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SELECTING EFFICIENT DIGITAL TRANSFORMATION STRATEGIES IN PUBLIC ADMINISTRATION: A NOVEL FRACTAL FUZZY-BASED DECISION-MAKING PERSPECTIVE

SELEÇÃO DE ESTRATÉGIAS EFICIENTES DE TRANSFORMAÇÃO DIGITAL NA ADMINISTRAÇÃO PÚBLICA: UMA NOVA PERSPECTIVA DE TOMADA DE DECISÃO BASEADA EM FRACTAL FUZZY

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Abstract
Digital transformation is increasingly viewed as a central mechanism for improving efficiency and service quality in public administration, yet public organizations often face difficulties in systematically prioritizing digital reform initiatives. The main challenge lies in evaluating alternative strategies under conditions of limited resources, institutional constraints, and uncertainty. Although the existing literature provides extensive discussions on digital government and public sector innovation, it offers relatively limited guidance on how

Resumo
A transformação digital é cada vez mais vista como um mecanismo central para melhorar a eficiência e a qualidade dos serviços na administração pública, mas as organizações públicas muitas vezes enfrentam dificuldades para priorizar sistematicamente as iniciativas de reforma digital. O principal desafio reside na avaliação de estratégias alternativas em condições de recursos limitados, restrições institucionais e incerteza. Embora a literatura existente ofereça discussões extensas sobre governo digital e inovação no setor público, ela

decision makers can objectively compare and rank digital transformation strategies using integrated and transparent analytical frameworks. In response to this gap, this study aims to develop a comprehensive decision-making model to support the prioritization of digital transformation strategies that enhance public sector efficiency. The proposed hybrid framework integrates the COWEB technique for determining criteria importance, the RATGOS approach for ranking strategic alternatives, and generalized fractal fuzzy sets to more effectively manage ambiguity in expert judgments. Evaluation criteria and strategic alternatives are identified through a detailed literature review and expert consultations. The results indicate that implementation complexity is the most influential criterion, while the adoption of AI based public service applications represents the most effective strategy. The study provides original methodological contributions and practical insights to support feasible, consistent, and sustainable digital transformation decisions in public administration.

Keywords: Public Sector Digital Transformation. Decision Making Models. Public Administration Efficiency. Fuzzy Logic Approaches. Strategic Prioritization.

oferece orientações relativamente limitadas sobre como os tomadores de decisão podem comparar e classificar objetivamente as estratégias de transformação digital usando estruturas analíticas integradas e transparentes. Em resposta a essa lacuna, este estudo visa desenvolver um modelo abrangente de tomada de decisão para apoiar a priorização de estratégias de transformação digital que aumentem a eficiência do setor público. A estrutura híbrida proposta integra a técnica COWEB para determinar a importância dos critérios, a abordagem RATGOS para classificar alternativas estratégicas e conjuntos fuzzy fractais generalizados para gerenciar de forma mais eficaz a ambiguidade nos julgamentos de especialistas. Os critérios de avaliação e as alternativas estratégicas são identificados por meio de uma revisão detalhada da literatura e consultas a especialistas. Os resultados indicam que a complexidade da implementação é o critério mais influente, enquanto a adoção de aplicativos de serviço público baseados em IA representa a estratégia mais eficaz. O estudo fornece contribuições metodológicas originais e insights práticos para apoiar decisões de transformação digital viáveis, consistentes e sustentáveis na administração pública.

Palavras-chave: *Transformação digital do setor público. Modelos de tomada de decisão. Eficiência da administração pública. Abordagens de lógica fuzzy. Priorização estratégica.*

1 INTRODUCTION

Digital transformation refers to the systematic integration of digital technologies into organizational processes, service delivery, and decision-making structures to improve performance and public value creation. In the public sector, digital transformation has become increasingly important due to rising service demands, budget constraints, and expectations for transparency and responsiveness. When designed properly, digital transformation can significantly enhance efficiency by reducing administrative burdens, accelerating service delivery, and improving coordination across public institutions. Integrated e government portals allow citizens to access multiple services through a single digital interface, which reduces transaction costs and simplifies interactions with public authorities (Henning and Langenbach, 2025). The digitalization of internal administrative processes such as human resources management, procurement, and document handling increases operational speed and reduces manual errors. Data driven decision support systems based on big data and analytics enable public managers to make more informed and timely policy decisions. Digital citizen participation platforms create new channels for feedback and engagement, which strengthens trust and service quality. The expansion of digital welfare and social service systems improves targeting and accessibility of public support (De la Cruz, 2025). Artificial intelligence based public service applications further enhance personalization and automation. At the same time, strengthening cybersecurity and digital infrastructure is essential to ensure system reliability, data protection, and long-term effectiveness of these initiatives.

The selection of digital transformation strategies in the public sector requires careful consideration of multiple criteria, since not all initiatives generate the same value or face similar constraints. Expected efficiency gains play a central role, as public institutions aim to improve service delivery and internal processes with limited resources. Implementation cost is another critical factor, including both initial investment requirements and long-term operational expenses (Casalini and Zavolokina, 2025). Administrative capacity and digital skills determine whether institutions can effectively manage and sustain new technologies. Political and organizational support is essential, as leadership commitment influences resource allocation and institutional acceptance. Citizen impact and accessibility must also be evaluated, since digital solutions should enhance inclusion rather than create new barriers. Data security and privacy risks represent major concerns, particularly when handling sensitive personal information. Legal and regulatory compatibility is necessary to ensure that digital applications comply with existing laws and administrative procedures (Alshibani et al., 2026). Implementation complexity affects timelines and coordination requirements across units. Finally, long term sustainability should be assessed to ensure that digital systems remain technically functional and financially viable over time, rather than becoming obsolete or burdensome for public organizations.

For digital transformation to effectively enhance efficiency in the public sector, it is essential to identify and prioritize the most appropriate strategies before large scale implementation begins. This prioritization enables public institutions to allocate resources more rationally and to implement the most impactful actions within limited timeframes. Without clear priorities, public organizations may face excessive costs, fragmented investments, and inefficient technology adoption processes. Such outcomes can negatively affect financial performance and reduce public trust in digital initiatives (Parnel et al., 2025). Despite the growing importance of this issue, the academic literature offers limited empirical and theoretical studies that systematically identify the most critical criteria guiding strategic prioritization in public sector digital transformation. This limitation represents a significant research gap, as decision makers often rely on fragmented evidence or ad hoc judgments. The absence of comprehensive evaluation frameworks increases the risk of misaligned investments and suboptimal outcomes. It also limits the ability of policymakers to compare alternative strategies in a transparent and consistent manner. Addressing this gap is therefore crucial for both academic research and practical policy design, as it can support more effective, efficient, and sustainable digital transformation processes in the public sector (Guan, 2025).

This study aims to develop prioritized strategies that can enhance efficiency in the public sector through digital transformation, motivated by the increasing need for rational, transparent, and cost-effective decision making in public administrations. The main motivation of the study arises from the lack of integrated and methodologically robust decision frameworks that can systematically evaluate digital transformation strategies under multiple and often conflicting criteria. To address this gap, a new multi criteria decision making model is proposed. Based on an extensive review of the relevant literature, comprehensive lists of evaluation criteria and strategic alternatives are identified. Expert judgments are then collected from ten specialists with academic and practical experience in public sector digitalization to ensure contextual relevance and reliability. The importance weights of the criteria are calculated using the newly developed COWEB technique, which is designed to capture expert consensus more effectively. Subsequently, the RATGOS approach is employed to rank the digital transformation strategies according to their overall performance. In addition, generalized fractal fuzzy sets, also introduced by the authors, are integrated into the proposed model to better handle uncertainty and vagueness in expert evaluations. Within this framework, the study seeks to answer the following research questions: (1) Which criteria are the most influential in prioritizing digital transformation strategies for public sector efficiency? (2) How can advanced fuzzy based decision-making techniques improve the robustness of strategy evaluation? (3) Which digital transformation strategies should be prioritized to maximize efficiency under practical constraints?

This study contributes to the literature by proposing an original hybrid decision making model that integrates the newly developed COWEB and RATGOS approaches with generalized fractal fuzzy sets for prioritizing public sector digital transformation strategies. It also addresses a significant research gap by systematically identifying and weighting the most critical criteria affecting efficiency, thereby offering a robust and transferable framework for both scholars and policymakers. The proposed decision-making model demonstrates several important advantages over previously developed approaches, which enhance its originality, robustness, and practical relevance. (1) The COWEB technique, developed by the authors, provides a significant methodological contribution by introducing a structured way to determine the most influential criterion prior to evaluating the remaining factors. By allowing experts to first identify the best performing criterion and then assess other criteria relative to this reference point, COWEB reduces inconsistency and cognitive burden in expert judgments. This sequential and reference-based structure leads to more stable and coherent weighting results compared to conventional techniques that treat all criteria simultaneously, often resulting in contradictory evaluations. (2) The integration of generalized fractal fuzzy sets further strengthens the proposed model by offering a more advanced representation of uncertainty. Unlike traditional fuzzy sets that rely on linear membership structures, these newly developed sets incorporate fractal geometry, which allows for a more flexible and detailed modeling of complex and ambiguous expert opinions. For example, fluctuations and irregular patterns in subjective assessments can be captured more effectively, leading to results that better reflect real decision environments. (3) The use of the RATGOS technique for strategy ranking introduces additional advantages through its reliance on geometric mean-based aggregation. This feature reduces the dominance of extreme values and ensures a more balanced evaluation of alternatives, which is particularly useful in multi-dimensional public sector decision problems where trade-offs are unavoidable.

The structure of the study is designed to ensure a clear and logical flow of analysis. Following the introduction, Section 2 examines the existing academic literature related to public sector digital transformation, efficiency improvement, and decision-making frameworks, with particular emphasis on unresolved issues and research gaps. Section 3 explains the proposed methodological framework, detailing the decision model, the applied techniques, and the expert evaluation process. The empirical findings and ranking results derived from the analysis are presented in Section 4. Section 5 provides an interpretative discussion of these results, linking them to theoretical insights and practical considerations. The study concludes in Section 6 by highlighting the main findings, discussing limitations, and offering recommendations for future studies.

2 LITERATURE REVIEW

Prioritizing digital reforms is not simply a technical procurement decision, but a complex process involving a delicate balance between the policy strategy and administrative capacity of the relevant institution. Indeed, when considered within the context of policy strategy, success in the digitalization process cannot be achieved solely through increasing technological capabilities; it also needs to be shaped by policy actions (Kühler et al., 2025). On this basis, the success of digital transformation is possible not with technological investments lacking a strategic foundation, but with technological capabilities that align with institutional goals (Shirwa et al., 2025). For such alignment, it is necessary to go beyond randomly made technological investments, thus ensuring the efficient use of public resources and digital governance, and to follow a methodological roadmap (Alshibani et al., 2026). At this point, Kalema (2025) interprets digital reforms implemented in developing countries through James Ferguson's concept of the "anti-political machine." According to this, presenting digital transformation projects as neutral technical reforms functions as an anti-political machine. However, digital reform processes are essentially purely political processes related to managing resource allocation and the balance of social power. In a study supporting this view, Daniel and Pettit (2025) empirically demonstrate that even data analytics used in strategic planning is not a neutral technical tool, but rather part of a multi-actor and complex political system. Of course, this political strategy building also necessitates a competent administrative capacity. Indeed, Ingaggiati et al. (2025) emphasize in their study that such digital reforms give rise to new rules, procedures, and control mechanisms; this, far from reducing bureaucracy, leads to the emergence of new and complex areas of expertise within institutions. On the other hand, according to the findings of Rizk and Lindgren's (2025) comprehensive study examining the role of automated decision-making systems in public administration, as decision-making processes become automated, administrative responsibility becomes blurred, pointing to a new administrative capacity problem. Therefore, the success of digital reforms depends not only on technical infrastructure but also on the development of administrative capacity.

On the other hand, current literature positions legal legitimacy not as a technical component of digital reforms, but as their raison d'être; therefore, legal risk analysis plays a vital role in prioritizing digital reforms. Indeed, while human-induced errors decrease with digitalization, they are replaced by systemic errors that affect many more people at once, becoming the subject of lawsuits. Thus, algorithmic errors cease to be a technical problem and become a legal problem (Gules-Guctas, 2025). In this respect, legal analysis of digital reforms is essential both for the security of personal data and for compliance with existing legislation (De la Cruz, 2025). Furthermore, the normative environment, which prioritizes the prevention of public harm over achieving systemic benefits, must also possess the ethical reasoning competence to manage value conflicts (de Fine Lict and Folland, 2025). Indeed, Gregory (2025), in his study, underlines that criticisms of algorithmic decision-making systems are generally confined to technical issues, and by making an ontological reading, emphasizes that the individual is a subject worthy of being heard, beyond being a statistical probability. From the perspective of legal philosophy, the rule of law is achieved not only through the application of rules but also through respect for human dignity. Therefore, although decision-making mechanisms may seem more transparent, faster, and unbiased with digitalization, treating the individual as a data set rather than a subject undermines human dignity. This ethical stance is also supported by the work of Henning and Langenbach (2025), who, based on empirical data obtained from a total of 4250 participants in three different public decision-making scenarios, found that the system loses its legitimacy when administrative decisions are not satisfactorily justified. On the other hand, Casalini and Zavolokina (2025), in their study examining 25 private digital platforms providing public services in areas such as transportation, health, and education in Italy, emphasize that this method can lead to a major destruction of data privacy, such as citizens' information falling into the hands of private companies. Furthermore, Liden (2025), in her study, points out that ethical principles can become a means of justification in the case of normative deficiency, and that although principles may seem perfect on paper, their abstract nature means they may not be implemented in practice; therefore, legal norms are always needed. Consequently, in the context of digital reforms, law is of paramount importance and cannot be exchanged for other technical criteria, acting as a veto mechanism for such projects.

Determining the economic rationality and efficiency of public investments goes beyond traditional cost-benefit analyses and budget discipline. In this context, the success of such public investments goes beyond financial outputs and is measured through multidimensional and value-oriented decision analyses (Parnel et al., 2025). For example, the main benefit of AI-supported systems is seen in the reduction of errors and the improvement of decision quality (Choi et al., 2025). Indeed, analyses conducted in the public sector have concluded that the use of AI increases job performance and efficiency in complex tasks (Zhang et al., 2025). At this point, Xu et al. (2025) conducted interviews with 18 senior managers and engineers to identify the obstacles to data use and applied the grounded theory method to them. In this context, they concluded that even if the technical infrastructure is sufficient, managerial obstacles such as lack of motivation and capacity hinder efficiency. In his study examining the contradiction between digitalization in the public sector, promised with time savings, and the time pressure experienced by public employees, Jørring et al. (2025) focuses on the destructive effects of such productivity pursuits in the field and points out that the time gained through digitalization can be lost again due to complex processes in the workflow. Guan (2025), in his study based on local government data in China, criticizes the presentation of digital governance as a miracle cure, and points out that hidden costs, such as the application burden brought about by technological systems, reduce productivity. Finally, Rulandari (2025) draws attention to the productivity-efficiency paradox in his study; although productivity is achieved by speeding up internal processes and reducing costs with digitalization, there is a decrease in the level of meeting citizens' needs and satisfaction, and a decrease in the quality of service. In this respect, the productivity resulting from digital reforms can turn into a cost item that undermines social trust.

While criteria such as social acceptance and inclusion are often treated merely as marketing elements in the design phase of public projects, the success of digital reforms largely depends on their impact on citizens. For example, the social acceptance of automated decision-making mechanisms is evaluated based on the extent to which the system serves the interests of citizens (Hillo et al., 2025). In this context, societal concerns stem not from algorithmic deficiencies in the system, but from citizens' perception of accountability mechanisms as inadequate due to the lack of a human interlocutor (Feng and Chandra, 2025). Indeed, the insistence on digitalization undertaken by public institutions to reduce costs and increase efficiency, especially in social services, leads to the failure to meet the human needs of citizens who want to express their concerns to a human and receive empathy in return, thus hindering efficiency (Lindgren and Madsen, 2025). When the issue is examined through the criterion of inclusion, Cao and Ma (2025) stand out with their study examining digital transformation through China's elderly care policy. This study methodologically demonstrates that digital tools do not reduce administrative and bureaucratic burdens on vulnerable groups such as the elderly but rather lead to learning costs and heavy psychological burdens. Similarly, Wang et al. (2025), in their study with 4816 participants on traffic penalty scenarios in China, show that when citizens prefer algorithmic decision-making systems, this preference stems not from a love of technology, but from a deeply ingrained belief that the administration sometimes fails to maintain neutrality towards a particular group in society. On the other hand, Toro-Maureira et al. (2025), in their study examining the Chilean example, state that when a public service is confined to a digital channel, citizens become dependent on this intermediary, undermining the principle of equal and free public services and leading to a hidden cost. Finally, Loefflad et al. (2025), in their study focusing on the social acceptance and impact of algorithmic governance systems through social credit systems in China, emphasize that the success of these systems depends on citizens' awareness and participation in the system.

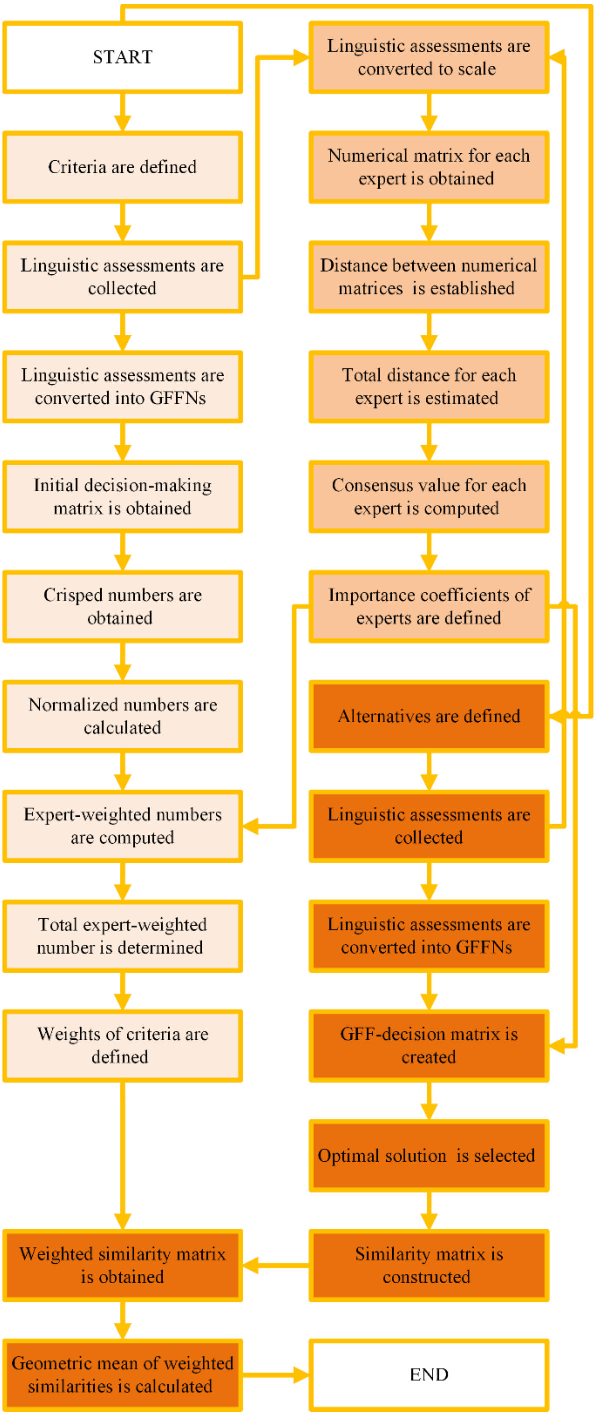
A literature review reveals several important findings. In recent years, digital projects have become quite popular due to the widespread use of digital tools such as automated decision-making mechanisms, artificial intelligence algorithms, and e-government applications. In this context, a significant portion of the research focuses on the performance indicators of these projects. Issues such as administrative capacity, policy strategy, legal legitimacy, increased efficiency, financial sustainability, impact on citizens, and inclusivity are highlighted. However, studies on which factors are prioritized are quite limited. This represents a significant gap in the literature on digital reforms. To address this gap, this study develops a new decision-making model and conducts a priority analysis.

3 METHODOLOGY

This section represents the formulations of generalized fractal fuzzy sets (GFFSs), distance-based experts' weightings, COWEB and RATGOS, respectively. GFFSs are used both for processing words and for obtaining comparisons by changing the type of fuzzy set used as the analysis input. In addition, a distance-based approach is offered for calculating the importance coefficients of experts. In the actual analysis phase, the weight values of the criteria are calculated by COWEB, while the ranking of alternatives is determined using the RATGOS method. The entire analysis process is visualized in Figure 1.

Figure 1

Entire Analysis Process



3.1 GFFSs

Fuzzy sets are used to express the belonging of an object in discourse universe to any given set. The elementality of an object is defined by grades of belonging, non-belonging, and indeterminacy. Fuzzy set types are constructed according to the conditions of these grades. Pythagorean fuzzy sets are constructed when the powers of the belonging and non-belonging grades are 2, while Fermatean fuzzy sets are formed when the powers are 3. If the dimensions of fractal geometric shapes are defined as powers, fuzzy sets such as KSFS, STFS, and CDFS are obtained. GFFSs are constructed by defining the power as a variable in this way (Kou et al., 2025). Alternatively, let D be a discourse space such that a GFFS has the form in Eq. (1) and all elements in that GFFS satisfy the condition in Eq. (2).

$$\tilde{G} = \{s, (\mu_{\tilde{G}}(s), \vartheta_{\tilde{G}}(s)) | s \in D\} \quad (1)$$

$$0 \leq \mu_{\tilde{G}}^{f}(s) + \vartheta_{\tilde{G}}^{f}(s) \leq 1 \quad (2)$$

where:

$\mu_{\tilde{G}}$ and $\vartheta_{\tilde{G}}: D \rightarrow [0, 1]$ are belonging and non-belonging grades.

In addition, f is power and equals to 2, 3, log(4)/log(3), log(3)/log(2) and log(2)/log(3) for PFSs, FFSs, KSFSs, STFSs, and CDFSs, respectively. The indeterminacy grade is described as Eq. (3).

$$\pi_{\tilde{G}}(s) = \sqrt[f]{1 - \mu_{\tilde{G}}^{f}(s) - \vartheta_{\tilde{G}}^{f}(s)} \quad (3)$$

Assume that $\tilde{G} = (\mu_{\tilde{G}}, \vartheta_{\tilde{G}})$ is a generalized fractal fuzzy number (GFFN), then the score value as well as the accuracy value for GFFN is computed using Eqs. (4) and (5), respectively.

$$\mathbb{S}(\tilde{G}) = \mu_{\tilde{G}}(s)^{f} - \vartheta_{\tilde{G}}(s)^{f} \quad (4)$$

$$\hbar(\tilde{G}) = \mu_{\tilde{G}}(s)^f + \vartheta_{\tilde{G}}(s)^f \qquad (5)$$

The normalized score function and uncertainty are defined with the help of Eqs. (6) and (7), respectively.

$$\mathbb{S}'(\tilde{G}) = \frac{(1+\mathbb{S}(\tilde{G}))}{2} \qquad (6)$$

$$\hbar'(\tilde{G}) = 1 - \hbar(\tilde{G}) \qquad (7)$$

Consider that $\tilde{G} = (\mu_{\tilde{G}}, \vartheta_{\tilde{G}})$, $\tilde{G}_1 = (\mu_{\tilde{G}_1}, \vartheta_{\tilde{G}_1})$ and $\tilde{G}_2 = (\mu_{\tilde{G}_2}, \vartheta_{\tilde{G}_2})$ are any three GFFNs and $a > 0$, $\lambda > 0$. Then some operational laws for GFFNs are identified by Eqs. (8) – (11).

$$\tilde{G}_1 \oplus \tilde{G}_2 = \left(\sqrt[f]{\frac{\mu_{\tilde{G}_1}^f + \mu_{\tilde{G}_2}^f - \mu_{\tilde{G}_1}^f \mu_{\tilde{G}_2}^f - (1-a)\mu_{\tilde{G}_1}^f \mu_{\tilde{G}_2}^f}{1-(1-a)\mu_{\tilde{G}_1}^f \mu_{\tilde{G}_2}^f}}, \frac{\vartheta_{\tilde{G}_1}\vartheta_{\tilde{G}_2}}{\sqrt[f]{a+(1-a)\left(\vartheta_{\tilde{G}_1}^f + \vartheta_{\tilde{G}_2}^f - \vartheta_{\tilde{G}_1}^f \vartheta_{\tilde{G}_2}^f\right)}} \right) \qquad (8)$$

$$\tilde{G}_1 \otimes \tilde{G}_2 = \left(\frac{\mu_{\tilde{G}_1}\mu_{\tilde{G}_2}}{\sqrt[f]{a+(1-a)\left(\mu_{\tilde{G}_1}^f + \mu_{\tilde{G}_2}^f - \mu_{\tilde{G}_1}^f \mu_{\tilde{G}_2}^f\right)}}, \sqrt[f]{\frac{\vartheta_{\tilde{G}_1}^f + \vartheta_{\tilde{G}_2}^f - \vartheta_{\tilde{G}_1}^f \vartheta_{\tilde{G}_2}^f - (1-a)\vartheta_{\tilde{G}_1}^f \vartheta_{\tilde{G}_2}^f}{1-(1-a)\vartheta_{\tilde{G}_1}^f \vartheta_{\tilde{G}_2}^f}} \right) \qquad (9)$$

$$\lambda \odot \tilde{G} = \left(\sqrt[f]{\frac{\left[1+(a-1)\mu_{\tilde{G}}^f\right]^\lambda - \left(1-\mu_{\tilde{G}}^f\right)^\lambda}{\left[1+(a-1)\mu_{\tilde{G}}^f\right]^\lambda + (a-1)\left(1-\mu_{\tilde{G}}^f\right)^\lambda}}, \frac{\sqrt[f]{a}\,\vartheta_{\tilde{G}}^\lambda}{\sqrt[f]{\left[1+(a-1)\left(1-\vartheta_{\tilde{G}}^f\right)\right]^\lambda + (a-1)\vartheta_{\tilde{G}}^{\lambda f}}} \right) \qquad (10)$$

$$\tilde{G}^\lambda = \left(\frac{\sqrt[f]{a}\,\mu_{\tilde{G}}^\lambda}{\sqrt[f]{\left[1+(a-1)\left(1-\mu_{\tilde{G}}^f\right)\right]^\lambda + (a-1)\mu_{\tilde{G}}^{\lambda f}}}, \sqrt[f]{\frac{\left[1+(a-1)\vartheta_{\tilde{G}}^f\right]^\lambda - \left(1-\vartheta_{\tilde{G}}^f\right)^\lambda}{\left[1+(a-1)\vartheta_{\tilde{G}}^f\right]^\lambda + (a-1)\left(1-\vartheta_{\tilde{G}}^f\right)^\lambda}} \right) \qquad (11)$$

Assume that $\tilde{G}_i = (\mu_{\tilde{G}_i}, \vartheta_{\tilde{G}_i})$ $(i = 1,2,\dots,n)$ are a combination of GFFNs. Generalized fractal fuzzy weighted averaging (GFFWA) operator is shown in Eq. (12).

$$\text{GFFWA}\left(\tilde{G}_1, \tilde{G}_2, \dots, \tilde{G}_n\right) = \sum_{i=1}^{n} w_i \tilde{G}_i = \left(\sqrt[f]{\frac{\prod_{i=1}^{n}\left(1+(a-1)\mu_{\tilde{G}_i}^{f}\right)^{w_i} - \prod_{i=1}^{n}\left(1-\mu_{\tilde{G}_i}^{f}\right)^{w_i}}{\prod_{i=1}^{n}\left(1+(a-1)\mu_{\tilde{G}_i}^{f}\right)^{w_i} + (a-1)\prod_{i=1}^{n}\left(1-\mu_{\tilde{G}_i}^{f}\right)^{w_i}}}, \frac{\sqrt[f]{a}\prod_{i=1}^{n}\left(\vartheta_{\tilde{G}_i}\right)^{w_i}}{\sqrt[f]{\prod_{i=1}^{n}\left(1+(a-1)\left(1-\vartheta_{\tilde{G}_i}^{f}\right)\right)^{w_i} + (a-1)\prod_{i=1}^{n}\vartheta_{\tilde{G}_i}^{w_i f}}} \right) \quad (12)$$

where:

$\sum_{i=1}^{n} w_i = 1$. Generalized fractal fuzzy weighted geometric (GFFWG) operator is given in Eq. (13).

$$\text{GFFWG}\left(\tilde{G}_1, \tilde{G}_2, \dots, \tilde{G}_n\right) = \prod_{i=1}^{n} w_i \tilde{G}_i = \left(\frac{\sqrt[f]{a}\prod_{i=1}^{n}\left(\mu_{\tilde{G}_i}\right)^{w_i}}{\sqrt[f]{\prod_{i=1}^{n}\left(1+(a-1)\left(1-\mu_{\tilde{G}_i}^{f}\right)\right)^{w_i} + (a-1)\prod_{i=1}^{n}\mu_{\tilde{G}_i}^{w_i f}}}, \sqrt[f]{\frac{\prod_{i=1}^{n}\left(1+(a-1)\vartheta_{\tilde{G}_i}^{f}\right)^{w_i} - \prod_{i=1}^{n}\left(1-\vartheta_{\tilde{G}_i}^{f}\right)^{w_i}}{\prod_{i=1}^{n}\left(1+(a-1)\vartheta_{\tilde{G}_i}^{f}\right)^{w_i} + (a-1)\prod_{i=1}^{n}\left(1-\vartheta_{\tilde{G}_i}^{f}\right)^{w_i}}} \right) \quad (13)$$

where:

Let $\tilde{G}_1 = \left(\mu_{\tilde{G}_1}, \vartheta_{\tilde{G}_1}\right)$
and $\tilde{G}_2 = \left(\mu_{\tilde{G}_2}, \vartheta_{\tilde{G}_2}\right)$ be two GFFNs. The Euclidean distance between these GFFNs is estimated using Eq. (14).

$$\Delta\left(\tilde{G}_1, \tilde{G}_2\right) = \sqrt{\left(\mu_{\tilde{G}_1}^{f} - \mu_{\tilde{G}_2}^{f}\right)^2 + \left(\vartheta_{\tilde{G}_1}^{f} - \vartheta_{\tilde{G}_2}^{f}\right)^2 + \left(\pi_{\tilde{G}_1}^{f} - \pi_{\tilde{G}_2}^{f}\right)^2} \quad (14)$$

3.2 Distance-based experts' weighting

In decision-making processes, reaching a consensus is generally valued. Therefore, adopting a shared opinion or having similar assessments is more prominent. For this reason, the approach of weighting expert assessments based on their proximity or distance has become preferred recently. The calculation of this approach can be explained as follows (Yaylali et al., 2025).

Firstly, linguistic assessments are collected from *e* experts. These linguistic assessments are converted to scale as Table 1.

Table 1

Linguistic Assessments, Scale and GFFNs

Linguistic Assessments	**GFFNs**	**Scale**
Very Very Low (VVL)	(.1 ,.9)	1
Very Low (VL)	(.1 ,.75)	2
Low (L)	(.25 ,.6)	3
Medium Low (ML)	(.4 ,.5)	4
Medium (M)	(.5 ,.4)	5
Medium High (MH)	(.6 ,.3)	6
High (H)	(.7 ,.2)	7
Very High (VH)	(.8 ,.1)	8
Very Very High (VVH)	(.9 ,.1)	9
Best (B)	(1 ,0)	10

Thus, numerical matrix for each expert is obtained as Eq. (15).

$$S^t = \begin{bmatrix} s_{11}^t & \cdots & s_{1r}^t \\ \vdots & \ddots & \vdots \\ s_{p1}^t & \cdots & s_{pr}^t \end{bmatrix} \quad (15)$$

where:

s_{ij}^t is the scale of row-i and column-j of expert-t. Next, distance between numerical matrices of expert-a and expert-b is established using Eq. (16).

$$D_{a,b} = \sqrt{\sum_{i=1}^{p} \sum_{j=1}^{r} \left(s_{ij}^a - s_{ij}^b\right)^2} \quad (16)$$

Afterwards, the total distance for each expert is estimated with Eq. (17).

$$TD_a = \sum_{b=1}^{e} D_{a,b} \quad (17)$$

Consensus value for each expert is computed via Eq. (18).

$$C_a = (TD_a)^{-1} \tag{18}$$

Finally, the importance coefficients of experts are defined using Eq. (19).

$$\rho_a = \frac{C_a}{\sum_{a=1}^{k} C_a} \tag{19}$$

3.3 GFF-COWEB

COWEB is an innovative approach that uses a best-of-criterion assessment process. This provides both the ease of comparison and a faster data collection process. The calculation of COWEB with GFFSs can be explained as follows (Eti et al., 2025).

Firstly, *n* criteria are defined, and the best criterion is selected by expert. The linguistic assessment of best criterion is “B”. Linguistic assessments of other criteria regarding best criterion are collected. After converting the linguistic assessments into numerical matrices and calculating the importance coefficients of the experts, the linguistic assessments are converted into GFFNs in Table 1. Thus, initial decision-making matrix formed in Eq. (20) is obtained.

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{k1} & \cdots & \tilde{x}_{kn} \end{bmatrix} \tag{20}$$

where:

$\tilde{x}_{ij} = \left(\mu_{\tilde{x}_{ij}}, \vartheta_{\tilde{x}_{ij}}\right)$ is the i-th expert's evaluation of the j-th criterion against the best criterion. Later, crisped numbers are obtained using Eq. (21).

$$x_{ij} = \mathbb{S}'\left(\tilde{x}_{ij}\right) \tag{21}$$

where:

$\mathbb{S}'$ is normalized score function defined in Eq. (6). Next, the normalized numbers are calculated by Eq. (22).

$$y_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \quad (22)$$

Afterwards, the normalized numbers are multiplied by the importance coefficients of experts with Eq. (23).

$$tw_{ij} = \rho_i y_{ij} \quad (23)$$

Behind, total expert-weighted number for each criterion is determined via Eq. (24).

$$z_j = \sum_{i=1}^{k} tw_{ij} \quad (24)$$

Finally, the weights of criteria are defined by Eq. (25).

$$\omega_j = \frac{z_j}{\sum_{j=1}^{n} z_j} \quad (25)$$

3.4 GFF-RATGOS

RATGOS is one of the accepted methods in the literature that considers the geometric mean of the proportional approach in ranking alternatives. The aim is to build a more robust model. The calculation of RATGOS with GFFSs can be explained as follows (Yüksel et al., 2025).

Firstly, *m* alternatives are defined, and linguistic assessments of alternatives regarding criteria are collected. After converting the linguistic assessments into numerical matrices and calculating the importance coefficients of the experts, the linguistic assessments are converted into GFFNs in Table 1. Next, the average of GFFNs is computed with GFFWA operator and importance coefficients of the experts. Thus, GFF-decision matrix formed in Eq. (26) is created.

$$\widetilde{D} = \begin{bmatrix} \tilde{d}_{11} & \cdots & \tilde{d}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{d}_{m1} & \cdots & \tilde{d}_{mn} \end{bmatrix} \quad (26)$$

where:

$\tilde{d}_{ij} = \left(\mu_{\tilde{d}_{ij}}, \vartheta_{\tilde{d}_{ij}}\right)$ is averaged GFFNs of the j-th criterion for the i-th alternative. Next, the optimal solution for each criterion is selected using Eqs. (27) and (28).

$$\tilde{\phi}_j = \left\{\tilde{d}_{ij} \left| \max_i \mathbb{S}'\left(\tilde{d}_{ij}\right)\right.\right\}; if\ j \in B \quad (27)$$

$$\tilde{\phi}_j = \left\{\tilde{d}_{ij} \left| \min_i \mathbb{S}'\left(\tilde{d}_{ij}\right)\right.\right\}; if\ j \in C \quad (28)$$

Afterwards, the similarity matrix is constructed with Eqs. (29) and (30).

$$h_{ij} = \frac{\mathbb{S}'(\tilde{d}_{ij})}{\mathbb{S}'(\tilde{\phi}_j)}; if\ j \in B \quad (29)$$

$$h_{ij} = \frac{\mathbb{S}'(\tilde{\phi}_j)}{\mathbb{S}'(\tilde{d}_{ij})}; if\ j \in C \quad (30)$$

Behind, the similarity matrix is multiplied by the weights of criteria via Eq. (31).

$$s_{ij} = \omega_j h_{ij} \quad (31)$$

Finally, the geometric mean of weighted similarities for each alternative is calculated by Eq. (32).

$$\gamma_i = \sqrt[n]{\prod_{j=1}^{n} s_{ij}} \quad (32)$$

4 ANALYSIS

This section represents the results of digital reforms. Firstly, types of digital reforms are determined and shown in Table 2 with abbreviations.

Table 2

Types of Digital Reforms

Digital Reform	Abb.
Development of Integrated E-Government Portals	IGEOV
Digitalization of Internal Administrative Processes	DIAPS
Introduction of Data-Driven Decision Support Systems	DDDSS
Implementation of Digital Citizen Participation Platforms	DCPPL
Expansion of Digital Welfare and Social Service Systems	DWSSS
Adoption of AI-Based Public Service Applications	AIPSA
Strengthening Cybersecurity and Digital Infrastructure	SCDIN

The development of integrated e government portals enables citizens to access multiple public services through a single digital interface, which reduces administrative workload and improves service delivery efficiency. The digitalization of internal administrative processes such as human resources, procurement, and document management increases operational speed and minimizes manual errors within public institutions. The introduction of data driven decision support systems allows public managers to use analytics and large scale data to improve policy formulation and resource allocation. Digital citizen participation platforms enhance communication between governments and citizens by enabling feedback, consultation, and engagement in a more efficient and transparent manner. The expansion of digital welfare and social service systems improves the targeting, monitoring, and accessibility of social support programs while reducing processing time. The adoption of AI based public service applications supports automation and personalization in service provision, leading to faster and more consistent outcomes. Finally, strengthening cybersecurity and digital infrastructure ensures the reliability, security, and sustainability of digital public services, which is essential for maintaining efficiency and public trust. A set of criteria is defined to select the most appropriate of these digital reforms. Criteria set for digital reforms is given in Table 3 with abbreviations and types.

Table 3

Criteria with Abbreviations and Type

Criterion	Abb.	Type
Expected Efficiency Gains	EEG	Max
Implementation Cost	IMP	Min
Administrative Capacity and Skills	ACS	Max
Political and Organizational Support	POS	Max
Citizen Impact and Accessibility	CIA	Max
Data Security and Privacy Risks	DSP	Min
Legal and Regulatory Compatibility	LRC	Max
Implementation Complexity	ICX	Min
Long-Term Sustainability	LTS	Max
Interoperability and Integration Potential	IIP	Max

Expected efficiency gains reflect the potential of a strategy to improve service delivery and internal processes by saving time and resources. Implementation cost includes both initial investment requirements and ongoing operational expenses that may affect budget feasibility. Administrative capacity and skills determine whether public institutions have the technical knowledge and human resources needed to successfully implement and manage digital initiatives. Political and organizational support is critical, as commitment from decision makers and senior management increases the likelihood of effective implementation. Citizen impact and accessibility assess how digital strategies affect service quality, inclusion, and ease of access for different social groups. Data security and privacy risks relate to the protection of sensitive information and the ability to prevent cyber threats and misuse of data. Legal and regulatory compatibility ensures that digital solutions comply with existing laws and administrative frameworks. Implementation complexity captures the level of technical difficulty, coordination, and time required to put a strategy into practice. Long term sustainability evaluates whether a digital initiative can remain functional and financially viable over time. Interoperability and integration potential measure the ability of new systems to work effectively with existing platforms and institutional structures.

4.1 Weighting criteria

Firstly, the best criterion among criteria in Table 3 is selected by each expert. Linguistic assessments of other criteria regarding best criterion are collected. The linguistic assessments for criteria are shared in Table 4.

Table 4

Linguistic Assessments for Criteria

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
1.Expert	H	H	H	B	M	ML	L	VVH	VH	VL
2.Expert	H	H	MH	B	M	ML	L	VVH	VH	VL
3.Expert	MH	VH	MH	VVH	M	L	L	B	H	VL
4.Expert	MH	VH	M	VH	MH	L	L	B	H	VVL
5.Expert	H	H	M	B	ML	L	L	VH	H	VVL
6.Expert	H	H	M	VVH	ML	L	L	B	H	VL
7.Expert	M	H	M	VVH	ML	ML	L	B	VH	L
8.Expert	M	VH	MH	VH	ML	ML	VL	B	H	VL
9.Expert	VH	B	ML	VH	M	L	L	VVH	VH	ML
10.Expert	H	H	ML	VVH	MH	ML	VL	VH	B	ML

The ten experts who conducted the assessment are all digital platform managers with at least 12 years of experience. These linguistic assessments are converted to scale as Table 1. The numerical assessments for criteria are summarised in Table 5.

Table 5

Numerical Assessments for Criteria

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
1.Expert	7	7	7	10	5	4	3	9	8	2
2.Expert	7	7	6	10	5	4	3	9	8	2
3.Expert	6	8	6	9	5	3	3	10	7	2
4.Expert	6	8	5	8	6	3	3	10	7	1
5.Expert	7	7	5	10	4	3	3	8	7	1
6.Expert	7	7	5	9	4	3	3	10	7	2
7.Expert	5	7	5	9	4	4	3	10	8	3
8.Expert	5	8	6	8	4	4	2	10	7	2
9.Expert	8	10	4	8	5	3	3	9	8	4
10.Expert	7	7	4	9	6	4	2	8	10	4

Next, Euclidean distances between numerical matrices of between experts for criteria are established using Eq. (16). The distance matrix for criteria is illustrated in Table 6.

Table 6

Distance Matrix for Criteria

	1.Expert	**2.Expert**	**3.Expert**	**4.Expert**	**5.Expert**	**6.Expert**	**7.Expert**	**8.Expert**	**9.Expert**	**10.Expert**
1.Expert		1.000	2.646	3.873	3.000	3.000	3.464	3.742	5.292	4.583
2.Expert	1.000		2.449	3.464	2.449	2.449	3.000	3.606	4.796	4.000
3.Expert	2.646	2.449		2.000	3.162	2.000	2.646	2.236	4.359	5.099
4.Expert	3.873	3.464	2.000		3.742	2.828	3.606	3.000	4.583	5.292
5.Expert	3.000	2.449	3.162	3.742		2.449	3.873	4.123	5.196	5.099
6.Expert	3.000	2.449	2.000	2.828	2.449		2.646	3.000	4.359	4.899
7.Expert	3.464	3.000	2.646	3.606	3.873	2.646		2.449	4.899	4.359
8.Expert	3.742	3.606	2.236	3.000	4.123	3.000	2.449		5.099	5.568
9.Expert	5.292	4.796	4.359	4.583	5.196	4.359	4.899	5.099		4.359
10.Expert	4.583	4.000	5.099	5.292	5.099	4.899	4.359	5.568	4.359	

Afterwards, the total distance for each expert is estimated with Eq. (17). Consensus value for each expert is computed via Eq. (18). The results for criteria are displayed in Table 7.

Table 7

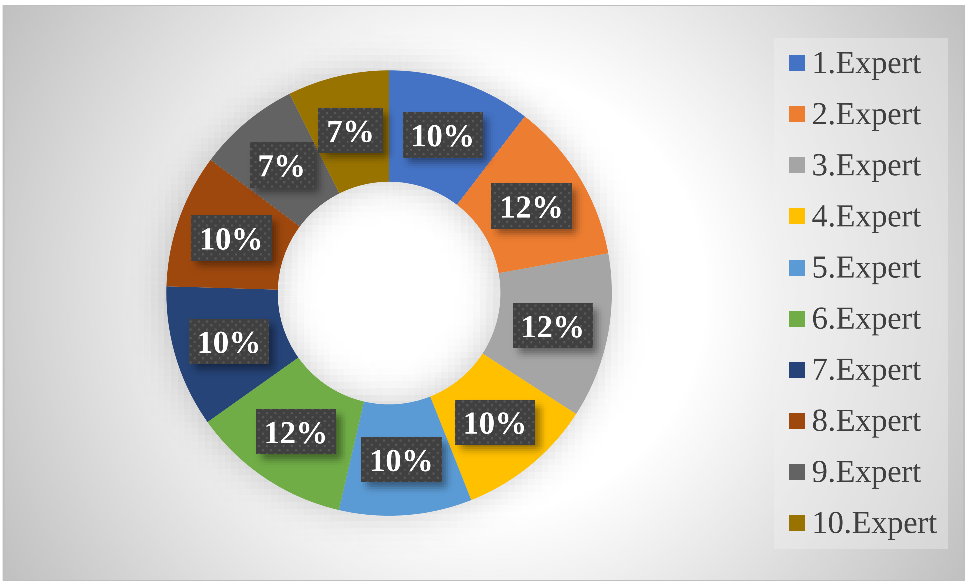
Total Distances and Consensus Values for Criteria

	1.Expert	**2.Expert**	**3.Expert**	**4.Expert**	**5.Expert**	**6.Expert**	**7.Expert**	**8.Expert**	**9.Expert**	**10.Expert**
Total Dist.	30.599	27.214	26.597	32.387	33.094	27.631	30.942	32.823	42.941	43.257
Consensus	.033	.037	.038	.031	.030	.036	.032	.030	.023	.023

Finally, the importance coefficients of experts for criteria are defined using Eq. (19). The importance coefficients for criteria are presented in Figure 2.

Figure 2

Importance Coefficients of Experts for Criteria



After calculating the importance coefficients of the experts, the linguistic assessments are converted into GFFNs in Table 1. Initial decision-making matrix is exhibited in Table 8.

Table 8

Initial Decision-making Matrix

	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
1.Expert	(.7 ,.2)	(.7 ,.2)	(.7 ,.2)	(1 ,0)	(.5 ,.4)	(.4 ,.5)	(.25 ,.6)	(.9 ,.1)	(.8 ,.1)	(.1 ,.75)
2.Expert	(.7 ,.2)	(.7 ,.2)	(.6 ,.3)	(1 ,0)	(.5 ,.4)	(.4 ,.5)	(.25 ,.6)	(.9 ,.1)	(.8 ,.1)	(.1 ,.75)
3.Expert	(.6 ,.3)	(.8 ,.1)	(.6 ,.3)	(.9 ,.1)	(.5 ,.4)	(.25 ,.6)	(.25 ,.6)	(1 ,0)	(.7 ,.2)	(.1 ,.75)
4.Expert	(.6 ,.3)	(.8 ,.1)	(.5 ,.4)	(.8 ,.1)	(.6 ,.3)	(.25 ,.6)	(.25 ,.6)	(1 ,0)	(.7 ,.2)	(.1 ,.9)
5.Expert	(.7 ,.2)	(.7 ,.2)	(.5 ,.4)	(1 ,0)	(.4 ,.5)	(.25 ,.6)	(.25 ,.6)	(.8 ,.1)	(.7 ,.2)	(.1 ,.9)
6.Expert	(.7 ,.2)	(.7 ,.2)	(.5 ,.4)	(.9 ,.1)	(.4 ,.5)	(.25 ,.6)	(.25 ,.6)	(1 ,0)	(.7 ,.2)	(.1 ,.75)
7.Expert	(.5 ,.4)	(.7 ,.2)	(.5 ,.4)	(.9 ,.1)	(.4 ,.5)	(.4 ,.5)	(.25 ,.6)	(1 ,0)	(.8 ,.1)	(.25 ,.6)
8.Expert	(.5 ,.4)	(.8 ,.1)	(.6 ,.3)	(.8 ,.1)	(.4 ,.5)	(.4 ,.5)	(.1 ,.75)	(1 ,0)	(.7 ,.2)	(.1 ,.75)
9.Expert	(.8 ,.1)	(1 ,0)	(.4 ,.5)	(.8 ,.1)	(.5 ,.4)	(.25 ,.6)	(.25 ,.6)	(.9 ,.1)	(.8 ,.1)	(.4 ,.5)
10.Expert	(.7 ,.2)	(.7 ,.2)	(.4 ,.5)	(.9 ,.1)	(.6 ,.3)	(.4 ,.5)	(.1 ,.75)	(.8 ,.1)	(1 ,0)	(.4 ,.5)

Later, the GFFNs are crisped using Eq. (21). The crisped matrix for criteria with f=2 is expressed in Table 9.

Table 9

Crisped Matrix for Criteria (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
1.Expert	.725	.725	.725	1.000	.545	.455	.351	.900	.815	.224
2.Expert	.725	.725	.635	1.000	.545	.455	.351	.900	.815	.224
3.Expert	.635	.815	.635	.900	.545	.351	.351	1.000	.725	.224
4.Expert	.635	.815	.545	.815	.635	.351	.351	1.000	.725	.100
5.Expert	.725	.725	.545	1.000	.455	.351	.351	.815	.725	.100
6.Expert	.725	.725	.545	.900	.455	.351	.351	1.000	.725	.224
7.Expert	.545	.725	.545	.900	.455	.455	.351	1.000	.815	.351
8.Expert	.545	.815	.635	.815	.455	.455	.224	1.000	.725	.224
9.Expert	.815	1.000	.455	.815	.545	.351	.351	.900	.815	.455
1.Expert	.725	.725	.455	.900	.635	.455	.224	.815	1.000	.455

Next, the crisped numbers are normalized by Eq. (22). The normalized matrix for criteria with f=2 is shown in Table 10.

Table 10

Normalized Matrix for Criteria (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
1.Expert	.112	.112	.112	.155	.084	.070	.054	.139	.126	.035
2.Expert	.114	.114	.100	.157	.085	.071	.055	.141	.128	.035
3.Expert	.103	.132	.103	.146	.088	.057	.057	.162	.117	.036
4.Expert	.106	.136	.091	.136	.106	.059	.059	.167	.121	.017
5.Expert	.125	.125	.094	.173	.079	.061	.061	.141	.125	.017
6.Expert	.121	.121	.091	.150	.076	.059	.059	.167	.121	.037
7.Expert	.089	.118	.089	.147	.074	.074	.057	.163	.133	.057
8.Expert	.092	.138	.108	.138	.077	.077	.038	.170	.123	.038
9.Expert	.125	.154	.070	.125	.084	.054	.054	.138	.125	.070
1.Expert	.113	.113	.071	.141	.099	.071	.035	.128	.157	.071

Afterwards, normalized matrix for criteria is multiplied by values in Figure 2. Thus, expert-weighted matrix is obtained. For this, Eq. (23) is used. The expert-weighted matrix for criteria with f=2 is given in Table 11.

Table 11

Expert-weighted Matrix for Criteria (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
1.Expert	.012	.012	.012	.016	.009	.007	.006	.015	.013	.004
2.Expert	.013	.013	.012	.018	.010	.008	.006	.017	.015	.004
3.Expert	.012	.016	.012	.017	.011	.007	.007	.019	.014	.004
4.Expert	.010	.013	.009	.013	.010	.006	.006	.016	.012	.002
5.Expert	.012	.012	.009	.017	.008	.006	.006	.014	.012	.002
6.Expert	.014	.014	.010	.017	.009	.007	.007	.019	.014	.004
7.Expert	.009	.012	.009	.015	.008	.008	.006	.017	.014	.006
8.Expert	.009	.013	.010	.013	.008	.008	.004	.016	.012	.004
9.Expert	.009	.011	.005	.009	.006	.004	.004	.010	.009	.005
1.Expert	.008	.008	.005	.010	.007	.005	.003	.009	.012	.005

Behind, expert-weighted number for each criterion is summed via Eq. (24). The results for criteria with f=2 are shared in Table 12.

Table 12

Total Expert-weighted Numbers of Criteria (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
Sum	.110	.126	.094	.148	.085	.065	.054	.153	.127	.040

Finally, the weights of criteria are defined by Eq. (25). Results are obtained with five different fuzzy sets. In other words, f=2,3,log(4)/(3),log(3)/log(2) and log(2)/log(3). The comparative results are summarized in Table 13.

Table 13

Comparative Weights for Criteria

Fuzzy Set	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
PFS	.110	.126	.094	.148	.085	.065	.054	.153	.127	.040
FFS	.104	.119	.092	.145	.085	.072	.063	.152	.120	.049
KSFS	.112	.129	.095	.149	.085	.062	.048	.153	.130	.035
STFS	.112	.128	.095	.149	.085	.063	.050	.153	.129	.036
CDFS	.110	.126	.095	.146	.086	.066	.053	.152	.127	.040

Table 13 demonstrates that implementation complexity emerges as the most influential criterion across all fuzzy set systems, indicating that decision makers place primary importance on the practical feasibility and manageability of digital transformation initiatives. In contrast, interoperability and integration potential is consistently ranked as the least important criterion, suggesting that it is perceived as a secondary concern when compared to more immediate implementation challenges.

Moreover, the identical priority ordering of all criteria under different fuzzy set structures highlights a high level of methodological robustness and internal consistency. This consistency confirms that the obtained results are not sensitive to the choice of fuzzy representation and therefore provide reliable guidance for strategic decision making in the public sector.

4.2 Ranking of types of digital reforms

Firstly, linguistic assessments of types of digital reforms regarding criteria are collected. The linguistic assessments for types of digital reforms are illustrated in Table 14.

Table 14

Linguistic Assessments for Types of Digital Reforms

	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	M	L	H	H	H	M	H	L	H	M
DIAPS	VH	L	H	VH	H	VL	VH	L	VH	H
DDDSS	H	L	MH	MH	MH	VL	MH	VL	H	H
DCPPL	MH	L	MH	MH	MH	L	H	ML	H	H
DWSSS	MH	M	M	M	M	ML	MH	M	M	M
AIPSA	VH	L	VH	H	H	VVL	VH	VVL	VVH	H
SCDIN	MH	ML	H	MH	MH	M	MH	ML	M	MH
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	H	M	H	M	MH	M	M	ML	H	H
DIAPS	H	VL	H	H	VH	L	VH	L	H	H
DDDSS	MH	ML	H	MH	H	ML	H	ML	MH	H
DCPPL	H	L	H	MH	H	ML	H	L	MH	H
DWSSS	MH	M	MH	MH	M	ML	M	ML	M	MH
AIPSA	H	VVL	VH	VH	VVH	VVL	VVH	VVL	H	VH
SCDIN	MH	ML	MH	H	H	L	H	ML	M	MH
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	M	M	M	MH	MH	ML	MH	L	MH	M
DIAPS	H	VL	VH	H	VH	L	VH	VL	VH	H
DDDSS	MH	VL	MH	H	H	VL	MH	VL	H	MH
DCPPL	MH	ML	H	MH	MH	L	MH	ML	MH	H
DWSSS	M	M	MH	M	MH	M	M	ML	MH	MH
AIPSA	VH	VL	VH	VH	VVH	VL	VH	VVL	VH	VH
SCDIN	MH	ML	MH	MH	H	L	H	L	ML	MH
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	M	L	H	MH	M	M	H	L	M	H
DIAPS	VH	VL	VH	VH	H	VL	H	VL	VH	H
DDDSS	MH	ML	MH	H	MH	L	H	ML	MH	MH
DCPPL	MH	L	MH	H	MH	L	MH	ML	MH	MH
DWSSS	M	ML	MH	M	MH	M	MH	M	MH	MH
AIPSA	VVH	VVL	H	H	VH	VL	H	L	H	VVH
SCDIN	H	M	H	MH	H	M	H	M	M	H
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**

IGEOV	H	L	MH	MH	H	L	MH	M	H	MH
DIAPS	VH	L	VH	H	H	VL	VH	VL	VH	H
DDDSS	H	L	MH	MH	MH	ML	H	L	MH	H
DCPPL	MH	ML	MH	H	MH	L	H	ML	H	H
DWSSS	MH	ML	MH	M	M	M	MH	ML	M	MH
AIPSA	VVH	VL	VH	VVH	VH	VVL	VH	VL	VVH	VVH
SCDIN	H	M	H	MH	H	M	H	ML	M	MH
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	M	M	H	M	H	ML	H	M	MH	MH
DIAPS	VH	VL	H	H	VH	VL	H	VL	VH	VH
DDDSS	MH	L	MH	MH	H	VL	MH	L	MH	H
DCPPL	H	ML	H	MH	H	ML	H	L	H	H
DWSSS	MH	ML	MH	M	M	ML	MH	ML	MH	MH
AIPSA	H	VL	VVH	VH	VH	L	H	VL	VH	H
SCDIN	MH	L	MH	H	H	L	H	L	L	MH
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	H	L	M	H	H	ML	MH	ML	H	MH
DIAPS	H	VL	VH	H	VH	L	VH	L	VH	H
DDDSS	H	ML	MH	MH	MH	VL	H	L	MH	MH
DCPPL	MH	ML	MH	H	H	ML	MH	L	MH	MH
DWSSS	M	ML	MH	M	M	M	M	ML	MH	MH
AIPSA	H	VL	H	VH	VVH	L	H	VVL	VH	VVH
SCDIN	H	M	H	MH	H	M	H	ML	M	H
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	M	L	M	M	H	M	H	L	M	M
DIAPS	VH	L	VH	VH	H	L	VH	VL	VH	H
DDDSS	H	VL	MH	MH	H	L	MH	L	MH	MH
DCPPL	H	ML	MH	H	H	L	H	ML	MH	H
DWSSS	M	M	M	M	M	M	M	M	MH	M
AIPSA	H	VVL	VVH	VVH	H	VL	VH	L	VVH	H
SCDIN	MH	L	H	MH	H	ML	H	ML	ML	H
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	MH	M	MH	MH	MH	M	H	M	MH	MH
DIAPS	VH	VL	H	H	VH	VL	H	L	H	H
DDDSS	MH	L	MH	MH	H	L	MH	L	MH	H
DCPPL	H	ML	MH	H	H	ML	MH	ML	H	MH
DWSSS	MH	M	M	MH	M	ML	M	ML	M	MH
AIPSA	VH	VVL	VH	VVH	H	L	H	VVL	VVH	VVH
SCDIN	MH	L	MH	MH	MH	L	H	ML	L	H
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	MH	L	M	H	H	ML	M	L	H	H
DIAPS	H	VL	VH	H	H	VL	H	VL	VH	VH
DDDSS	H	VL	H	MH	H	L	H	VL	H	H
DCPPL	MH	L	MH	MH	H	L	MH	ML	MH	MH
DWSSS	MH	ML	MH	MH	MH	ML	M	ML	M	M
AIPSA	VVH	VL	VH	VH	VVH	VVL	VH	VL	VH	VVH
SCDIN	H	ML	H	H	H	ML	H	ML	M	MH

These linguistic assessments for types of digital reforms are converted to scale as Table 1. The numerical assessments for types of digital reforms are displayed in Table 15.

Table 15

Numerical Assessments for Types of Digital Reforms

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
IGEOV	5	3	7	7	7	5	7	3	7	5
DIAPS	8	3	7	8	7	2	8	3	8	7
DDDSS	7	3	6	6	6	2	6	2	7	7
DCPPL	6	3	6	6	6	3	7	4	7	7
DWSSS	6	5	5	5	5	4	6	5	5	5
AIPSA	8	3	8	7	7	1	8	1	9	7
SCDIN	6	4	7	6	6	5	6	4	5	6
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	7	5	7	5	6	5	5	4	7	7
DIAPS	7	2	7	7	8	3	8	3	7	7
DDDSS	6	4	7	6	7	4	7	4	6	7
DCPPL	7	3	7	6	7	4	7	3	6	7
DWSSS	6	5	6	6	5	4	5	4	5	6
AIPSA	7	1	8	8	9	1	9	1	7	8
SCDIN	6	4	6	7	7	3	7	4	5	6
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	5	5	5	6	6	4	6	3	6	5
DIAPS	7	2	8	7	8	3	8	2	8	7
DDDSS	6	2	6	7	7	2	6	2	7	6
DCPPL	6	4	7	6	6	3	6	4	6	7
DWSSS	5	5	6	5	6	5	5	4	6	6
AIPSA	8	2	8	8	9	2	8	1	8	8
SCDIN	6	4	6	6	7	3	7	3	4	6
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	5	3	7	6	5	5	7	3	5	7
DIAPS	8	2	8	8	7	2	7	2	8	7
DDDSS	6	4	6	7	6	3	7	4	6	6
DCPPL	6	3	6	7	6	3	6	4	6	6
DWSSS	5	4	6	5	6	5	6	5	6	6
AIPSA	9	1	7	7	8	2	7	3	7	9
SCDIN	7	5	7	6	7	5	7	5	5	7
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	7	3	6	6	7	3	6	5	7	6
DIAPS	8	3	8	7	7	2	8	2	8	7
DDDSS	7	3	6	6	6	4	7	3	6	7
DCPPL	6	4	6	7	6	3	7	4	7	7
DWSSS	6	4	6	5	5	5	6	4	5	6
AIPSA	9	2	8	9	8	1	8	2	9	9
SCDIN	7	5	7	6	7	5	7	4	5	6
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	5	5	7	5	7	4	7	5	6	6
DIAPS	8	2	7	7	8	2	7	2	8	8
DDDSS	6	3	6	6	7	2	6	3	6	7
DCPPL	7	4	7	6	7	4	7	3	7	7
DWSSS	6	4	6	5	5	4	6	4	6	6
AIPSA	7	2	9	8	8	3	7	2	8	7
SCDIN	6	3	6	7	7	3	7	3	3	6
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	7	3	5	7	7	4	6	4	7	6
DIAPS	7	2	8	7	8	3	8	3	8	7

DDDSS	7	4	6	6	6	2	7	3	6	6
DCPPL	6	4	6	7	7	4	6	3	6	6
DWSSS	5	4	6	5	5	5	5	4	6	6
AIPSA	7	2	7	8	9	3	7	1	8	9
SCDIN	7	5	7	6	7	5	7	4	5	7
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	5	3	5	5	7	5	7	3	5	5
DIAPS	8	3	8	8	7	3	8	2	8	7
DDDSS	7	2	6	6	7	3	6	3	6	6
DCPPL	7	4	6	7	7	3	7	4	6	7
DWSSS	5	5	5	5	5	5	5	5	6	5
AIPSA	7	1	9	9	7	2	8	3	9	7
SCDIN	6	3	7	6	7	4	7	4	4	7
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	6	5	6	6	6	5	7	5	6	6
DIAPS	8	2	7	7	8	2	7	3	7	7
DDDSS	6	3	6	6	7	3	6	3	6	7
DCPPL	7	4	6	7	7	4	6	4	7	6
DWSSS	6	5	5	6	5	4	5	4	5	6
AIPSA	8	1	8	9	7	3	7	1	9	9
SCDIN	6	3	6	6	6	3	7	4	3	7
	EEG	**IMP**	**ACS**	**POS**	**CIA**	**DSP**	**LRC**	**ICX**	**LTS**	**IIP**
IGEOV	6	3	5	7	7	4	5	3	7	7
DIAPS	7	2	8	7	7	2	7	2	8	8
DDDSS	7	2	7	6	7	3	7	2	7	7
DCPPL	6	3	6	6	7	3	6	4	6	6
DWSSS	6	4	6	6	6	4	5	4	5	5
AIPSA	9	2	8	8	9	1	8	2	8	9
SCDIN	7	4	7	7	7	4	7	4	5	6

Next, distances between numerical matrices of experts for types of digital reforms are established using Eq. (16). The Euclidean distances are shared in Table 16.

Table 16

Distance Matrix for Types of Digital Reforms

	1.Expert	**2.Expert**	**3.Expert**	**4.Expert**	**5.Expert**	**6.Expert**	**7.Expert**	**8.Expert**	**9.Expert**	**10.Expert**
1.Expert		8.775	7.416	8.124	7.000	7.874	7.874	7.141	8.000	7.348
2.Expert	8.775		7.483	8.660	7.746	7.280	7.681	8.832	7.280	7.416
3.Expert	7.416	7.483		8.062	7.616	6.557	6.856	6.782	7.000	6.557
4.Expert	8.124	8.660	8.062		7.416	8.832	7.211	8.062	8.367	7.616
5.Expert	7.000	7.746	7.616	7.416		8.062	6.245	7.616	7.550	6.083
6.Expert	7.874	7.280	6.557	8.832	8.062		8.124	7.141	5.831	8.367
7.Expert	7.874	7.681	6.856	7.211	6.245	8.124		8.062	7.483	6.633
8.Expert	7.141	8.832	6.782	8.062	7.616	7.141	8.062		7.141	8.062
9.Expert	8.000	7.280	7.000	8.367	7.550	5.831	7.483	7.141		8.000
10.Expert	7.348	7.416	6.557	7.616	6.083	8.367	6.633	8.062	8.000	

Afterwards, the distances for each expert in Table 16 is summed with Eq. (17). Next, consensus value for each expert is computed via Eq. (18). The results for types of digital reforms are presented in Table 17.

Table 17

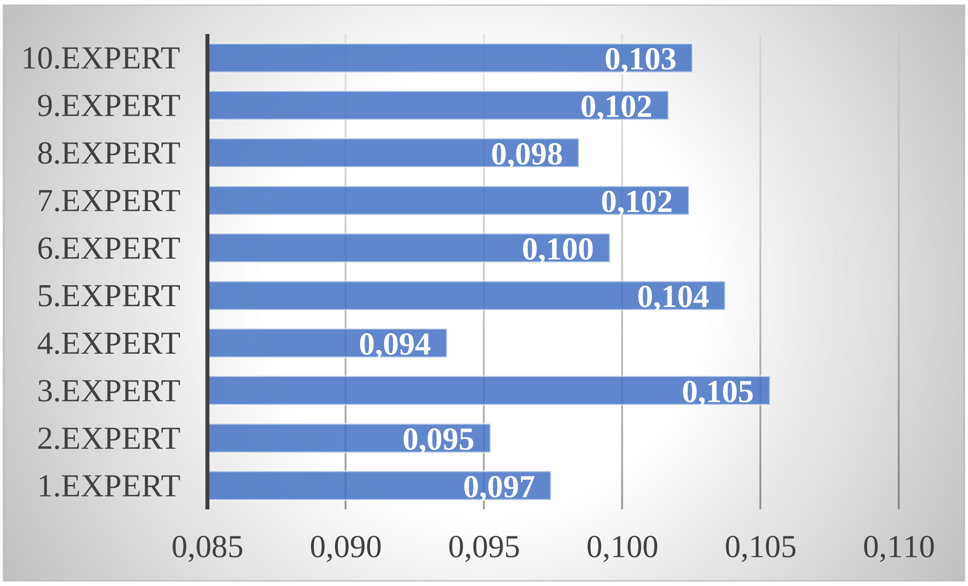
Total Distances and Consensus Values for Types of Digital Reforms

	1.Expert	**2.Expert**	**3.Expert**	**4.Expert**	**5.Expert**	**6.Expert**	**7.Expert**	**8.Expert**	**9.Expert**	**10.Expert**
Total Dist.	69.553	71.154	64.330	72.350	65.334	68.069	66.170	68.841	66.652	66.083
Consensus	.014	.014	.016	.014	.015	.015	.015	015	.015	.015

Finally, the importance coefficients of experts for types of digital reforms are defined using Eq. (19). These coefficients are visualized in Figure 3.

Figure 3

Importance Coefficients of Experts for Types of Digital Reforms



After calculating the importance coefficients of the experts, the linguistic assessments in Table 14 are converted into GFFNs in Table 1. Next, these GFFNs are averaged with GFFWA operator and importance coefficients of the experts in Figure 3. Thus, GFF-decision matrix formed in Eq. (26) is created. This matrix for f=2 is exhibited in Table 18.

Table 18

GFF-Decision Matrix (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
IGEOV	(.595,.306)	(.378,.51)	(.612,.289)	(.612,.289)	(.659,.241)	(.443,.457)	(.64,.26)	(.378,.511)	(.641,.259)	(.61,.291)
DIAPS	(.765,.132)	(.161,.702)	(.766,.131)	(.734,.164)	(.756,.141)	(.177,.686)	(.766,.132)	(.177,.686)	(.784,.115)	(.724,.174)
DDDSS	(.655,.244)	(.277,.609)	(.623,.277)	(.623,.277)	(.665,.235)	(.25,.633)	(.655,.245)	(.258,.621)	(.635,.265)	(.664,.235)
DCPPL	(.644,.256)	(.351,.537)	(.634,.266)	(.655,.245)	(.664,.235)	(.32,.558)	(.654,.246)	(.364,.528)	(.645,.255)	(.664,.235)
DWSSS	(.564,.337)	(.454,.447)	(.574,.327)	(.534,.367)	(.534,.367)	(.455,.447)	(.544,.357)	(.433,.469)	(.554,.346)	(.574,.327)
AIPSA	(.812,.132)	(.123,.788)	(.813,.115)	(.827,.114)	(.832,.123)	(.162,.754)	(.782,.132)	(.143,.787)	(.838,.114)	(.843,.123)
SCDIN	(.645,.255)	(.401,.494)	(.664,.235)	(.634,.266)	(.683,.217)	(.401,.492)	(.692,.208)	(.387,.508)	(.444,.454)	(.644,.255)

Next, the optimal solution for each criterion is selected using Eqs. (27) and (28). According to types of criteria in Table 3, the optimal solutions for f=2 are expressed in Table 19.

Table 19

Optimal Solutions (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
Optimal	(.812,.132)	(.123,.788)	(.813,.115)	(.827,.114)	(.832,.123)	(.162,.754)	(.782,.132)	(.143,.787)	(.838,.114)	(.843,.123)

Afterwards, the similarity matrix is constructed with Eqs. (29) and (30). This matrix for f=2 is shown in Table 20.

Table 20

Similarity Matrix (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
IGEOV	.767	.447	.784	.773	.820	.464	.842	.454	.796	.759
DIAPS	.955	.739	.953	.905	.926	.816	.985	.715	.948	.881
DDDSS	.834	.559	.796	.785	.827	.693	.859	.588	.789	.817
DCPPL	.822	.472	.808	.820	.827	.579	.858	.469	.800	.817
DWSSS	.734	.392	.742	.689	.686	.455	.733	.414	.703	.721
AIPSA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
SCDIN	.823	.430	.841	.797	.847	.499	.901	.449	.587	.796

Behind, the weighted similarity matrix is obtained by multiplying with the weights of criteria via Eq. (31). This matrix for f=2 is given in Table 21.

Table 22

Weighted Similarity Matrix (f=2)

	EEG	IMP	ACS	POS	CIA	DSP	LRC	ICX	LTS	IIP
IGEOV	.084	.056	.074	.114	.070	.030	.045	.069	.101	.030
DIAPS	.105	.093	.090	.134	.079	.053	.053	.109	.120	.035
DDDSS	.091	.070	.075	.116	.070	.045	.046	.090	.100	.032
DCPPL	.090	.059	.076	.121	.070	.038	.046	.072	.101	.032
DWSSS	.080	.049	.070	.102	.058	.030	.039	.063	.089	.029
AIPSA	.110	.126	.094	.148	.085	.065	.054	.153	.127	.040
SCDIN	.090	.054	.079	.118	.072	.033	.048	.069	.074	.032

Finally, the geometric mean of weighted similarities for each type of digital reforms is calculated by Eq. (32). Ranking scores are obtained with five different fuzzy sets. The comparative geometric means of types of digital reforms are presented in Table 23.

Table 23

Comparative Rankings for Types of Digital Reforms

Fuzzy Set	PFS	FFS	KSFS	STFS	CDFS
IGEOV	.062	.067	.058	.059	.063
DIAPS	.081	.083	.080	.080	.084
DDDSS	.069	.072	.066	.067	.070
DCPPL	.065	.070	.062	.063	.066
DWSSS	.056	.063	.052	.053	.057
AIPSA	.092	.094	.090	.091	.092
SCDIN	.062	.068	.058	.059	.063

Table 23 indicates that, across all fuzzy set systems, the adoption of AI based public service applications is identified as the most optimal type of digital reform, reflecting its strong potential to enhance efficiency, automation, and service quality in the public sector. In contrast, the expansion of digital welfare and social service systems is ranked as the least suitable alternative, suggesting that it may face greater implementation challenges or deliver comparatively lower efficiency gains under current conditions. In addition, the fact that the ranking order of all digital reform types remains unchanged across different fuzzy set structures demonstrates a high degree of result stability. This uniformity confirms the robustness and consistency of the proposed decision-making model, reinforcing the reliability of the findings for guiding strategic digital transformation policies.

5 DISCUSSION

The findings indicate that implementation complexity is the most influential criterion affecting the ability of digital transformation initiatives to enhance efficiency in the public sector. This result suggests that even well-designed digital strategies may fail to deliver expected benefits if they are difficult to implement within existing administrative structures. Implementation complexity reflects issues such as technical difficulty, coordination among institutions, organizational resistance, and time requirements, all of which directly shape practical outcomes. When complexity is high, public institutions may experience delays, cost overruns, and reduced employee acceptance, which in turn weaken efficiency gains (Uster, 2025). This relationship is strongly aligned with the existing literature, which emphasizes that feasibility and administrative simplicity are key success factors in public sector reforms. The results highlight the importance of designing digital transformation strategies that are compatible with institutional capacities and operational routines (Odularu, 2025). Policymakers should therefore prioritize phased implementation approaches, capacity building programs, and clear governance structures to reduce complexity. Simplifying procedures, strengthening interdepartmental coordination, and providing continuous technical support can further improve implementation outcomes. From a policy perspective, strategies that explicitly assess and manage implementation challenges are more likely to generate sustainable efficiency improvements and avoid the risks associated with overly ambitious or poorly aligned digital reforms (Mwita and Kitole, 2025).

The adoption of AI based public service applications emerges as the most prioritized strategy for improving efficiency through digital transformation in the public sector. This finding indicates that artificial intelligence is perceived as a powerful tool for enhancing automation, accuracy, and speed in public service delivery. AI based applications enable public institutions to process large volumes of data, reduce manual workload, and offer more personalized and consistent services to citizens (Anshari et al., 2025). The strong relationship between AI adoption and efficiency improvement is consistent with prior studies, which emphasize the transformative potential of intelligent systems in public administration. However, realizing these benefits requires careful strategic planning and policy design. Public institutions must ensure that AI applications are aligned with service needs, ethical standards, and legal frameworks (Papadopoulos et al., 2025). Investment in data quality, digital skills, and organizational readiness is also critical for effective implementation. Policymakers should focus on pilot projects, transparent algorithms, and continuous performance evaluation to build trust and institutional learning (Muhammad et al., 2025). By embedding AI strategies within a broader digital governance framework, public administrations can enhance efficiency while maintaining accountability and public value creation.

6 CONCLUSION

This study was conducted to determine the most appropriate digital transformation strategies for improving efficiency in the public sector by employing a systematic and analytical evaluation approach. In line with this objective, an original decision-making framework was developed by combining the COWEB method, the RATGOS ranking technique, and generalized fractal fuzzy sets introduced by the authors. Evaluation criteria and strategic alternatives were identified through an extensive review of prior studies, and expert assessments were obtained from ten professionals with relevant experience. The empirical findings reveal that implementation complexity plays a decisive role in shaping efficiency outcomes, while AI based public service applications stand out as the most effective strategic option. These results offer practical guidance for public institutions seeking to balance innovation with feasibility. From an academic perspective, the study contributes to the literature by presenting a novel methodological integration and by providing a structured tool for prioritizing digital transformation initiatives under conditions of uncertainty.

Nevertheless, several limitations should be considered when interpreting the results of this research. The reliance on expert-based evaluations may introduce subjectivity, as judgments can vary depending on individual experience and institutional context. Moreover, the scope of the proposed model is limited to a specific set of criteria and strategic alternatives, which may restrict its generalizability to other public sector settings. The use of generalized fractal fuzzy sets, although effective in capturing uncertainty, also increases the analytical complexity of the framework. Future research could overcome these constraints by involving a broader and more diverse group of experts, incorporating quantitative performance indicators, and applying the model in different countries or policy domains. In addition, extending the framework with comparative or dynamic analyses may further strengthen its explanatory power and practical applicability.

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All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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