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Making AI Work for Government: Critical Success Factors Analysis Using R-SWARA

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Abstract

Artificial Intelligence (AI) stands at the forefront of modern technology and is extensively leveraged by the public sector to enhance management and service delivery. Despite its potential, many organizations face challenges in AI implementation, including organizational readiness, strategic vision, and leadership support, with the organization dimension being the most critical, followed by technology, process, and environment. Addressing these challenges requires a focus on organizational readiness, strategic vision, and leadership support, alongside improvements in technology, processes, and environmental factors. This study aims to quantify the Critical Success Factors (CSFs) for successful AI implementation within the Directorate General of Taxes (DGT), offering actionable insights for decision-making and resource allocation. The research utilizes the Rough Stepwise Weighted Assessment Ratio Analysis (R-SWARA) method to analyze and prioritize the CSFs for AI implementation, focusing on dimensions such as technology, organization, process, and environment. The findings highlight the importance of organizational readiness, strategic vision, and leadership support in driving successful AI integration within DGT. Organization is identified as the most critical factor, followed by technology, process, and environment. This research provides valuable insights for DGT and other public sector organizations, aiding in strategic resource allocation and AI strategy refinement to enhance operational efficiency through AI adoption.

Keywords: *artificial intelligence; government; critical success factors*

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1. Introduction

The third wave of digital era governance is marked by a large quantity of data, the capability of machines to replace human tasks, data science and artificial intelligence technologies maximizing the productivity of organizations and enabling the interconnectedness and interdependence of various parts of the administrative system [1]. The era of data science and artificial intelligence has arrived, including in the public sector.

Artificial Intelligence (AI) is at the forefront of modern technology, yet its definition remains elusive and subject to constant evolution [2]. Its categorization exemplifies AI's diversity as 'narrow' or 'weak' AI, designed explicitly for distinct tasks, far from mirroring human cognitive capabilities [3]. The AI landscape encompasses many techniques and approaches, including cognitive mapping, case-based reasoning, fuzzy logic, machine learning, genetic algorithms, artificial neural networks, multi-agent systems, and natural language processing [4].

Within this complex domain, only a fraction of data science projects, approximately 13%, successfully transition into production, highlighting the challenges of harnessing AI's potential [5]. A significant majority of corporate executives, nearly 76%, acknowledge the obstacles they encounter when implementing and expanding the use of AI within their organizations [6].

The public sector has leveraged AI to enhance its management and service delivery [7]. The transformative and disruptive capabilities of AI implementation in the public sector fall into three main domains: (1) bolstering the internal operational efficiency of public administration, (2) augmenting decision-making processes within public administration, and (3) improving the interaction between citizens and the government. These improvements involve providing more efficient and

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comprehensive services and promoting citizen involvement and participation in public sector activities [8], [9].

However, the challenges in AI implementation are particularly pronounced in the public sector due to its unique constraints and requirements. According to the United Nations, Indonesia's rank in the E-Government Development Index has changed from 88 to 77 from 2020 to 2022, partly due to the implementation of AI in government. The Directorate General of Taxes (DGT) of the Ministry of Finance in Indonesia has incorporated AI components into various systems and processes. For instance, Compliance Risk Management (CRM) at DGT integrates machine learning into its modelling process, and deep learning is used for named entity recognition (NER) in tax invoices. The model, once trained, can identify and categorize numerous tax invoices, a task beyond human capacity due to the sheer volume of data [10].

Understanding the critical success factors (CSFs) in AI implementation takes centre stage in this context. Existing research on AI in the public sector spans various facets, including definition and attributes, techniques and technologies, uses and applications, results, impacts, benefits, challenges, determinants, strategies, best practices, guidelines, and ethical considerations [9]. Several studies have discussed the critical success factors of AI adoption across sectors. These studies, conducted by Merhi (2023), Dora (2022), and Kumar (2023), respectively, discuss CSFs in AI in the private sector [11], the food industry supply chain sector [12], and the healthcare supply chain sector [13]. However, there remains a noticeable dearth of scholarly literature addressing CSFs, especially within the public sector [14].

This research aims to bridge this gap by quantifying the CSFs for AI adoption, focusing on the DGT as a case study. Recognizing that AI systems are intricately connected to organizational elements, our study addresses the following research questions: *What is the relative importance of each critical success factor in implementing artificial intelligence compared to others within DGT?*

In this research paper, we utilize the Rough Stepwise Weighted Assessment Ratio Analysis (R-SWARA) method to analyze and prioritize alternatives in the context of critical success factors for AI implementation, focusing on the DGT. By employing R-SWARA, we aim to provide valuable insights that can inform decision-makers and stakeholders in the public sector. The R-SWARA method is a decision-making technique that facilitates evaluating and prioritizing alternatives based on multiple criteria. Developed by Zavadskas et al. in 2018 [15] as an extension of the SWARA method introduced by Kersuliene et al. in 2010 [16], R-SWARA offers a structured approach to decision-making in complex scenarios where various factors must be considered.

This research aims to offer tangible advantages to the Directorate General of Taxes (DGT) and the broader public sector. Through an in-depth analysis of CSFs in AI implementation at DGT, we aim to provide DGT with insights to inform their decision-making processes. Understanding the significance of each factor can enable more strategic allocation of resources and the refinement of AI strategies. Furthermore, this research can serve as a valuable reference for other public sector organizations seeking to enhance their operational efficiency through AI adoption. This research is expected to empower better decision-making and contribute to more effective governance in public sector AI adoption.

The research follows a systematic structure consisting of five main sections: introduction, research methodology, results, discussion, and conclusion. Each section serves a distinct purpose in advancing understanding and contributing to the scholarly discourse on the topic. In the subsequent sections, we delve deeper into the research methodology, present the findings, and critically analyze and interpret them. This structured approach ensures clarity, coherence, and rigour throughout the study, guiding readers through a logical progression of ideas and insights.

2. Research Methods

In this study, a research framework is proposed, namely measuring the importance measure of CSFs in adopting AI in government agencies using the Rough Stepwise Weighted Assessment Ratio Analysis (R-SWARA) method. The measurement requires an expert judgment to prioritize the criterion of the CSF. These experts are individuals in charge of the AI project accordingly. They include project director, project manager, project coordinator, business analyst, data scientist, data engineer, and statistician.

The research object chosen for this study is the Compliance Risk Management and Business Intelligence project at the Directorate General of Taxes, Ministry of Finance, Indonesia. The project has adopted/incorporated artificial intelligence.

For instance, Compliance Risk Management - General Risk employs logistic regression to assign weight to predictors forecasting taxpayers' compliance levels. Meanwhile, in CRM Appraisal, the LightGBM algorithm is utilized. Another example is using deep learning in the Business Intelligence Named Entity Recognition project. Tax invoice data containing various commodity names being traded are grouped using a deep learning algorithm after the formation of manually labelled training data.

A literature review was conducted on studies that discuss the adoption of AI. From examining these case studies, several frameworks were identified and used as approaches in each respective study. According to the author, the author chose an approach that is the most comprehensive and applicable to the research object.

The Technology-Organization-Process-Environment framework was chosen because it offers a more comprehensive perspective [17], considering the research object's internal and external factors. The conceptual model of the CSFs of AI adoption in government agencies is shown in Figure 1.

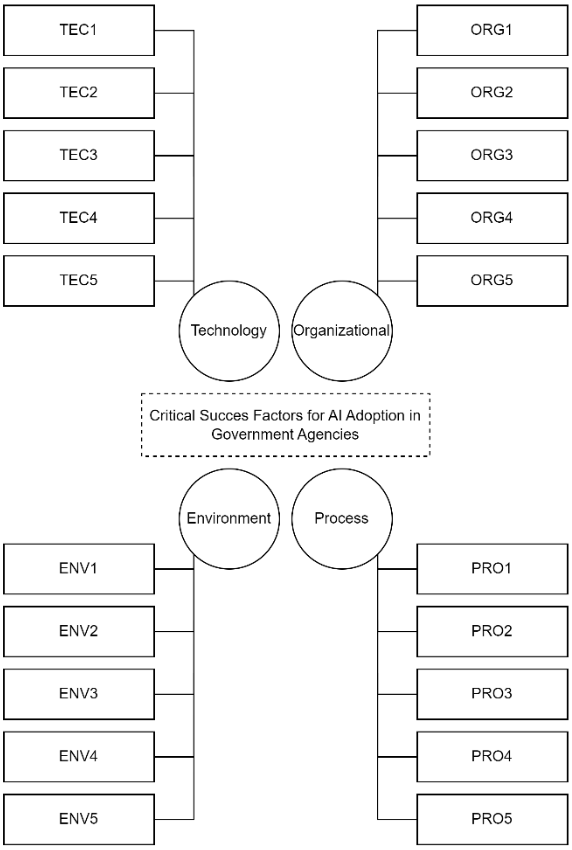

Figure 1. Conceptual Model of CSF of AI Adoption in Government Agencies

The subdimension of the CSFs is taken from Merhi's paper, and some adjustments are made to align with the research object. The criteria used by Merhi were chosen because they are more general. This is because Merhi's research targets various sectors, so these criteria are more suitable for application in the government sector than other research focusing on certain sectors. The overview of the primary and secondary dimensions of the CSFs is illustrated in Table 1.

From the results of the literature review, the main dimensions of CSFs and their sub-dimensions were identified. Subsequently, prioritization was conducted according to scale, and weights were assigned to each CSF. The prioritization and weighting were performed on the main dimensions of CSF and the sub-dimensions within each main dimension. This process was carried out by experts in the CRMBI project. Their profiles can be seen in the respective Table 2.

Table 1. Main and subdimension of CSFs AI adoption in government agencies

Main Dimension CSFs	Sub Dimension CSFs
Technology (TEC)	IT infrastructure (TEC1) Low data quality (TEC2) Insufficient quantity of data (TEC3) Data governance issues (TEC4) Integration complexity (TEC5) Security and confidentiality (TEC6)
Organization (ORG)	Ambiguous strategic vision (ORG1) Top management support (ORG2) Organizational culture (ORG3) Organization structure (ORG4) Lack of visibility on benefits (ORG5)
Process (PRO)	Project champion (PRO1) Resistance (PRO2) Lack of technical expertise (PRO3) Ethics issues (PRO4) Responsibility and accountability (PRO5)
Environment (ENV)	High cost of AI (ENV1) Competitive Pressure (ENV2) Effective collaboration with partners and stakeholders (ENV3) Customer/user satisfaction (ENV4)

Table 2. Expert on CRMBI Project

Expert	Job Profile	Domain experience
Expert 1	Project director	>10 years
Expert 2	Project manager	>10 years
Expert 3	Project manager	>10 years
Expert 4	Project manager	>10 years
Expert 5	Project manager	>10 years
Expert 6	Project Coordinator	>10 years
Expert 7	Project Coordinator	>10 years
Expert 8	Project Coordinator	>10 years
Expert 9	Project Coordinator	>10 years
Expert 10	Project Coordinator	>10 years
Expert 11	Project Coordinator	>10 years
Expert 12	Project Coordinator	<5 years
Expert 13	Business analyst	> 10 years
Expert 14	Data scientist	5 - 10 years
Expert 15	Business analyst	> 10 years
Expert 16	Business analyst	> 10 years
Expert 17	Statistician	> 10 years
Expert 18	Business analyst	> 10 years
Expert 19	Data Engineer	< 5 years
Expert 20	Data scientist	> 10 years
Expert 21	Business analyst	< 5 years
Expert 22	Data Engineer	> 10 years
Expert 23	Data Engineer	5 - 10 years
Expert 24	Business analyst	> 10 years
Expert 25	Data Engineer	< 5 years
Expert 26	Data scientist	> 10 years
Expert 27	Statistician	5 - 10 years
Expert 28	Data scientist	> 10 years
Expert 29	Business analyst	< 5 years
Expert 30	Data Engineer	5 - 10 years
Expert 31	Statistician	5 - 10 years
Expert 32	Business analyst	> 10 years

Once the criteria of the CSFs have been prioritized, the next step involves calculating the ranking using the R-SWARA method. This step will involve applying the established weights to each criterion and evaluating the alternatives accordingly. The R-SWARA method comprises the subsequent steps [15]:

Step 1: Establish a collection of criteria that are involved in the process of making decisions.

Step 2: Assemble a group of k specialists who will evaluate the importance of the criteria. Prior to proceeding, it is imperative to prioritize the criteria based on their significance, arranging them in descending order of importance. Subsequently, sj- is calculated by considering the second criterion to evaluate the significance of how much criterion c_1 is more relevant than criteria c_{1-n}.

Step 3: Transforming the individual responses of experts to create a collective rough matrix c_j. The responses of the experts denoted as $k_1, k_2, \ldots, k_n$ should be transformed into a preliminary group matrix using Equations 1- 3 mentioned by Zavadskas et al. [15]:

$$RN(C_j) = [c_j^L, c_j^U]_{1xm} \quad (1)$$

Step 4: Normalize the matrix $RN(C_j)$ to obtain matrix $RN(S_j)$ (Equation 2).

$$RN(S_j) = [s_j^L, s_j^U]_{1xm} \quad (2)$$

The elements of the matrix $RN(S_j)$ are obtained by applying Equation 3.

$$RN(S_j) = \frac{[c_j^L, c_j^U]}{\max_r [c_r^L, c_r^U]} \quad (3)$$

The first element of the matrix $RN(S_j)$, $[s_j^L, s_j^U] = [1.00, 1.00]$, because $j = 1$. For others, $j > 1$, Equation 3 can be operated using Equation 4.

$$RN(S_j) = \left[\frac{c_j^L}{max(c_r^L)}; \frac{c_j^U}{max(c_r^U)}\right] \; j = 2, 3, \ldots, m \quad (4)$$

Step 5: Calculate the matrix $RN(K_j)$ (Equation 5).

$$RN(K_j) = [k_j^L, k_j^U]_{1xm} \quad (5)$$

by applying Equation 6.

$$RN(K_j) = [s_j^L + 1, s_j^U + 1]_{1xm} \; j = 2, 3, \ldots, m \quad (6)$$

Step 6: Compute the matrix of recalculated weights $RN(Q_j)$ (Equation 7).

$$RN(Q_j) = [q_j^L, q_j^U]_{1xm} \quad (7)$$

The elements of the matrix $RN(Q_j)$ are acquired through the application of Equation 8.

$$RN(Q_j) = \left[q_j^L = \begin{cases} 1.00 \; j = 1 \\ \frac{q_{j=1}^L}{k_j^U} > 1 \end{cases}, q_j^U = \begin{cases} 1.00 \; j = 1 \\ \frac{q_{j=1}^U}{k_j^L} > 1 \end{cases} \right] \quad (8)$$

Step 7: The process of determining the matrix of relative weight values $RN(W_j)$ (Equation 9).

$$RN(W_j) = [w_j^L, w_j^U]_{1xm} \quad (9)$$

The calculation of the individual weight values of criteria is done using Equation 10.

$$[w_j^L, w_j^U] = \left[\frac{[q_j^L, q_j^U]}{\sum_{j=1}^{m}[q_j^L, q_j^U]}\right] \quad (10)$$

3. Results and Discussions

3.1 Results

The result for the main dimension of CSFs is presented in Table 3. The table showcases the rankings provided by 32 experts on the CSFs for implementing Artificial Intelligence (AI) within the CRMBI project. The rankings, from 1 to 4, signify the experts' varying perceptions of importance for four key factors:

Technology (TEC): The experts' opinions differ, with some considering it highly important (ranked 1 or 2) and others less crucial (ranked 3 or 4).

Organization (ORG): Generally, experts agree on its significance, with most assigning lower rankings (1 or 2), indicating a higher priority for organizational aspects in AI adoption.

Process (PRO): The experts' opinions vary widely. Some rank it as a high priority (1 or 2), while others consider it less crucial (3 or 4).

Environment (ENV): Similar to technology and process, rankings are diverse. However, there's a tendency to assign slightly lower rankings (1 or 2), signifying relatively higher importance for environmental factors in AI implementation.

Table 3. Expert’s ranking on main dimensions of the CSFs of AI adoption in the CRMBI Project

Main CSFs	TEC	ORG	PRO	ENV
Expert 1	1	2	3	4
Expert 2	4	1	3	2
Expert 3	1	3	2	4
Expert 4	1	2	3	4
Expert 5	3	2	4	1
Expert 6	2	1	3	4
Expert 7	4	1	2	3
Expert 8	4	1	3	2
Expert 9	3	2	1	4
Expert 10	2	1	3	4
Expert 11	3	1	2	4
Expert 12	4	1	3	2
Expert 13	3	4	2	1
Expert 14	4	2	3	1
Expert 15	2	1	4	3
Expert 16	2	1	4	3
Expert 17	1	3	4	2
Expert 18	2	4	1	3
Expert 19	2	1	3	4
Expert 20	1	3	2	4
Expert 21	3	2	1	4
Expert 22	4	1	3	2
Expert 23	3	1	4	2
Expert 24	1	3	2	4
Expert 25	1	2	3	4
Expert 26	2	1	3	4
Expert 27	1	3	2	4
Expert 28	1	4	2	3
Expert 29	3	1	4	2
Expert 30	4	1	3	2
Expert 31	3	4	1	2
Expert 32	2	1	3	4

3.2 Computational Analysis

In this section, we will follow the earlier step to employ the R-SWARA method for each main dimension of CSFs in government agencies. We will substitute the value from Table III. The equations (1) to (6) below are from Zavadskas et al. [15] section rough set theory. The purpose of the computation is to calculate the lower and upper limits of the number set in each main dimension of CSFs in Table 3.

$\widetilde{TEC}$
$= \left\{ \begin{matrix} 1,4,1,1,3,2,4,4,3,2,3,4,3,4,2,2,1,2,2,1,3,4,3,1,1,2, \\ 1,1,3,4,3,2 \end{matrix} \right\}$
$\underline{Lim}(1) = 1$
$\overline{Lim}(1) = 2.406$
$\underline{Lim}(2) = 1.470$
$\overline{Lim}(2) = 2.956$
$\underline{Lim}(3) = 1.960$
$\overline{Lim}(3) = 3.4667$
$\underline{Lim}(4) = 2.406$
$\overline{Lim}(4) = 4$
$TEC^L = 1.665$
$TEC^U = 3.158$
$\widetilde{ORG}$
$= \left\{ \begin{matrix} 2,1,3,2,2,1,1,1,2,1,1,1,4,2,1,1,3,4,1,3,2,1,1,3,2,1, \\ 3,4,1,1,4,1 \end{matrix} \right\}$
$\underline{Lim}(1) = 1$
$\overline{Lim}(1) = 1.906$
$\underline{Lim}(2) = 1.304$
$\overline{Lim}(2) = 2.813$
$\underline{Lim}(3) = 1.607$
$\overline{Lim}(3) = 3.444$
$\underline{Lim}(4) = 1.906$
$\overline{Lim}(4) = 4$
$ORG^L = 1.286$
$ORG^U = 2.607$
$\widetilde{PRO}$
$= \left\{ \begin{matrix} 3,3,2,3,4,3,2,3,1,3,2,3,2,3,4,4,4,1,3,2,1,3,4,2,3,3, \\ 2,2,4,3,1,3 \end{matrix} \right\}$
$\underline{Lim}(1) = 1$
$\overline{Lim}(1) = 2.688$
$\underline{Lim}(2) = 1.667$
$\overline{Lim}(2) = 2.929$
$\underline{Lim}(3) = 2.385$
$\overline{Lim}(3) = 3.300$
$\underline{Lim}(4) = 2.688$
$\overline{Lim}(4) = 4$
$PRO^L = 2.089$
$PRO^U = 3.262$
$\widetilde{ENV}$
$= \left\{ \begin{matrix} 4,2,4,4,1,4,3,2,4,4,4,2,1,1,3,3,2,3,4,4,4,2,2,4,4,4, \\ 4,3,2,2,2,4 \end{matrix} \right\}$
$\underline{Lim}(1) = 1$
$\overline{Lim}(1) = 3$
$\underline{Lim}(2) = 1.750$
$\overline{Lim}(2) = 3.207$
$\underline{Lim}(3) = 2.118$
$\overline{Lim}(3) = 3.75$
$\underline{Lim}(4) = 3$
$\overline{Lim}(4) = 4$
$ENV^L = 2.323$
$ENV^U = 3.644$

Based on the calculation, a rough group matrix is formed using the formula (7) as presented in Table 4.

Table 4. Rough Group Matrix $RN(C_j)$ for the Main Dimension of CSFs

$RN(C_{ORG})$	$[1.286, 2.607]$
$RN(C_{TEC})$	$[1.665, 3.158]$
$RN(C_{PRO})$	$[2.089, 3.262]$
$RN(C_{ENV})$	$[2.323, 3.644]$

The next step is to normalize the lower and upper limit values from the $RN(C_j)$ using equation (8). All values from Table 4 will be normalized by dividing it using the maximum value i.e., $RN(C_{ENV})$ $[2.323, 3.644]$, except $RN(C_{ORG})$, because the organization dimension of CSFs has a lower value, which reflects the most important factor. The $RN(C_{ORG})$ will be assigned the value 1 for both the lower and upper limits.

The complete matrix for normalized rough group matrix $RN(S_j)$ is presented in Table 5.

Table 5. Rough Group Matrix $RN(S_j)$ for Main Dimension of CSFs

$RN(S_{ORG})$	$[1.000, 1.000]$
$RN(S_{TEC})$	$[0.457, 1.359]$
$RN(S_{PRO})$	$[0.573, 1.404]$
$RN(S_{ENV})$	$[0.637, 1.569]$

Afterward, the matrix will be reevaluated by adding 1 to each value, i.e., form the equation (12), to represent the relation of j and j-1 from the equation explanation before. Once again, this step excludes the organization dimension of the CSFs, it still bears the value of 1. This step will yield a new rough group matrix $RN(K_j)$ as shown on Table 6.

Table 6. Rough Group Matrix $RN(K_j)$ for the Main Dimension of CSFs

$RN(K_{ORG})$	$[1.000, 1.000]$
$RN(K_{TEC})$	$[1.457, 2.359]$
$RN(K_{PRO})$	$[1.573, 2.404]$
$RN(K_{ENV})$	$[1.637, 2.569]$

Once again, after the relation of *j* and *j-1* is represented in the rough group matrix $RN(K_j)$, we need to recalculate the weights using equation (14) to yield a rough group matrix $RN(Q_j)$ as depicted in Table 7.

Table 7. Rough Group Matrix $RN(Q_j)$ for the Main Dimension of CSFs

$RN(Q_{ORG})$	$[1.000, 1.000]$
$RN(Q_{TEC})$	$[0.424, 0.686]$
$RN(Q_{PRO})$	$[0.176, 0.436]$
$RN(Q_{ENV})$	$[0.069, 0.266]$

Finally, we will employ equation (16) to fill the matrix $RN(W_j)$ in equation (15). The result would be the final weight with minimum and maximum weight for each dimension of CSFs. Next, we calculate the crisp value by averaging each dimension's minimum and maximum values. The result is depicted in Table 8.

Table 8. Weights and Rankings of Main Dimension of CSFs of AI Adoption in Government Agency

Main CSF	Weights		Crisp	Rank
	min	max		
TEC	0.177	0.411	0.294	2
ORG	0.419	0.599	0.509	1
PRO	0.074	0.261	0.168	3
ENV	0.029	0.160	0.094	4

Similarly, the experts were asked to assess the most and least significant sub-dimension CSFs inside the CSFs category, following the same process.

Table 9. Final Global Weight and Ranking of CSFs of AI Adoption in CRMBI Project

Main CSF	Local weight	Sub-CSF	Local weight	Global weight	Global ranking
TEC	0.294	TEC1	0.278	0.082	5
		TEC2	0.418	0.123	3
		TEC3	0.181	0.053	7
		TEC4	0.118	0.035	11
		TEC5	0.070	0.021	15
		TEC6	0.040	0.012	18
ORG	0.509	ORG1	0.172	0.088	4
		ORG2	0.462	0.235	1
		ORG3	0.283	0.144	2
		ORG4	0.097	0.049	8
		ORG5	0.054	0.028	14
PRO	0.168	PRO1	0.420	0.070	6
		PRO2	0.118	0.020	16
		PRO3	0.183	0.031	12
		PRO4	0.062	0.010	19
		PRO5	0.278	0.047	9
ENV	0.094	ENV1	0.156	0.015	17
		ENV2	0.082	0.008	20
		ENV3	0.487	0.046	10
		ENV4	0.301	0.028	13

The global weight and rank of all the subdimensions of AI adoption in government agencies were calculated by combining the ratings provided by experts. The result is presented in Table 9.

3.3 Findings

The findings derived from the CSF analysis for AI adoption within a government agency present insightful implications. Table 8 demonstrates the weights assigned for each CSF—Technology (TEC), Organization (ORG), Process (PRO), and Environment (ENV)—as well as their corresponding Crisp scores and ranks.

Organization (ORG) emerges as the most substantial determinant, carrying the highest weight (0.509) and achieving the top rank (1) among the CSFs. This weight implies that organizational factors are most significant in successfully adopting AI within the government agency. This outcome aligns with existing research emphasizing the pivotal role of organizational readiness, leadership support, and cultural alignment in AI implementation [18], [19], [20].

However, this result is not in accordance with Merhi's results, which placed the organization in third position, with a weight that was significantly smaller than first place [11]. This happens because of significant differences in research objects between this research and Merhi's research. Merhi's research case selection was in a developed country (United States of America) with a much better level of organizational maturity than government agencies in Indonesia. This statement is backed by Neumann, who states that organizational factors appear to be less critical at the determined and managed level of AI adoption [21].

Following closely, Technology (TEC) secures the second-highest weight (0.294) and is positioned at rank 2. The weight signifies a significant but slightly lower impact compared to organizational factors. This suggests that while technological capabilities are crucial, their importance might be marginally subordinate to organizational readiness in ensuring the successful incorporation of AI. This can be explained again using Neumann's research, citing Kraaijenbrink et al. [22]. During the initial phase of a potentially significant area, the organization aims to get the required resources and competencies and establish a suitable organizational structure to utilize them [21].

Process (PRO) and Environment (ENV) attain lower weights of 0.168 and 0.094, respectively, and rank 3 and 4 in priority. These scores indicate that process-related aspects and the external environment are comparatively less critical in influencing the successful adoption of AI within the government agency. Nonetheless, these factors should not be disregarded, as they still contribute to the overall landscape of AI implementation.

It is evident from this analysis that while technological aspects hold importance, the organizational dynamics within the agency play a dominant role in driving successful AI adoption. This underscores the necessity for strategic focus on aligning organizational structures, leadership support, and cultural readiness to achieve successful AI integration within government agencies. Additionally, while process and environmental factors might hold lesser weight, they still warrant attention to create a comprehensive framework for successful AI implementation.

In the Technology (TEC) dimension, 'insufficient quantity of data' (TEC3) emerges with a moderate local weight (0.181) but maintains a comparatively higher global ranking (7). This suggests its critical role in AI adoption, indicating that despite its lower local impact, it holds substantial importance at a broader level. Conversely, 'low data quality' (TEC2) exhibits a high local weight (0.418), signifying its perceived significance within the agency, which aligns with its notable global ranking (3). This is aligned with the results of Weber et al., which say that organizations must have data management capabilities [17] to provide adequate data for AIs since data collecting poses a significant obstacle in the field of machine learning [23], [24]. 'IT infrastructure' (TEC1) maintains a notable global ranking at 5th, showcasing its significance in the broader context of AI adoption strategies. Locally, it stands out prominently, securing the 2nd position, highlighting its perceived importance within the agency's considerations for successful AI integration, which aligns with Kumar's research results [13].

Moving to the Organization (ORG) dimension, 'top management support' (ORG2) garners the highest local weight (0.462) and secures the top global ranking. This reaffirms the critical role of leadership backing in AI adoption, in line with Maroufkhani et al. [25], and Solaimini and Swaak [14]. Interestingly, 'organization culture' (ORG3) showcases a substantial local weight, indicating its perceived importance, yet its global ranking slightly trails 'top management support' (ORG2). This suggests that while organizational culture is recognized locally, its global impact might differ, albeit still crucially aligned with Neumann's result [21].

Within the Process (PRO) dimension, 'project champion' (PRO1) appears to hold the highest local weight (0.420), signifying its perceived importance at the agency level. Moreover, its global ranking is within the top ten of the lists, with 6th position. 'Lack of technical expertise' (PRO5), despite a lower local weight, maintains a relatively higher global ranking, suggesting its substantial role despite its seemingly lower local emphasis.

Finally, the Environmental (ENV) dimension showcases 'effective collaboration with partners and stakeholders' (ENV3) with a notable local weight and an escalated global ranking. This indicates its pivotal role in successfully adopting AI within the agency, highlighting the significance of partnerships and stakeholder engagement at a broader level.

These local weights and global rankings collectively illustrate the varying degrees of importance assigned to different sub-dimensions within each CSF. While certain factors hold substantial local importance, their global rankings might differ, emphasizing the need for a comprehensive understanding and strategic focus on the elements that significantly impact the successful integration of AI within the government agency.

3.4 Implications

The critical success factors analysis for AI adoption within government agencies reveals pivotal areas demanding attention for successful implementation. The implications drawn from these findings offer comprehensive insights crucial for strategizing and planning:

Firstly, within the organizational realm (ORG category), factors like 'top management support', 'organization culture', and 'ambiguous strategic vision' emerge as cornerstones. This underscores the paramount need for a clear, adaptable organizational structure supported by visionary leadership. Without these elements, the potential success of AI adoption might be hindered, irrespective of technological capabilities.

Secondly, technological readiness (TEC category) assumes significance through factors such as 'low data quality', 'IT infrastructure', 'insufficient quantity of data', and 'data governance issues'. These highlight the critical necessity for robust technological frameworks and seamless data management systems, both pivotal for the effective integration and utilization of AI within government settings.

Thirdly, considerations related to project management and execution (PRO Category) become evident. Elements like 'project champion', 'responsibility and accountability', 'lack of technical expertise', and 'resistance' underscore the significance of strong leadership, skilled personnel, and the need to address resistance during the implementation phase.

Moreover, environmental considerations (ENV Category), including 'customer/user satisfaction' and 'effective collaboration with partners and stakeholders', highlight the importance of aligning AI initiatives with user needs and fostering collaborative relationships for successful AI deployment.

The analysis also flags potential challenges and risks, emphasizing factors such as 'integration complexity,' 'ethics issues,' and 'security and confidentiality.' Managing these risks and navigating ethical considerations throughout the AI adoption process emerge as critical tasks.

The rankings and weights assigned to each factor aid in prioritizing interventions. Factors holding higher global weights and lower rankings warrant immediate attention to bolster the prospects of successful AI adoption.

In summary, these implications stress the significance of a comprehensive, multifaceted strategy. Addressing technological, organizational, project management, and environmental aspects concurrently is essential for a successful AI adoption journey within government agencies.

3.5 Limitations and Future Research

The selection of the CSFs based on a literature review seems to generalize and apply to the object organization, even though the organization may have unique characteristics. Respondents only came from one organization, DGT, so the results require adjustment to apply to other organizations with different characteristics. However, the overall framework of this research is still suitable for other organizations.

In future research, the ideal thing to do after conducting a literature review is to conduct an in-depth qualitative assessment to verify critical success factors in adopting artificial intelligence. Only then can quantitative measurements be carried out to determine the weight of each factor.

4. Conclusions

In conclusion, this research endeavours to bridge the critical gap in understanding the pivotal factors for successful AI adoption within the Directorate General of Taxes (DGT). By quantifying the relative importance of each CSF in AI implementation, this study has shed light on the intricate interplay between technological aspects and organizational readiness.

The findings underscore the importance of organizational factors, notably top management support, organization culture, and strategic vision, in driving successful AI adoption within DGT. Contrary to some prior research, this study highlights the unique context of DGT and emphasizes the necessity for tailored strategies that align with the specific organizational dynamics of the agency.

Moreover, the research provides actionable insights that benefit DGT and the broader public sector. Understanding the relative importance of each CSF enables more strategic resource allocation and refinement of AI strategies within DGT. Furthermore, this research is a valuable reference for other public sector organizations aiming to enhance operational efficiency through AI adoption, contributing to more effective governance.

This study aims to empower decision-making within DGT by offering nuanced insights into the critical factors influencing AI implementation. By doing so, it aspires to pave the way for more effective utilization of AI technologies, foster efficiency, and contribute to advancing governance practices within the public sector.

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