The proposed decision model for assessing organizational readiness for AI was developed as a hierarchical, tree-like structure that embeds thirteen criteria into four categories—namely, technology, organization, environment, and individual readiness. The proposed decision model comprises four categories: technology, organization, and environment, derived from the TOE framework, and individual readiness, derived from the UTAUT model. The TOE framework is well-suited for assessing external and organizational factors that influence technology adoption as it focuses on technological, organizational, and environmental factors. However, the TOE framework does not explicitly address individual-level factors that are critical to understanding user acceptance and readiness, especially in the public sector, where acceptance often depends on employee attitudes and behavior.

To address this gap, the proposed model includes individual readiness based on UTAUT, which was specifically developed to explain individual technology acceptance and use. UTAUT includes constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, which are directly relevant to assessing whether people are ready, willing, and able to adopt and use new technologies. By integrating the individual level of UTAUT with the organizational and contextual aspects of TOE, the proposed model provides a comprehensive view of AI readiness that captures both the systemic (TOE) and human (UTAUT) dimensions of adoption.

Secondly, we created a structured questionnaire that was distributed to municipal managers. In this structured questionnaire, we asked managers to rate the relative importance of each criterion and category. They were asked to make pairwise comparisons between the criteria in each category and pairwise comparisons between all four categories. Managers had to rate each comparison on a scale of one to nine, where one meant that both criteria were equally important; three meant that the first criterion was moderately more important than the second; five meant that the first criterion was significantly more important than the second; seven meant that the first criterion was very significantly more important than the second; and nine meant that the first criterion was extremely more important than the second. Managers used pairwise comparisons to prioritize the evaluation criteria. Manager participation was voluntary, respondents were informed of the purpose of our study, and anonymity and confidentiality were guaranteed so we did not influence their judgment in the pairwise comparison.

Third, since our questionnaire was distributed to numerous municipal managers and we conducted numerous pairwise comparisons, we applied AHP to our group decision problem. 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. Finally, we calculated the consistency index (CI) and consistency ratio (CR) to check whether the collected pairwise comparisons are consistent.

Lastly, we developed our model and tested it on synthetic cases (see Figure 2). Figure 3 shows the general structure of the decision support model.

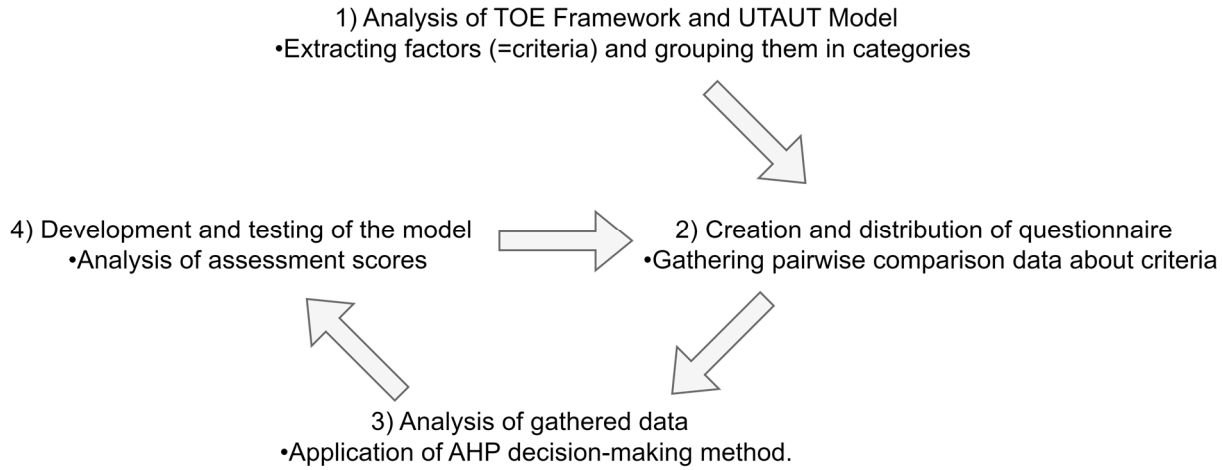


Figure 2. Steps to create and test proposed decision model.

After collecting the managers' questionnaire responses, we analyzed them using AHP [40]. First, we created the pairwise comparison matrices. For each level (e.g., criteria), we constructed a reciprocal matrix,

$$A = [a_{ij}] \quad (1)$$

where

- a_{ij} represents the relative importance of element I compared to element j;
- $a_{ji} = 1/a_{ij}$ and $a_{ii} = 1$.

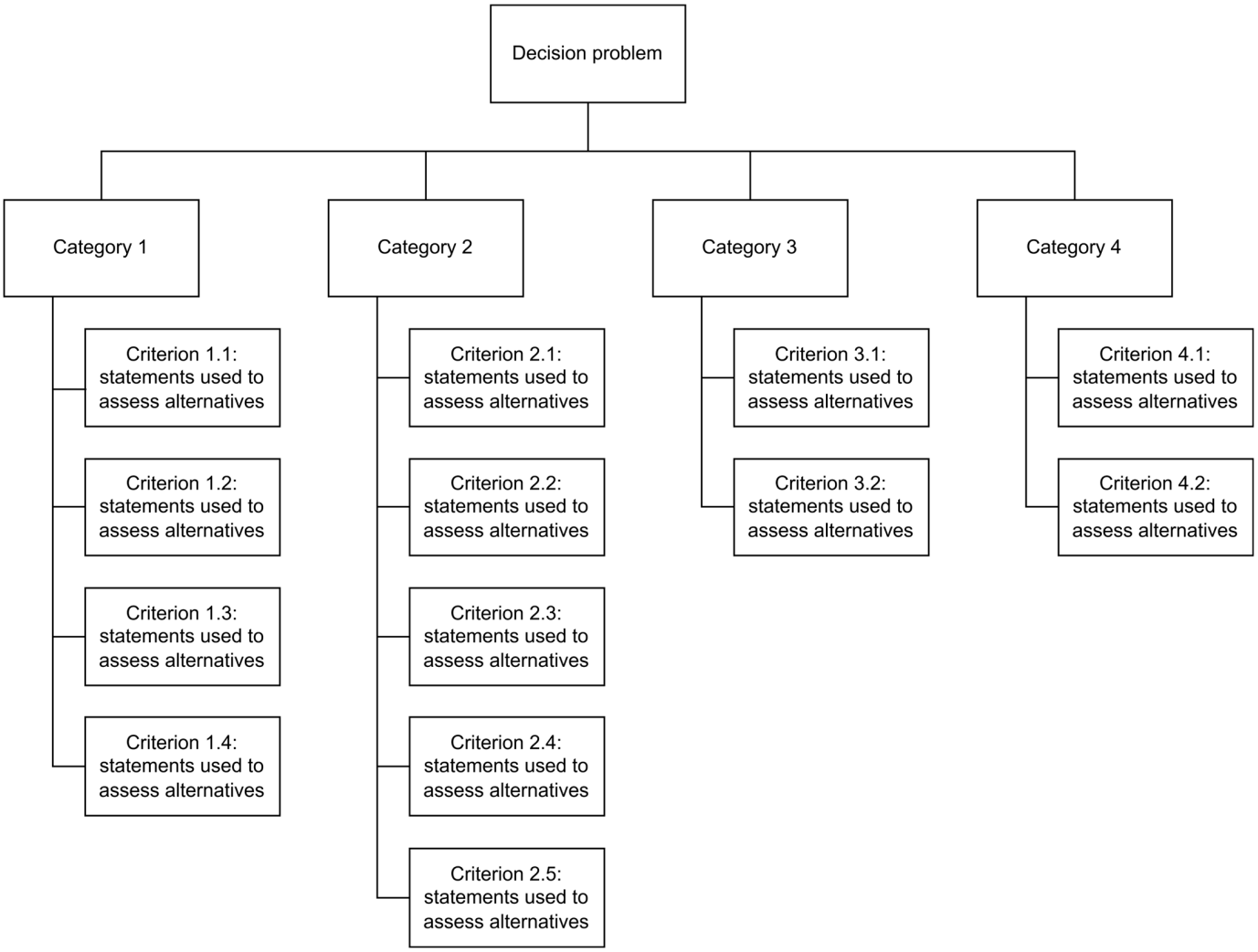


Figure 3. Hierarchical decision model.

Once we had created pairwise comparison matrices for all respondents, we aggregated the individual judgments using the geometric mean and combined the pairwise-comparison matrices into a single matrix. We then normalized these new matrices and calculated priority vectors. By calculating the priority vectors, we obtained a weighting for each category and for all criteria used in our decision model. The priority vectors (weights) were calculated using the eigenvector method:

Let

$$A * w = \lambda_{max} * w \tag{2}$$

where

- A is the comparison matrix;
- w is the eigenvector of priorities;
- λ_{max} is the maximum eigenvalue of matrix A.

We normalized the resulting eigenvector w so

$$\sum_{i=1}^{n} w_i = 1 \tag{3}$$

Once we calculated the lambda max, we calculated the CI. We used the principal eigenvalue, lambda max, calculated from

$$\lambda_{max} = \frac{1}{n}\sum_{i=i}^{n}\left(\frac{(A*w)_i}{w_i}\right) \quad (4)$$

The consistency index was then computed as follows:

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (5)$$

Finally, we calculated the consistency ratio:

$$CR = \frac{CI}{RI} \quad (6)$$

where RI is the random index that depends on the matrix size n, shown in Table 3.

Table 3. Values of random index.

n	RI
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

All calculations, including aggregation, normalization, eigenvalue approximation, and consistency checks, were implemented in Microsoft Excel. User-defined formulas based on the standard AHP method were used, enabling transparent and reproducible calculation of weights and consistency measures.

If CI is 0, the pairwise comparisons are perfectly consistent; if CI is close to 0, most pairwise comparisons are largely consistent, which is also acceptable. If CI > 0.1, the pairwise comparisons are too inconsistent, and a review is required. The situation is similar to the CR. Matrices with CR < 0.1 are considered sufficiently consistent. The whole procedure was also repeated for the second-level criteria.

We also calculated global weights for all criteria:

$$gw_{cij} = w_{ci} * w_{cij} \quad (7)$$

The attributes at the lowest level (i.e., the basic attributes) have a scale with yes/partially/no options/values, i.e., for each basic criterion presented, a question is defined that must be answered on a yes/partially/no scale. This three-point scale is translated into numerical values 1 (yes), 0.5 (partially), and 0 (no).

The overall score of the organization is calculated with a bottom-up approach using the weighted average. In general, we first calculate the score for the first-level categories:

- Score for the category technology is calculated as follows:

$$S_{c1} = \sum_{j=1}^{n} e_{c1j} * w_{c1j} \quad (8)$$

- Score for the category organization is calculated as outlined below:

$$S_{c2} = \sum_{j=1}^{n} e_{c2j} * w_{c2j} \quad (9)$$

- Score for the category environment is calculated as follows:

$$S_{c3} = \sum_{j=1}^{n} e_{c3j} * w_{c3j} \quad (10)$$

- Score for the category individual readiness is calculated as detailed below:

$$S_{c4} = \sum_{j=1}^{n} e_{c4j} * w_{c4j} \quad (11)$$

Finally, we calculate the overall score for the organization.

- Overall score for the organization:

$$S_0 = \sum_{j=1}^{m} S_{ci} * w_{ci} \quad (12)$$

All the variables used are explained in Table 4.

Table 4. Variables used in the evaluation of organizational readiness for artificial intelligence.

Variables	Explanation
S_0	final score of the organization
S_{ci}	score for category i
S_{c1}	score for category technology
S_{c1}	score for category organization
S_{c1}	score for category environment
S_{c1}	score for category individual readiness
e_{C1j}	end user assessment for an alternative under criterion j of category technology
e_{C2j}	end user assessment for an alternative under criterion j of category organization
e_{C3j}	end user assessment for an alternative under criterion j of category environment
e_{C4j}	end user assessment for an alternative under criterion j of category individual readiness
w_{ci}	global weight of category i
w_{c1j}	local weight of criterion j within category technology
w_{c2j}	local weight of criterion j within category organization
w_{c3j}	local weight of criterion j within category environment
w_{c4j}	local weight of criterion j within category individual readiness
gw_{cij}	global weight of criterion j in category i.
i	1, 2, . . ., m number of top-level categories
j	1, 2, . . ., n number of criteria in that subcategory

The resulting overall score is a normalized value between 0 and 1, which we express as a percentage (0–100%) for clarity and interpretability, as is common in AHP-based decision models. This percentage represents the relative proximity of the organization to full readiness for artificial intelligence adoption.

The readiness of an organization for artificial intelligence is based on the overall percentage (0–100%). There are five readiness levels, namely initial level (0–20%), basic

level (20.1–40%), developing level (40.1–60%), advanced level (60.1–80%), and optimized level (80.1–100%) (see Table 5).

Table 5. Readiness levels based on the overall percentages.

Readiness Level	Percentages
Initial level	0–20%
Basic level	20.1–40%
Developing level	40.1–60%
Advanced level	60.1–80%
Optimized level	80.1–100%

The initial level means that the organization is not yet ready for the implementation of AI. An organization that has achieved enough points to be classified at the basic level is at an early stage of readiness for the use of AI. An organization that is rated at the developing level is an organization that is moving towards readiness for AI implementation. Organizations that are well-prepared for AI implementation are classified at an advanced level. Organizations that are fully prepared for the implementation and optimization of AI use are classified at the "optimized" level.

4. Results

4.1. Structure of the Decision Model

Figure 4 below presents the proposed decision model. The proposed decision model is hierarchical and consists of four categories, namely technology, organization, environment, and individual readiness. Each category consists of several criteria that are relevant for assessing an organization's readiness to adopt AI.

To support a consistent and meaningful assessment, each criterion is operationalized through a set of guiding statements that the decision-maker considers during the assessment process. These statements serve to clarify the intent and scope of each criterion to ensure that the assessments are based on a common understanding of the underlying dimensions being assessed.

The following list presents all the criteria grouped under their respective categories, along with their associated guiding statements.

1. 1. Technology
    a. 1.1. Perceived direct benefits of artificial intelligence
        i. 1.1.1. The use of artificial intelligence is beneficial for the municipality;
        ii. 1.1.2. The use of artificial intelligence will enable the municipality to perform analyses faster;
        iii. 1.1.3. The use of artificial intelligence will increase efficiency and effectiveness in performing municipal tasks;
        iv. 1.1.4. The use of artificial intelligence will help improve data accuracy;
        v. 1.1.5. The use of artificial intelligence will help improve data security;
        vi. 1.1.6. The use of artificial intelligence will help reduce administrative errors.
    b. 1.2. Effort expectancy of artificial intelligence
        i. 1.2.1. It will be easy for municipal employees to acquire the skills needed to use artificial intelligence;
        ii. 1.2.2. Learning to use artificial intelligence will be easy for municipal employees;

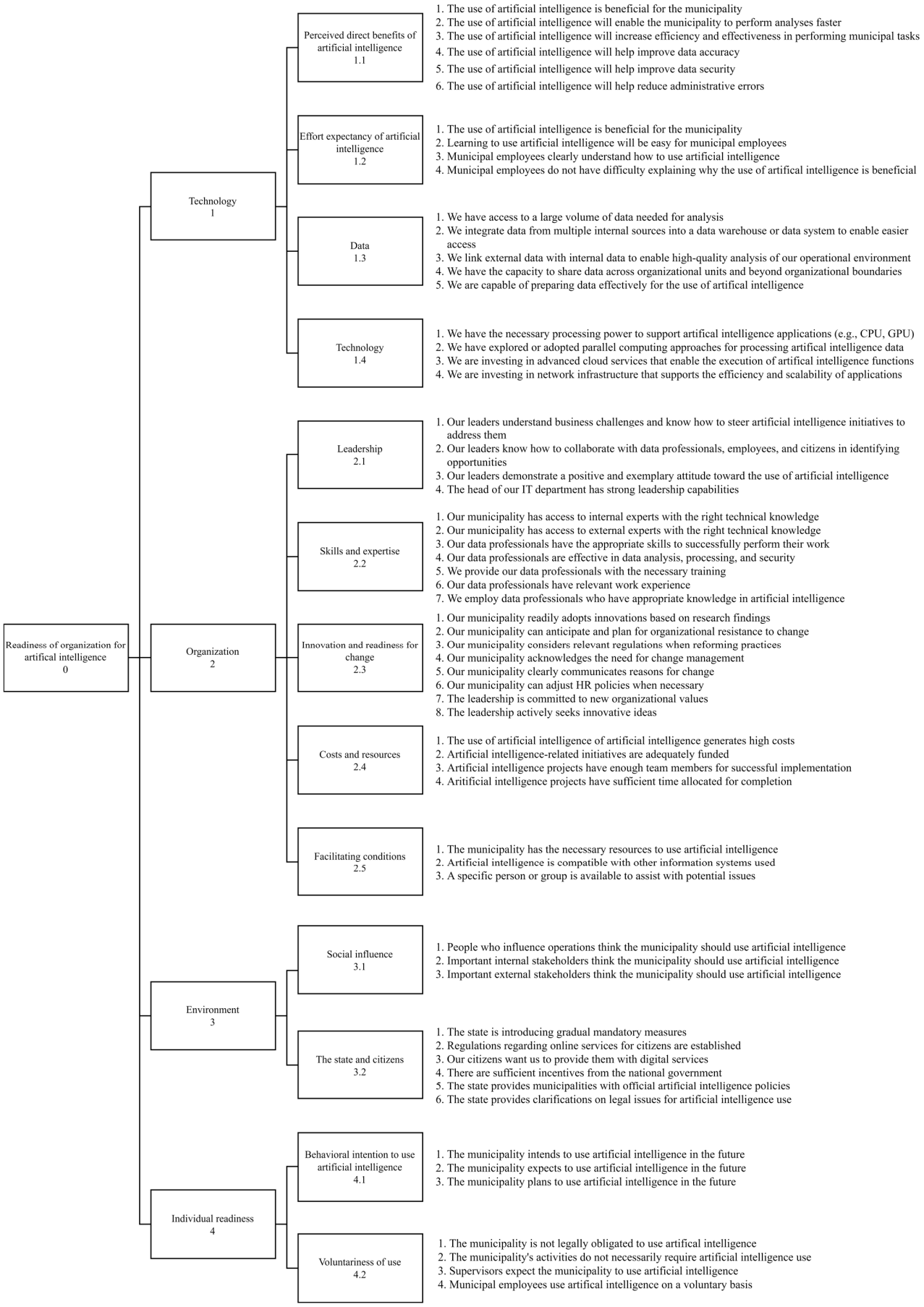


Figure 4. Proposed decision model.

iii. 1.2.3. Municipal employees clearly understand how to use artificial intelligence;
iv. 1.2.4. Municipal employees do not have difficulty explaining why the use of artificial intelligence is beneficial.

c. 1.3. Data
i. 1.3.1. We have access to a large volume of data needed for analysis;
ii. 1.3.2. We integrate data from multiple internal sources into a data warehouse or data system to enable easier access;
iii. 1.3.3. We link external data with internal data to enable high-quality analysis of our operational environment;
iv. 1.3.4. We have the capacity to share data across organizational units and beyond organizational boundaries;
v. 1.3.5. We are capable of preparing data effectively for the use of artificial intelligence.

d. 1.4. Technology
i. 1.4.1. We have the necessary processing power to support artificial intelligence applications (e.g., CPU, GPU);
ii. 1.4.2. We have explored or adopted parallel computing approaches for processing artificial intelligence data;
iii. 1.4.3. We are investing in advanced cloud services that enable the execution of artificial intelligence functions;
iv. 1.4.4. We are investing in network infrastructure that supports the efficiency and scalability of applications.

2. 2. Organization
a. 2.1. Leadership
i. 2.1.1. Our leaders understand business challenges and know how to steer artificial intelligence initiatives to address them;
ii. 2.1.2. Our leaders know how to collaborate with data professionals, employees, and citizens in identifying opportunities;
iii. 2.1.3. Our leaders demonstrate a positive and exemplary attitude toward the use of artificial intelligence;
iv. 2.1.4. The head of our IT department has strong leadership capabilities.

b. 2.2. Skills and abilities
i. 2.2.1. Our municipality has access to internal experts with the right technical knowledge;
ii. 2.2.2. Our municipality has access to external experts with the right technical knowledge;
iii. 2.2.3. Our data professionals have the appropriate skills to successfully perform their work;
iv. 2.2.4. Our data professionals are effective in data analysis, processing, and security;
v. 2.2.5. We provide our data professionals with the necessary training;
vi. 2.2.6. Our data professionals have relevant work experience;
vii. 2.2.7. We employ data professionals who have appropriate knowledge in AI.

c. 2.3. Innovation and readiness for change
i. 2.3.1. Our municipality readily adopts innovations based on research findings;
ii. 2.3.2. Our municipality can anticipate and plan for organizational resistance to change;

iii. 2.3.3. Our municipality considers relevant regulations when reforming practices;
iv. 2.3.4. Our municipality acknowledges the need for change management;
v. 2.3.5. Our municipality clearly communicates reasons for change;
vi. 2.3.6. Our municipality can adjust HR policies when necessary;
vii. 2.3.7. The leadership is committed to new organizational values;
viii. 2.3.8. The leadership actively seeks innovative ideas.

d. 2.4. Costs and resources
   i. 2.4.1. The use of artificial intelligence generates high costs;
   ii. 2.4.2. Artificial intelligence-related initiatives are adequately funded;
   iii. 2.4.3. AI projects have enough team members for successful implementation;
   iv. 2.4.4. AI projects have sufficient time allocated for completion.

e. 2.5. Facilitating conditions
   i. 2.5.1. The municipality has the necessary resources to use artificial intelligence;
   ii. 2.5.2. Artificial intelligence is compatible with other information systems used;
   iii. 2.5.3. A specific person or group is available to assist with potential issues.

3. 3. Environment
   a. 3.1. Social influence
      i. 3.1.1. People who influence operations think the municipality should use AI;
      ii. 3.1.2. Important internal stakeholders think the municipality should use AI;
      iii. 3.1.3. Important external stakeholders think the municipality should use AI.
   b. 3.2. The state and the citizens
      i. 3.2.1. The state is introducing gradual mandatory measures;
      ii. 3.2.2. Regulations regarding online services for citizens are established;
      iii. 3.2.3. Our citizens want us to provide them with digital services;
      iv. 3.2.4. There are sufficient incentives from the national government;
      v. 3.2.5. The state provides municipalities with official AI policies;
      vi. 3.2.6. The state provides clarifications on legal issues for AI use.

4. 4. Individual readiness
   a. 4.1. Behavioral intention to use artificial intelligence
      i. 4.1.1. The municipality intends to use artificial intelligence in the future;
      ii. 4.1.2. The municipality expects to use artificial intelligence in the future;
      iii. 4.1.3. The municipality plans to use artificial intelligence in the future.
   b. 4.2. Voluntariness of use
      i. 4.2.1. The municipality is not legally obligated to use artificial intelligence;
      ii. 4.2.2. The municipality's activities do not necessarily require AI use;
      iii. 4.2.3. Supervisors expect the municipality to use artificial intelligence;
      iv. 4.2.4. Municipal employees use artificial intelligence on a voluntary basis.

In the next subsection, the results gathered will be presented.

4.2. Outputs of the Decision Model

The data collected using questionnaires and analyzed using the AHP decision method are presented in the following tables and figures. The values for the weights (priority vectors), consistency index (CI), and consistency ratio (CR) were calculated based on the formulas described in the Methodology Section (see Section 3.3. Proposed Model, Equations (2)–(6).

Specifically,

- The weights were derived using the principal eigenvector of the aggregated pairwise comparison matrices;
- CI was calculated $CI = \frac{\lambda_{max} - n}{n-1}$;
- CR was calculated as $CR = \frac{CI}{RI}$, where RI is the random index.

Table 6 shows the weights, CI, and CR of the categories at level 1. After the first round of data gathering, the most important criterion based on managers' responses to the questionnaire is individual readiness, the second most important is organization, the third is technology, and the least important is the environment. The consistency index and consistency ratio are below 0.1, which means that they are sufficiently consistent. After the second round of data gathering, the criteria weights and ranking changed. The most important criterion is still individual readiness, and the second most important is organization. Environment and technology change order, where environment is now the third most important criterion, and the least important criterion is technology. The consistency index and consistency ratio also stayed below 0.1.

Table 6. Weights, CI, and CR for first level.

Variable	Category	Weight—First Round	Weight—Second Round
w_{C1}	Technology	18.5%	18.0%
w_{C2}	Organization	28.4%	29.5%
w_{C3}	Environment	16.4%	20.1%
w_{C4}	Individual readiness	36.6%	32.3%
CI_1	Consistency index	0.022	0.0036
CR_1	Consistency ratio	0.024	0.004

In the technology category (Table 7), criterion importance ranking after the first round of data gathering is as follows: data are the most important criterion; technology is in second place; the effort expectancy of artificial intelligence is in third place; and the least important criterion is the perceived direct benefits of artificial intelligence. Consistency index and consistency ratio are 0.043 and 0.047, respectively, which means that the weights are sufficiently consistent.

Table 7. Weights, CI, and CR for category technology.

Variable	Category	Weight—First Round	Weight—Second Round
w_{C11}	Perceived direct benefits of artificial intelligence	16.1%	21.4%
w_{C12}	Effort expectancy of artificial intelligence	22.4%	23.8%
w_{C13}	Data	35.4%	31.4%
w_{C14}	Technology	26.2%	23.4%
CI_{C1}	Consistency index	0.043	0.0024
CR_{C1}	Consistency ratio	0.047	0.0027

After the second round of data gathering, the importance of the criteria has changed. Data are still the most important criterion, effort expectancy of artificial intelligence is second, closely followed by technology, and the least important is the perceived direct benefits of artificial intelligence. Consistency index and consistency ratio change to 0.0024 and

0.0027, respectively, which means that as they stayed below 0.1, the weights are sufficiently consistent.

Table 8 shows the weights, CI, and CR in the organization category. After the first round of data gathering, the most important criterion is skills and expertise, the second is innovation and readiness for change, the third is costs and resources, the fourth is leadership, and the least important criterion is facilitating conditions. Weights are sufficiently consistent as the consistency index and consistency ratio are below 0.1. After the second round of data gathering, the most important criterion becomes innovation and readiness for change; the second is skills and expertise; the third criterion is leadership; fourth is facilitating conditions; and the least important criterion is costs and resources. Consistency index is 0.0052 and consistency ratio is 0.0046, which means that weights are sufficiently consistent.

Table 8. Weights, CI, and CR for category organization.

Variable	Category	Weight—First Round	Weight—Second Round
w_{C21}	Leadership	17.0%	19.5%
w_{C22}	Skills and expertise	27.3%	22.5%
w_{C23}	Innovation and readiness for change	22.4%	26.2%
w_{C24}	Costs and resources	19.8%	14.7%
w_{C25}	Facilitating conditions	13.5%	17.1%
CI_{C2}	Consistency index	0.032	0.0052
CR_{C2}	Consistency ratio	0.029	0.0046

The environment category (Table 9) has only two criteria, and after both rounds of data gathering, social influence is much more important than the state and citizens.

Table 9. Weights, CI, and CR for category environment.

Variable	Category	Weight—First Round	Weight—Second Round
w_{C31}	Social influence	71.0%	61.9%
w_{C32}	The state and citizens	29.0%	38.1%
CI_{C3}	Consistency index	0	0
CR_{C3}	Consistency ratio	0	0

Table 10 shows the weights and the consistency ratio for the category individual readiness. After both rounds of data gathering, voluntariness is much more important than the behavioral intention to use artificial intelligence. Tables 9 and 10 also show a perfect CI and CR, which means that all pairwise judgments are perfectly aligned.

Table 10. Weights, CI, and CR for category individual readiness.

Variable	Category	Weight—First Round	Weight—Second Round
w_{C41}	Behavioral intention to use artificial intelligence	31.8%	38.3%
w_{C42}	Voluntariness of use	68.2%	61.7%
CI_{C4}	Consistency index	0	0
CR_{C4}	Consistency ratio	0	0

Table 11 shows the global weights and ranks for all criteria, based on both rounds of data collection. These weights were calculated using the hierarchical aggregation formula, shown in Equation (7), in which the local weight of each criterion was multiplied by the weight of its parent category to obtain its global weight.

Table 11. Global weights for all criteria.

Variable	Category	Global Weight—First Round	Global Rank—First Round	Global Weight—Second Round	Global Rank—Second Round
w_{C11}	Perceived direct benefits of artificial intelligence	3.0%	13th	3.8%	13th
w_{C12}	Effort expectancy of artificial intelligence	4.1%	11th	4.3%	10–11th
w_{C13}	Data	6.6%	5th	5.6%	8th
w_{C14}	Technology	4.9%	8th	4.2%	12th
w_{C21}	Leadership	4.8%	9–10th	5.8%	7th
w_{C22}	Skills and expertise	7.8%	4th	6.6%	6th
w_{C23}	Innovation and readiness for change	6.3%	6th	7.7%	4–5th
w_{C24}	Costs and resources	5.6%	7th	4.3%	10–11th
w_{C25}	Facilitating conditions	3.8%	12th	5.1%	9th
w_{C31}	Social influence	11.7%	2nd–3rd	12.5%	2nd
w_{C32}	The state and citizens	4.8%	9–10th	7.7%	4–5th
w_{C41}	Behavioral intention to use artificial intelligence	11.7%	2nd–3rd	12.4%	3rd
w_{C42}	Voluntariness of use	25.0%	1st	20.0%	1st

In both rounds, the three most important criteria remained the same: voluntariness of use, social influence, and behavioral intention to use artificial intelligence. These criteria have the greatest influence on the overall readiness score due to their high global weights. In addition, three other criteria are worth mentioning: skills and expertise (from the first round of data gathering), innovation and readiness for change, and the state and citizens (after both rounds of data gathering). The criterion skills and expertise exceeded the average global weight in the first round of data gathering, while innovation and readiness for change and the state and citizens exceeded the average in the second round of data gathering.

Figures 5 and 6 show the assessment results for all synthetic organizations after the first round of data gathering based on four categories on a radar chart. The radar chart shows the score on a scale from 0 to 100 for each organization it received in the corresponding category.

The final assessment results after the first round of data gathering for our synthetic cases can be seen in Figures 7 and 8. The colors of the bars depend on the readiness classes the synthetic organization is in.

The proposed decision model is acceptable as it provides a clear differentiation between the alternatives, with clear point gaps that justify their classification into meaningful ranking groups or classes. Our synthetic organizations were ranked in three out of five groups, with one synthetic organization narrowly missing the worst group (less than 1%). The proposed decision model is robust. Minor changes do not affect the class boundaries, and it is consistent as the final ranking matches the preferences of municipal 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.

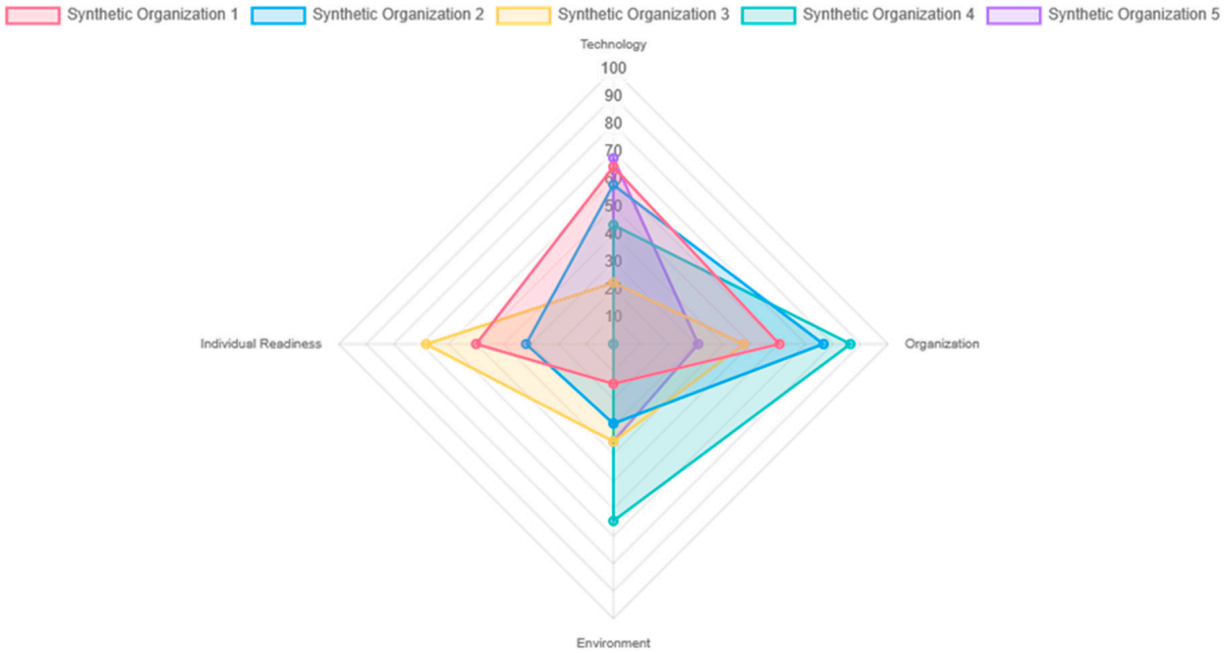


Figure 5. Assessment scores for synthetic organizations 1–5 for all four categories—first round.

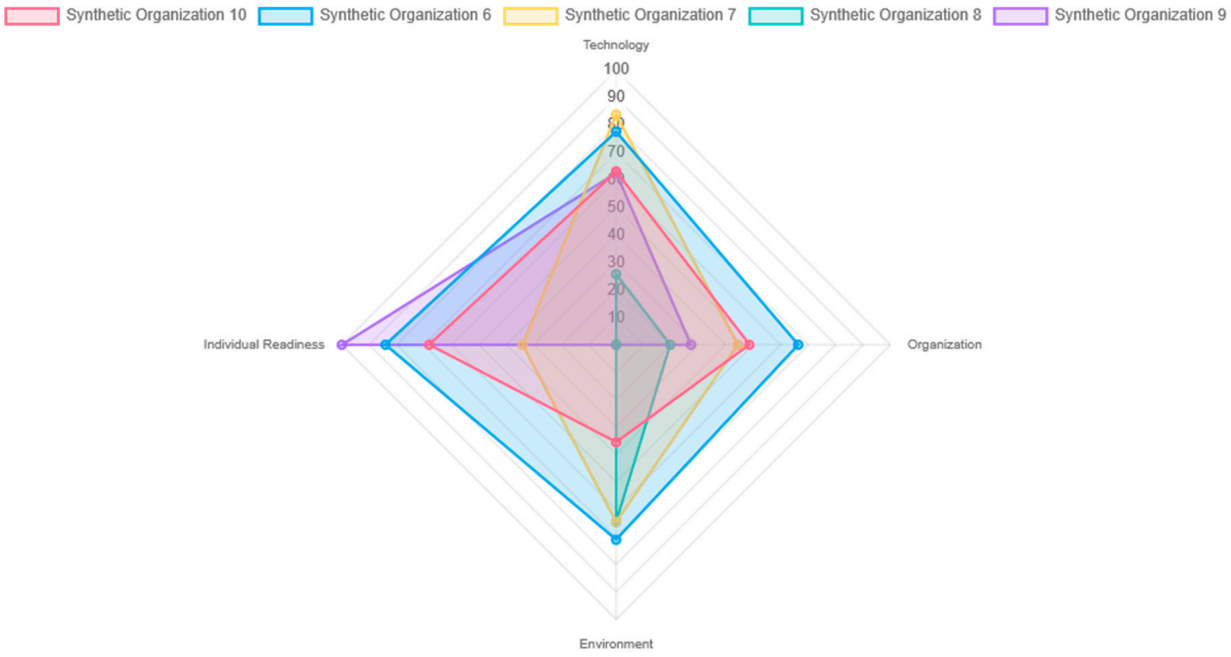


Figure 6. Assessment scores for synthetic organizations 6–10 for all four categories—first round.

Figures 9 and 10 show the assessment results after the second round of data gathering for all synthetic organizations based on four categories or a radar chart. The radar chart shows the score on a scale from 0 to 100 for each organization it received in the corresponding category.

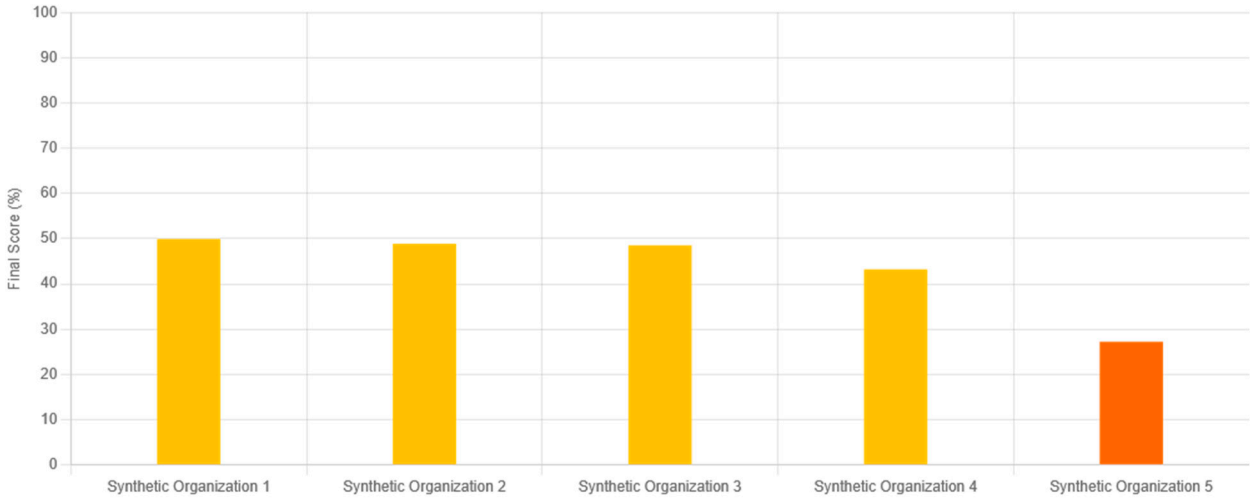


Figure 7. Final assessment scores for synthetic organizations 1–5—first round.

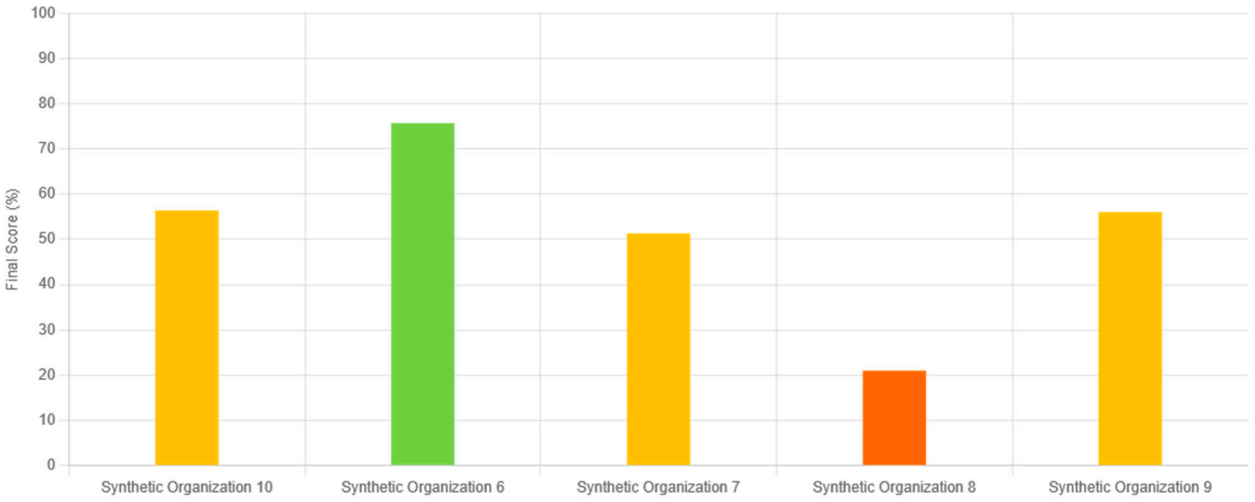


Figure 8. Final assessment scores for synthetic organizations 6–10—first round.

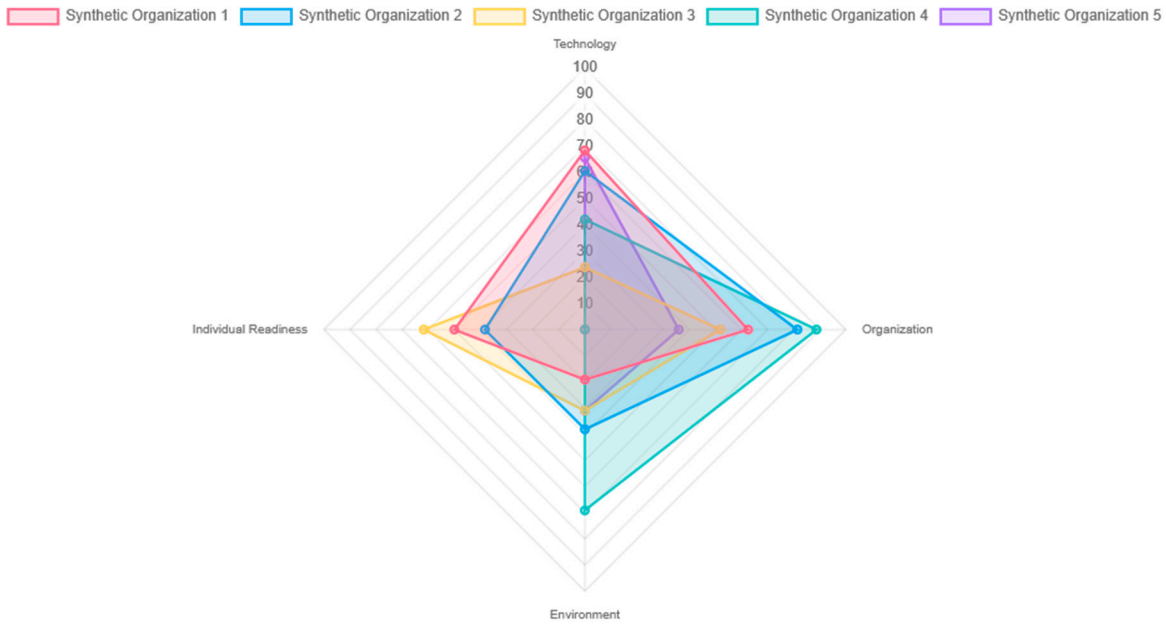


Figure 9. Assessment scores for synthetic organizations 1–5 for all four categories—second round.

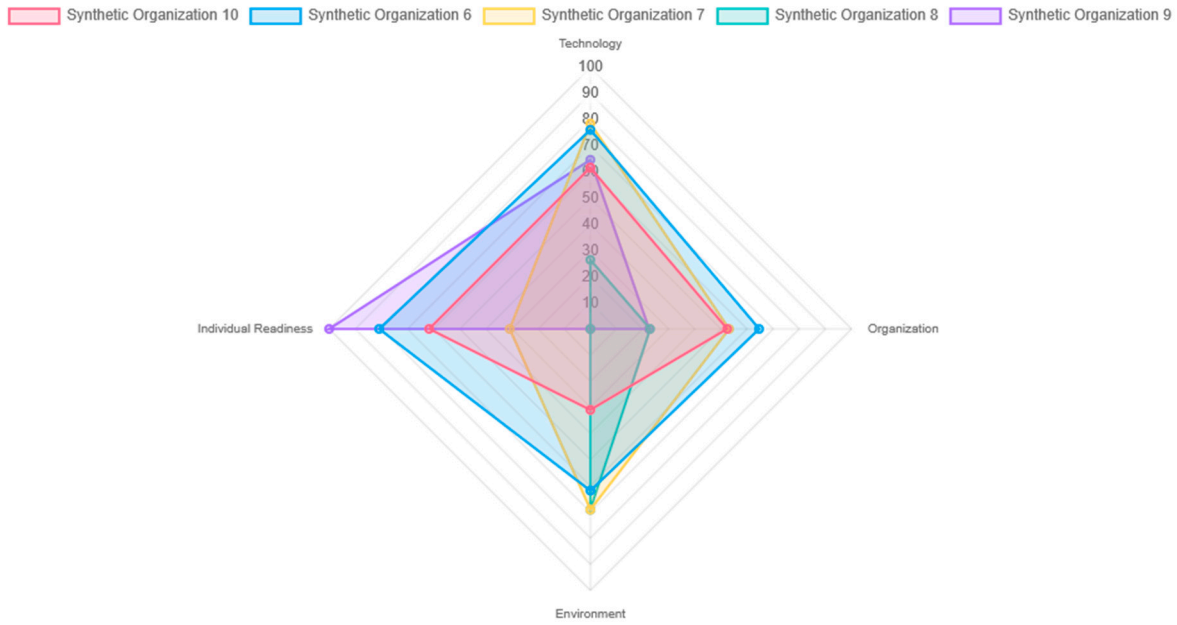


Figure 10. Assessment scores for synthetic organizations 6–10 for all four categories—second round.

The final assessment results after the second round of data gathering for our synthetic cases can be seen in Figures 11 and 12. The colors of the bars depend on the readiness classes the synthetic organization is in.

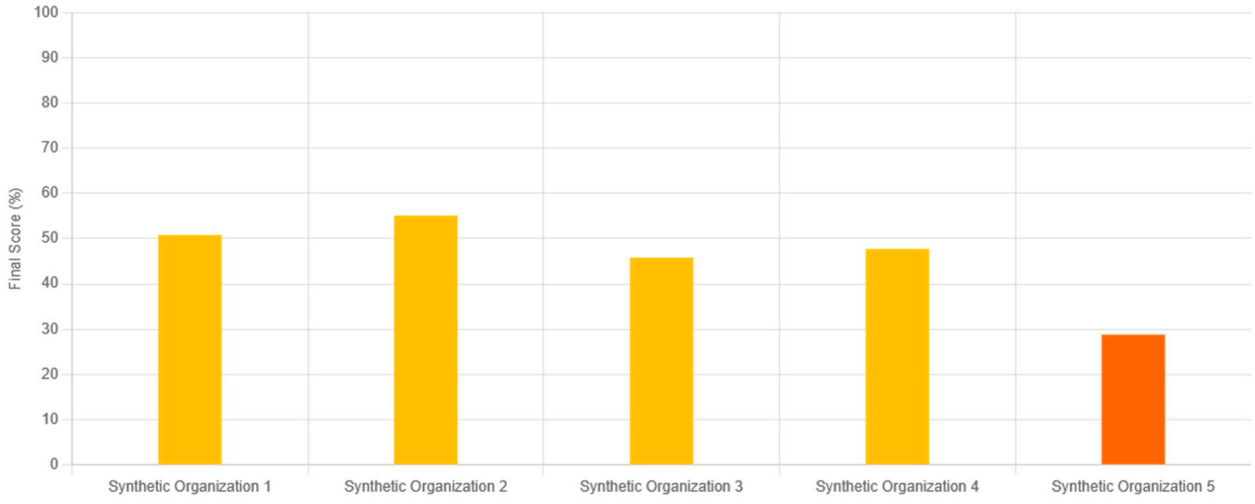


Figure 11. Final assessment scores for synthetic organizations 1–5—second round.

After the second round of data gathering, the results changed a little bit; this difference was due to the updated weights. The proposed decision model provides a clear differentiation between the alternatives, with clear point gaps that justify their classification into meaningful ranking groups or classes. Our synthetic organizations were still ranked in three out of five groups, although the overall difference between the best and the worst synthetic organization is lower because the criteria are more evenly weighted (see Table 11). We can see that minor changes do not affect the class boundaries, and they are consistent as the final ranking matches the preferences of municipal managers.

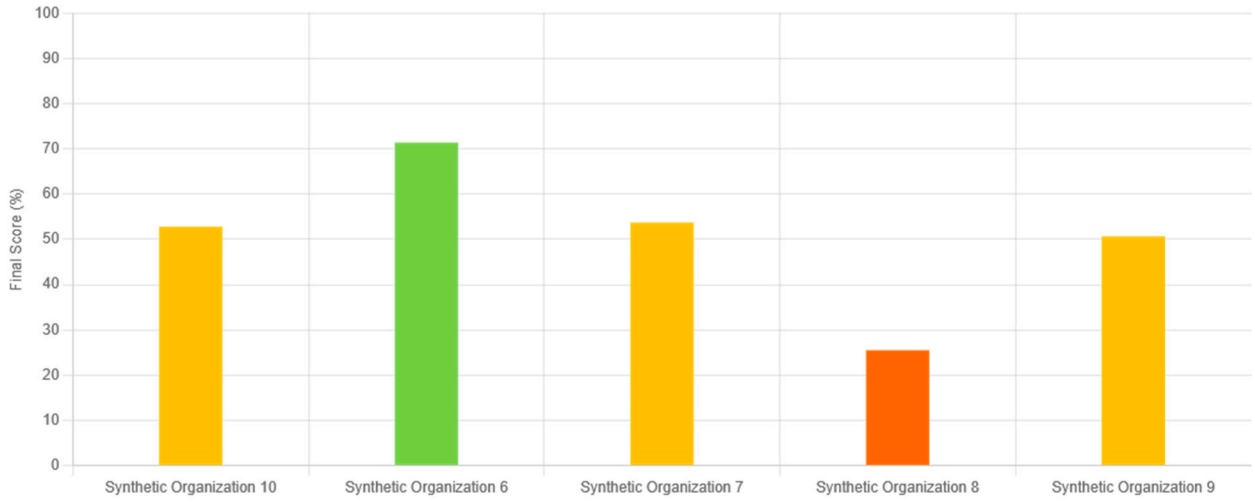


Figure 12. Final assessment scores for synthetic organizations 6–10—second round.

5. Discussion

This study developed and empirically validated a dual-level model for assessing AI readiness in the public sector by combining the TOE framework and the AHP method. By integrating individual-level perceptions with organizational-level decision structures, the model enables systematic prioritization of readiness factors relevant to public administration.

The proposed model addresses notable gaps in the literature. First, while much of the existing research on AI adoption has focused on private-sector contexts or technical implementations, few studies provide a structured, multi-level framework for public managers. The scrutinization of AI implementation in a Belgian public trade agency has pointed out that AI adoption must be supported by organizational change and intangible investments (e.g., training and the redesign of workflows) [47]. An EU-wide survey of public managers—involving integration of UTAUT and TOE frameworks—has pointed out that organizational factors (leadership support, innovative culture, and having a clear AI strategy) are the strongest drivers of AI adoption, and successful AI adoption requires both competence development and governance innovation [48]. Similarly, the analysis involving selected Swiss public sector organizations, and focusing on TOE dimensions, has pointed out that technology fit and organizational culture are the most critical dimensions for the adoption of AI, whereas environmental factors like public trust, transparency, and regulatory compliance are shaping the implementation of AI [49].

Clearly, there has been a lack of integrated approaches focusing on the intentions to use AI, focusing on the public sector context; and the focus of those studies has been mostly on factor identification, i.e., exposition of drivers and inhibitors of AI utilization. By providing a structured, multi-level framework for public managers, this work contributes to ongoing debates at the intersection of digital government, public sector innovation, and decision-support systems. The AHP-based tool developed here offers a transparent mechanism for diagnosing readiness and informing resource allocation, particularly useful in small and medium-sized municipalities and other similar public organizations, which often face constraints in available expertise and infrastructure. In addition, it shall make judgments and calculations easy because of paired comparisons, and it enables multi-criteria decision-making, as portrayed by the evidence from its practical utilization elsewhere [50]. Furthermore, we have extended the approach by considering the dynamic context induced by stages—the approach proposed as highly warranted by [51]. We have also focused

on the application of AHP to the areas where this approach is less frequently applied, as suggested by [52,53].

Second, from a theoretical perspective, this study extends the TOE framework by incorporating behavioral variables from UTAUT into a multi-level operational model tailored to public administration, thereby addressing another notable gap in the literature. Namely, although there has been a tendency recently, although not sufficiently documented yet, to combine UTAUT and TOE (i.e., technology–organization–environment theory and the unified theory of acceptance and use of technology) frameworks, there has been a lack of empirical investigations practically evaluating it. The push for this integration has been motivated by the fact that this enhances predictive power and provides a multi-dimensional view of specific technology adoption behavior under investigation. According to the systematic review of overlaps and distinctions among these two frameworks, it has been emphasized that no single framework is universally sufficient, and integration offers a more nuanced understanding of adoption dynamics, enabling more accurate, context-sensitive predictions. Namely, while UTAUT captures user-centric variables, TOE adds depth by considering structural and contextual constraints, and integration becomes especially useful for tailoring adoption strategies to specific sectors [54].

It needs to be stressed that these kinds of integration procedures have been rather scarce in the literature, focusing on different technologies, and supporting more TOE-based factors. For instance, ref. [55] have provided a ten-factor framework of four contexts from both TOE and UTAUT to provide insights into technology adoption. Their results show that technology adoption is more driven by TOE factors than by individual factors. Similarly, ref. [56] have tested the intention to adopt IoT and revealed that almost all variables in TOE have significant direct impacts on intention, while no variables in UTAUT have significant direct impacts. Similarly, the findings on the intentions to use blockchain technology suggest that cybersecurity concerns including technological, organizational, and environmental factors significantly affect the adoption of blockchain. Specifically, the behavioral use of blockchain should relate to the unique attributes of the technology on top of social and organizational attributes [57]. Following, for e-government implementation in developing countries, the study uncovered substantial issues rooted in organizational limitations like limited awareness and inadequate top-management support. The scarcity of essential infrastructure exacerbates these issues, and the crucial role of clear regulations and unwavering top-management support is needed as success in the e-government adoption and implementation depends on the synergy between organizational, technological, and environmental factors [37]. In addition, the investigation of the barriers preventing consumers from using FinTech services in the banking industry highlighted mainly TOE-based promoters and inhibitors to the usage of FinTech, and the promoters included self-efficacy, electronic word-of-mouth, system quality, bank image, and performance expectancy [58].

In contrast, there has been rather limited evidence on the importance of individual factors within the integrated context, e.g., studies examining the factors influencing science teachers' intentions to adopt humanoid robots in educational settings revealed the moderating role of professional experience in the adoption process. Within these findings, performance expectancy, hedonic motivation, and social influence were strong UTAUT predictors; however, organizational readiness, technical infrastructure, and policy support were critical TOE factors. Interestingly, professional experience moderated adoption as in-service teachers responded more to organizational factors, while pre-service teachers were more influenced by personal motivation [38]. Therefore, our findings provide important evidence on UTAUT and TOE frameworks' integration in the context of AI, where both are perceived as important, thus balancing the evidence missing in the existing literature.

6. Conclusions

This study developed and empirically validated a dual-level model for assessing AI readiness in the public sector by combining the TOE framework and the AHP method. By integrating individual-level perceptions with organizational-level decision structures, the model enables systematic prioritization of readiness factors relevant to public administration. This research was guided by the main question: what are the most relevant organizational and individual-level factors that determine AI readiness in the public sector, and how can they be prioritized using a structured decision-making model? The three most relevant factors are as follows: voluntariness of use, social influence, and behavioral intention to use artificial intelligence. The findings provide an evidence-based answer by identifying organizational culture, top-management support, and perceived usefulness as the most influential criteria across sampled municipalities.

Methodologically, it demonstrates how AHP can be applied to structure judgments and generate actionable insights for AI-related decision-making in government settings. In practice, the model serves as a decision-support tool that municipal leaders can use to assess readiness, identify capability gaps, and align investments with strategic objectives. Some limitations of the research can be identified. The relatively small sample limits statistical generalizability, and the national focus on Slovenian municipalities might limit applicability in other governance contexts, even though we have ensured analytical soundness. Furthermore, the exclusive use of the Web of Science may have resulted in relevant studies indexed elsewhere being omitted.

Future research could extend this study in several important directions. First, cross-national validation in diverse governance systems, such as Nordic, Asian, or federal contexts, would test the model's transferability and illuminate how institutional structures shape AI readiness. Second, longitudinal studies could track how readiness evolves throughout the different phases of AI implementation, providing a dynamic view of change processes and organizational adaptation. Third, to address growing citizen expectations around transparency and ethics in public sector AI, future models could incorporate trust, fairness, and public acceptability as additional factors, enriching the UTAUT dimension. More broadly, this study lays the groundwork for future AI readiness frameworks. At the same time, while the current sample and geographic scope limit generalizability, the hybrid methodology and dual-level design offer a robust foundation. Researchers are encouraged to build on this integrated approach to capture the multi-level complexities of AI adoption better. For practitioners, the model offers a flexible tool that, when adapted to local conditions, can support more informed and context-sensitive AI integration strategies.

To sum up, this research contributes to the development of a replicable, evidence-informed framework for assessing and supporting AI readiness in the public sector. It reinforces the need for multidimensional approaches to digital transformation that consider not only technological infrastructure but also organizational capacity and human agency.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytic Hierarchy Process
AI	Artificial intelligence
BIM	Building Information Modeling
CI	Consistency index
CIO	Chief Information Office
GMM	Geometric mean method
CR	Consistency ratio
GDPR	General Data Protection Regulation
HR	Human resources
ICT	Information and Communication Technology
MCDM	Multi-criteria decision-making
RQ	Research question
TAM	Technology Acceptance Model
TOE	Technology–organization–environment
TRAM	Technology Readiness and Acceptance Model
TRI	Technology Readiness Index
UTAUT	Unified theory of acceptance and use of technology

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