

Evaluation and Prioritization of Digital Transformation Strategies in Public Finance Using a T-Spherical Fuzzy Set-Based Entropy and MAUT Approach

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ARTICLE INFO	ABSTRACT
Article history: Received 6 July 2026 Received in revised form 26 August 2026 Accepted 30 September 2026 Available online 5 October 2026 Keywords: Public Finance; Digital Transformation; T-Spherical Fuzzy Sets; Entropy; MAUT	This study aims to improve the effectiveness and efficiency of public finance in the context of digital transformation and Industry 4.0 and to determine sustainable digital transformation strategies and a corresponding roadmap. In this context, an integrated decision-making model based on T-spherical fuzzy sets was developed to address gaps in strategic planning, data management, and technology adaptation. Within the proposed model, the entropy method is used to determine objective criterion weights, while Multi-Attribute Utility Theory (MAUT) is employed to evaluate and rank the alternatives. According to the results, “Stakeholder Participation” is the most influential criterion, with a weight of 0.1339, while the A5 “Data Analytics and Business Intelligence” strategy is identified as the highest-priority alternative. The robustness analysis confirms the stability and consistency of the obtained results, supporting the reliability of the proposed decision-making framework.

1. Introduction

The effectiveness of fiscal policy and its functions-such as ensuring stability in the economic cycle, achieving income-distribution objectives and collecting resources to support public expenditures-depends on the ability of governments to use information and technology. During recessions or periods of prosperity, the decisions that governments make regarding tax policies and investment services such as social security, health and infrastructure differ [1]. The reason for this lies in the reliability and detail of the information that the government possesses about economic actors. By transforming the processes of collecting, processing and using this information, digitalization reshapes the design and implementation of fiscal policies.

While computerization has become routine in government practices, digitalization offers a comprehensive transformation through deep-learning technologies. These technologies enable computers to acquire independent learning ability and to perform functions such as design, scientific-hypothesis generation and even music composition [2]. Today, although data collection and storage

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capacity have increased substantially and digitalization has produced major effects in every field of the world, public finance is still at an early stage in this process and faces various obstacles. Kotinaet *al.*, [3] state that digitalization is a major challenge for public finance and requires governments to take faster steps in this area, emphasizing that a delay has occurred because of global problems such as regional wars, terrorism and the pandemic. Although the increasing demand for digital public services accelerates the transformation process, this is only a small part of the transformation. On the other hand, structural problems persist-particularly in developing countries-such as the inefficient allocation of resources and the inadequate exploitation of digitalization opportunities at the local level [4, 5].

The digital transformation process does not mean merely renewing the technological infrastructure; it also necessitates a fundamental transformation of public-finance processes. The use of advanced technologies such as data analytics, artificial intelligence and automation offers important opportunities for the more efficient management of public resources. However, various challenges also exist in this process, such as data security, ethical issues and the adaptation of personnel to technological innovations. By addressing the critical points in the integration of the digital transformation process into public finance, the research aims to reveal in which areas this transformation provides progress and in which areas it requires improvement. The study emphasizes that stakeholder participation and the establishment of regulatory frameworks are critical elements in the success of digital transformation. While the active participation of stakeholders ensures that projects are shaped according to needs and that efficiency increases, regulatory policies enhance the reliability of the processes. Consequently, the sustainability of digital-transformation projects will be possible through flexible regulatory frameworks and continuous feedback mechanisms.

In the literature, there are gaps regarding digital-transformation strategies and the criteria used to evaluate these strategies. To address these gaps, this study not only proposes a set of strategies and criteria but also develops a decision-making model that combines the entropy and MAUT methods with T-spherical fuzzy sets. This model enables uncertainties to be handled effectively and allows digital-transformation strategies in public finance to be evaluated precisely. While the entropy method provides objective criterion weighting through its data-driven approach, the MAUT method provides a simple and clear alternative-ranking process. The advantages of the proposed model are important in terms of prioritizing digital-transformation strategies and creating an effective roadmap for this process.

After a comprehensive introduction, the remainder of the study is structured as follows. Section 2 presents the results of a comprehensive literature review, noting the contributions of previous studies as well as the unfilled research gaps and theoretical-evaluation deficiencies in the literature. Section 3 introduces the implementation steps and the basic algorithm of the proposed decision-making approach. Section 4 summarizes the results obtained by applying the proposed integrated decision-making procedure to address the decision problem concerning the evaluation and prioritization of digital-transformation strategies in public finance and to produce reasonable solutions. Section 5 checks the consistency, validity and reliability of the proposed model and of the obtained results by presenting the results of the comprehensive robustness tests carried out for this purpose. Section 6 evaluates and discusses the results obtained in the application. This section also presents the limitations of the study and recommendations for future studies.

2. Literature Review

In this study, a comprehensive literature review was carried out to identify the existing research gaps as well as the contributions provided by previous studies. For this purpose, international and local citation databases were examined using the keywords noted in the study, and the studies obtained were recorded. Within this scope, studies that focus directly or indirectly on digital transformation in

public finance are addressed. Accordingly, the Mendeley, Web of Science, Elsevier, Springer and Ulakbim citation databases were examined comprehensively, and studies on this subject were collected. The impact of digital transformation on public finance has been extensively addressed in the academic literature in recent years, and research in this field has concentrated around certain trends and developments. The studies have generally examined the effects of digitalization on public finance, the opportunities and challenges encountered in this process, the changes brought about by technological innovations, and regional differences. The main trends and current developments in the literature are summarized below.

The effects of digitalization on public finance have been addressed both in the context of efficiency gains in operational processes and the transformation of the management paradigm. For example, Molchanova [6, 7] emphasized how digitalization automates public financial-management processes through platforms such as the “Electronic Budget” and optimizes budget-planning and expenditure-control processes. These studies highlighted that digitalization brings transparency, accountability and effectiveness to public financial management.

The effects of digital transformation in different countries have also been examined in the studies. Pantieliieva *et al.*, [8] addressed the effects of digitalization on the national economy in Ukraine, focusing on the weaknesses and threats of this process. Lima *et al.*, [9], on the other hand, emphasized the contribution of digitalization in Cabo Verde to national growth by increasing efficiency in public finance, and evaluated the country's success in the GovTech maturity index. This diversity shows that digitalization produces results that vary according to the national context.

The role of artificial intelligence (AI), blockchain and other advanced technologies in digitalization processes has frequently been emphasized in the literature. Mosteanu & Faccia [10] stated that blockchain and AI reduce the risks of error and fraud and increase the reliability of public-finance processes stated. Vovchenko *et al.*, [11], on the other hand, examined the use of artificial intelligence in tax administration and social-security platforms and concluded that these technologies bring flexibility and speed to the processes.

The potential of digitalization to increase transparency in public finance has been addressed in many studies. Pudryket *al.*, [12] demonstrated that digital technologies are an important tool in the fight against corruption and that their integration into the 2030 Sustainable Development Agenda is critical in this process. Similarly, Matviienko [13] emphasized that digital transformation makes budgeting processes fairer by increasing tax revenues.

The contribution of digital transformation to sustainable public finance has been examined particularly in the context of strategic planning. Tsindelianiet *al.*, [14] and Volkova [15] stated that digitalization is a catalyst for fiscal sustainability, but that long-term planning and universal steps are of critical importance in this process. Mulendeeva [16] offered recommendations for improving digital-transformation strategies in Russia.

The challenges encountered in the digitalization process have concentrated around topics such as data security and infrastructure deficiencies. Mosteanu and Faccia [10] and El-Manaseer El-Manaseer *et al.*, [17] emphasized cybersecurity risks and the importance of data management, stating that improvements should be made in these areas. Shichanin [18], on the other hand, demonstrated that digitalization introduces new problems and risks to public financial control, but that the transformation of regulations is critical in this process.

When the studies summarized above are examined comprehensively and in detail, the advantages that digitalization provides to public finance, the challenges encountered, and its contributions in terms of sustainability stand out in particular. The common findings of the studies show that digital transformation increases efficiency, transparency and security in public finance. In particular, digital technologies contribute to the more effective execution of processes such as budget management, tax

collection, financial control and the monitoring of public expenditures. In addition, there are findings indicating that the use of technologies such as artificial intelligence (AI), blockchain and electronic document-management systems increases financial security by reducing the risks of fraud and error. Moreover, the results of various studies indicating that digitalization contributes to economic growth and to sustainability in public administration share similar directions.

2.1 Common Findings and Inferences from Previous Studies

The common findings and inferences of the previous studies in the relevant literature can be summarized as follows.

- i. **Efficiency and Effectiveness Improvement:** Digital transformation increases operational efficiency by automating business processes in public finance. Thanks to digital tools such as information technologies and AI, it becomes possible to complete budget processes more quickly and without errors. Studies such as Blizkiy & Lebedinskaya [7] reveal how information technologies accelerate these processes and improve quality.
- ii. **Transparency and Accountability:** Digital transformation stands out as a factor that supports transparency and accountability in public finance. The use of digital tools provides important contributions, particularly in the fight against corruption and in ensuring the effective use of public funds. In this context, the study by Pudryket *al.*, [12] shows that digitalization serves the Sustainable Development Goals (SDGs) by increasing transparency and plays an important role in the fight against corruption.
- iii. **Security and Data Management:** The impact of digital transformation on public finance also manifests itself in the fields of data security and cybersecurity. While digital technologies provide important advantages in terms of protecting financial information and reducing the risk of fraud, new challenges have emerged in the fields of data management and cybersecurity. The studies of Matviienko [13] and Vovchenkoet *al.*, [11] addressed these aspects of digital transformation comprehensively.
- iv. **Adaptation to the Digital Economy:** Many studies emphasize that digitalization is important in terms of making public finance compatible with the digital economy. In particular, research conducted in Russia and Ukraine [6, 8] reveals that the integration of public finance into the digital economy is a strategic necessity for economic growth and development.
- v. **Use of New Technologies:** The benefits that innovative technologies such as artificial intelligence, blockchain and electronic document-management systems provide in public finance are widely emphasized in the literature. These technologies are considered important in terms of reducing error rates, increasing the accuracy of financial reports and accelerating processes. The studies of Mosteanu & Faccia [10] and Efremova [19] detail the applications of these technologies in public finance.

2.2 Differences Among Previous Studies

There are important differences among the previous studies in terms of the findings obtained, the insights and the points of focus. These differences can be evaluated as follows.

- i. **Geographical and Economic Context:** The countries on which the studies focus show important differences in terms of their approach to the digital-transformation process. For example, studies conducted in countries such as Russia and Ukraine address the effects of digital transformation on public finance in the context of local economic and political challenges [13, 14]. On the other hand, studies conducted in African countries such as Cabo Verde foreground the contribution of digital transformation to economic growth more strongly [9].

- ii. Purpose and Focus of Digitalization: Some studies focus on increasing transparency, the fight against corruption and accountability in public finance [12], while some other studies question the relationship between digital transformation and the sustainability of public finance [3].
- iii. Digital Technologies Used: The digital technologies used in the literature differ. For example, while Senturk [20] addresses digitalization in public internal-audit activities in Türkiye, Mosteanu & Faccia [10] examined the advantages of artificial-intelligence and blockchain technologies in public finance. This situation offers various perspectives on the contributions that different digital tools provide to public finance.
- iv. Risks and Challenges: The studies also touch upon the risks and challenges that digitalization brings, in addition to the advantages it offers to public finance. For example, while Matvienko [13] states that digitalization introduces new challenges in the field of cybersecurity and data management, other studies foreground the requirements of strategic transformation.

2.3 General Trends in the Literature

In the literature, it is generally observed that digitalization has a transformative effect on public finance and that this process makes public-finance management more efficient, transparent and secure. While studies that concentrate on transparency, accountability and efficiency emphasize the benefits provided by digital transformation, they also draw attention to the importance of the regulatory framework required for digitalization to be implemented effectively. In addition, it is observed that digital transformation is regarded as a strategic necessity for financial sustainability and public finance. It is frequently emphasized that digital technologies offer innovative solutions in public-finance management and provide a more secure financial environment by reducing the risk of fraud. Nevertheless, the cybersecurity and data-management challenges that digitalization brings with it are among the topics that attract attention in the literature.

general trend in the literature that digital transformation is used as an effective tool in public finance and that public finance will, in the future, be shaped in line with the opportunities offered by digitalization general trend. However, many studies also recommend that, in this process, public finance should be supported by a more flexible, secure and strategic digital infrastructure.

2.4 Research and Theoretical Gaps in the Literature

Although the existing studies on the effects and challenges of digitalization on public finance provide important contributions, they also bring with them certain theoretical gaps and research needs. The general principles and theoretical framework of digital transformation have not been sufficiently explained in the literature, and the comparative analysis of strategies in different countries in particular has not been a focus. While most studies remain limited to the local context, they offer incomplete assessments from a global perspective. These studies, which concentrate on the benefits of digitalization, generally do not address in depth the risks encountered in the process, such as cybersecurity, data management and cultural adaptation. Although the effect of digital transformation on the sustainability of public finance is emphasized, concrete recommendations on how this relationship can be strengthened or which digital tools would be more effective are limited. In addition, how digital technologies are to be integrated into policy-making processes has not been detailed.

The limited use of multi-criteria decision-making methods is another important deficiency that hinders the multidimensional analysis of the digital-transformation process. Yet evaluating financial, technical and social criteria together can increase the effectiveness of transformation processes. Furthermore, the effect of digitalization on uncertainty management, the continuous change of technological innovations, and unforeseen risks has been addressed inadequately. More comprehensive studies are needed on topics such as data security and artificial intelligence.

In general, the existing literature contains deficiencies from both theoretical and methodological perspectives. In order to manage digital-transformation processes effectively, it is important to increase the number of studies that include comparative analyses, uncertainty-management strategies and multi-criteria evaluation methods. Addressing these deficiencies can significantly increase the sustainability and effectiveness of digital transformation in public finance.

3. Proposed T-Spherical Fuzzy Set-Based Mathematical Model

This section presents an explanation of the proposed decision model and its implementation steps.

3.1 Preliminaries on T-Spherical Fuzzy Sets

In this section, T-SFSs and the proposed model are presented in detail. T-SFSs were preferred because they cover the general structure of sets such as spherical fuzzy sets (SFS), picture fuzzy sets (PFS) and q-Rung Orthopair fuzzy sets (q-ROF) [21]. The following subsections address T-SFSs and the proposed model, respectively.

Definition 1. [22–24] In the universe of discourse X , a T-SFS “ G ” is defined as given in Equation (1).

$$G = \{ \langle x, \mu_G(x), \eta_G(x), \vartheta_G(x) \rangle \mid x \in X \}, \quad (1)$$

Here, $\mu_G(x): X \rightarrow [0,1]$, $\eta_G(x): X \rightarrow [0,1]$ and $\vartheta_G(x): X \rightarrow [0,1]$. In Equation (1), $\mu_G(x)$ denotes the membership degree, $\eta_G(x)$ denotes the abstinence degree and $\vartheta_G(x)$ denotes the non-membership degree. In addition, the condition $0 \leq \mu_G^t(x) + \eta_G^t(x) + \vartheta_G^t(x) \leq 1, t \geq 1, \forall x \in X$ must be satisfied. On the other hand, the “refusal degree” is $\pi_G(x) = \sqrt[t]{1 - \mu_G^t(x) - \eta_G^t(x) - \vartheta_G^t(x)}$ is defined as.

Definition 2. For the sake of simplicity, a T-spherical fuzzy number (μ, η, ς) is defined as [21, 24, 25]. Here two different T-spherical fuzzy numbers $g_1 = (\mu_1, \eta_1, \varsigma_1)$ and $g_2 = (\mu_2, \eta_2, \varsigma_2)$ is shown. Some mathematical operations are shown below between Equations (2) and (5). Here $\lambda > 0$ must be satisfied [23].

$$g_1 \oplus g_2 = \langle (1 - (1 - \mu_1^t)(1 - \mu_2^t))^{1/t}, ((1 - \mu_1^t)(1 - \mu_2^t) - (1 - \mu_1^t - \eta_1^t)(1 - \mu_2^t - \eta_2^t))^{1/t}, ((1 - \mu_1^t - \eta_1^t)(1 - \mu_2^t - \eta_2^t) - (1 - \mu_1^t - \eta_1^t - \varsigma_1^t)(1 - \mu_2^t - \eta_2^t - \varsigma_2^t))^{1/t} \rangle \quad (2)$$

$$g_1 \otimes g_2 = \langle ((1 - \varsigma_1^t - \eta_1^t)(1 - \varsigma_2^t - \eta_2^t) - (1 - \varsigma_1^t - \eta_1^t - \varsigma_1^t)(1 - \varsigma_2^t - \eta_2^t - \varsigma_2^t))^{1/t}, ((1 - \varsigma_1^t)(1 - \varsigma_2^t) - (1 - \varsigma_1^t - \eta_1^t)(1 - \varsigma_2^t - \eta_2^t))^{1/t}, (1 - (1 - \varsigma_1^t)(1 - \varsigma_2^t))^{1/t} \rangle \quad (3)$$

$$\lambda * g_1 = \langle (1 - (1 - \mu_1^t)^\lambda)^{1/t}, ((1 - \mu_1^t)^\lambda - (1 - \mu_1^t - \eta_1^t)^\lambda)^{1/t}, ((1 - \mu_1^t - \eta_1^t)^\lambda - (1 - \mu_1^t - \eta_1^t - \varsigma_1^t)^\lambda)^{1/t} \rangle \quad (4)$$

$$g_1^\lambda = \langle ((1 - \varsigma_1^t - \eta_1^t)^\lambda - (1 - \varsigma_1^t - \eta_1^t - \mu_1^t)^\lambda)^{1/t}, ((1 - \varsigma_1^t)^\lambda - (1 - \varsigma_1^t - \eta_1^t)^\lambda)^{1/t}, (1 - (1 - \varsigma_1^t)^\lambda)^{1/t} \rangle \quad (5)$$

On the other hand, as in spherical fuzzy sets, $g_1 \oplus g_2 = g_2 \oplus g_1$, $g_1 \otimes g_2 = g_2 \otimes g_1$, $\lambda g_1 \oplus \lambda g_2 = \lambda(g_1 \oplus g_2)$, $\lambda_1 g_1 \oplus \lambda_2 g_1 = g_1(\lambda_1 \oplus \lambda_2)$, $(g_1 \otimes g_2)^\lambda = g_1^\lambda \otimes g_2^\lambda$, and $g_1^{\lambda_1} \otimes g_1^{\lambda_2} = g_1^{\lambda_1 + \lambda_2}$ hold [23].

Definition 3. The T-Spherical Weighted Averaging Interaction (T-SWAI) operator and the T-Spherical Weighted Geometric Interaction (T-SWGI) operator $g_j = \langle \mu_j, \eta_j, \varsigma_j \rangle$ ($j = 1, \dots, n$) such as different are used for aggregating T-spherical fuzzy sets and numbers. For this purpose, Equation (6) is used for T-SWAI, while Equation (7) defines T-SWGI. Here $w = (w_1, w_2, \dots, w_n)$, $w_j \in [0,1]$, and $\sum_{j=1}^n w_i = 1$ [23].

$$T-SWAI_w(g_1, g_2, \dots, g_n) = \langle (1 - \prod_{j=1}^n (1 - \mu_j^t)^{w_j})^{1/t}, (\prod_{j=1}^n (1 - \mu_j^t)^{w_j} - \prod_{j=1}^n (1 - \mu_j^t - \eta_j^t)^{w_j})^{1/t}, (\prod_{j=1}^n (1 - \mu_j^t - \eta_j^t)^{w_j} - \prod_{j=1}^n (1 - \mu_j^t - \eta_j^t - \varsigma_j^t)^{w_j})^{1/t} \rangle \quad (6)$$

$$T-SWGI_w(g_1, g_2, \dots, g_n) = \langle (\prod_{j=1}^n (1 - \varsigma_j^t - \eta_j^t)^{w_j} - \prod_{j=1}^n (1 - \varsigma_j^t - \eta_j^t - \mu_j^t)^{w_j})^{1/t}, (\prod_{j=1}^n (1 - \varsigma_j^t)^{w_j} - \prod_{j=1}^n (1 - \varsigma_j^t - \eta_j^t)^{w_j})^{1/t}, (1 - \prod_{j=1}^n (1 - \varsigma_j^t)^{w_j})^{1/t} \rangle \quad (7)$$

Definition 4. Here $g_1 = (\mu_1, \eta_1, \varsigma_1)$ and $g_2 = (\mu_2, \eta_2, \varsigma_2)$ be two different T-spherical fuzzy numbers. g_1 and g_2 The Minkowski distance measure between is computed using Equation (8) under the condition $p > 0$

$$M_p(g_1, g_2) = \left(|\mu_1^t - \mu_2^t|^p + |\eta_1^t - \eta_2^t|^p + |\varsigma_1^t - \varsigma_2^t|^p \right)^{1/p} \quad (8)$$

$M_p(g_1, g_2)$ $p = 1$ when g_1 and g_2 is defined as the Hamming or Taxicab distance between . $p = 2$ when, g_1 and g_2 between $M_p(g_1, g_2)$ is defined as the euclidean distance [23].

Definition 5: the score $\mathcal{S}(g)$ and accuracy $\mathcal{A}(g)$ functions are defined using Equations (9) and (10). Here $g = (\mu, \eta, \varsigma)$ [23].

$$\mathcal{S}(g) = (1 + \mu^t - \eta^t - \varsigma^t)/2 \quad (9)$$

$$\mathcal{A}(g) = \varsigma^t + \eta^t + \mu^t \quad (10)$$

3.2 Determination of Expert Weights (Reputation)

The first three steps of the proposed model concern determining the reputation degree of the experts participating in the evaluation process in order to solve the problem. In this process, linguistic evaluations are first made for each characteristic by considering the characteristics of the experts.

Step 1: Construction of the aggregated initial decision matrix for the experts: At this stage, the experts participating in the evaluation process $U_p = \{U_1, U_2, \dots, U_z\}, (p = 1, 2, \dots, z)$ are evaluated within the framework of their abilities, expertise and characteristics.

The linguistic matrices obtained from the expert evaluations are associated with the corresponding T-spherical fuzzy numbers and, by being aggregated with the T-SWAI operator in Equation (6), a complete consensus is achieved as shown in Equation (11).

$$\theta_{pl}^{(agg)} = \left[\begin{aligned} & \left(1 - \prod_{k=1}^g (1 - \mu_{pl}^t)^{\gamma_k} \right)^{1/t}, \\ & \left(\prod_{k=1}^g (1 - \mu_{pl}^t)^{\gamma_k} - \prod_{k=1}^g (1 - \mu_{pl}^t - \eta_{pl}^t)^{\gamma_k} \right)^{1/t}, \\ & \left(\prod_{k=1}^g (1 - \mu_{pl}^t - \eta_{pl}^t)^{\gamma_k} - \prod_{k=1}^g (1 - \mu_{pl}^t - \eta_{pl}^t - \varsigma_{pl}^t)^{\gamma_k} \right)^{1/t} \end{aligned} \right] \quad (11)$$

$(p = 1, 2, \dots, z), (l = 1, 2, \dots, b), (k = 1, 2, \dots, g)$

Here g the number of professionals, $\gamma_k : \{\gamma_1, \gamma_2, \dots, \gamma_g\}$, while the symbols denote the weight coefficients of the experts $\sum_{k=1}^g \gamma_k = 1$. In this way, the aggregated initial decision matrix is constructed as shown in Equation (12).

$$\tilde{M}^{agg} = [\tilde{\theta}_{pl}^{agg}]_{z \times b} = \begin{matrix} & K_1 & K_2 & K_3 & \dots & K_b \\ \begin{matrix} U_1 \\ U_2 \\ U_3 \\ \vdots \\ U_z \end{matrix} & \begin{bmatrix} \tilde{\theta}_{11}^{(agg)} & \tilde{\theta}_{12}^{(agg)} & \tilde{\theta}_{13}^{(agg)} & \dots & \tilde{\theta}_{1b}^{(agg)} \\ \tilde{\theta}_{21}^{(agg)} & \tilde{\theta}_{22}^{(agg)} & \tilde{\theta}_{23}^{(agg)} & \dots & \tilde{\theta}_{2b}^{(agg)} \\ \tilde{\theta}_{31}^{(agg)} & \tilde{\theta}_{32}^{(agg)} & \tilde{\theta}_{33}^{(agg)} & \dots & \tilde{\theta}_{3b}^{(agg)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{\theta}_{z1}^{(agg)} & \tilde{\theta}_{z2}^{(agg)} & \tilde{\theta}_{z3}^{(agg)} & \dots & \tilde{\theta}_{zb}^{(agg)} \end{bmatrix} \end{matrix} \quad (12)$$

Here $\tilde{\theta}_{pl}^{agg} = (\mu_{pl}^{(agg)}, \eta_{pl}^{(agg)}, \vartheta_{pl}^{(agg)})$ and $\tilde{\theta}_{pl}^{agg}$ p-th expert.

Step 2: Calculation of the aggregated weight degree of each expert based on T-spherical fuzzy numbers: After the aggregated initial decision matrix is constructed, the relative significance values of each characteristic of the experts $\wp = \{\wp_1, \wp_2, \dots, \wp_b\}, (l = 1, 2, \dots, b)$ are determined, and these weights are multiplied by the elements of the T-SF matrix and the resulting values are summed. Finally, the final reputation degrees of the experts (λ_p) is determined using Equation (13).

$$\left[\begin{aligned} & \left(1 - \prod_{l=1}^b (1 - \mu_{pl}^t)^{\wp_l} \right)^{1/t}, \\ & \left(\prod_{l=1}^b (1 - \mu_{pl}^t)^{\wp_l} - \prod_{l=1}^b (1 - \mu_{pl}^t - \eta_{pl}^t)^{\wp_l} \right)^{1/t}, \\ & \left(\prod_{l=1}^b (1 - \mu_{pl}^t - \eta_{pl}^t)^{\wp_l} - \prod_{l=1}^b (1 - \mu_{pl}^t - \eta_{pl}^t - \vartheta_{pl}^t)^{\wp_l} \right)^{1/t} \end{aligned} \right] \quad (13)$$

Here $\lambda_p = (\mu_p, \eta_p, \vartheta_p), (p = 1, 2, \dots, z)$ and $\sum_{l=1}^b \wp_l = 1$.

Step 3: Calculation of the final weight coefficient for each expert: The values are converted into score values using the score function given in Equation (9), and, as shown in Equation (14), these values $\psi_p = \{\psi_1, \psi_2, \dots, \psi_z\}, (p = 1, 2, \dots, z)$ are normalized to determine the final weights of the experts.

$$\psi_p = \frac{Sc(\lambda_p)}{\sum_{p=1}^z Sc(\lambda_p)}, (p = 1, 2, \dots, z) \quad (14)$$

Here the condition that the sum of the expert weights equals one $\sum_{p=1}^z \psi_p = 1$ must be satisfied.

3.3 Entropy Method

In the real world, the relative importance of the selection criteria differs; therefore, these weights must be calculated for a realistic performance analysis [26], who proposed the concept of entropy-based on probability theory and measuring the uncertainty of information-for this purpose. The weight of the selection criteria represents the relative importance of each factor in the decision-making process [27]. Although there are many multi-criteria decision-making techniques for determining criterion weights, the entropy method, which is based solely on numerical data, is one of the most suitable techniques. The entropy method is reliable and easy to use in information measurement [28]. This method evaluates uncertainty through probability theory and measures the usefulness of the

factors [29]. Entropy weights measure the uncertainty in information based on probability theory [30]. The method consists of the following steps:

Step 4. Construction of the initial decision matrix: At this stage $n \times m$ matrix consisting of elements that represent the evaluation scores of the alternatives with respect to the criteria, with dimensions $n \times m$, is constructed. Equation (15) shows the constructed decision matrix.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (15)$$

Here X denotes the initial decision matrix, while x_{ij} bir i -th alternative j denotes the value with respect to the j -th criterion.

Step 5. Normalization of the matrix elements: In the fifth step of the model, the second step of the entropy method, the elements of the initial decision matrix are normalized using Equation (16). The entropy method uses the vector-normalization procedure for standardization [31].

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (16)$$

Step 6. Calculation of the entropy value of each criterion: In this step, the entropy value of each criterion is calculated with the help of Equation (17).

$$e_j = \frac{-1}{\ln(n)} \sum_{i=1}^m x_{ij} \ln(x_{ij}); \quad \forall j \quad (17)$$

Step 7. Calculation of the divergence value of each criterion: In this step, the divergence value of each criterion is calculated using Equation (18).

$$d_j = 1 - e_j; \quad \forall j \quad (18)$$

Step 8. Calculation of the final weight value of each criterion: In the eighth step of the proposed model, the final step of the entropy method, the relative weight value of each criterion is calculated using Equation (19).

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (19)$$

3.4 MAUT Method

The Multi-Attribute Utility Theory (MAUT) method is a decision-making tool developed and introduced into the literature by Løken [32]. The MAUT method works systematically to rank alternatives [33], and offers a logical and applicable way of choosing among conflicting objectives [34]. In addition, since the method can reach a result with a small number of implementation steps and calculations, it is an extremely useful and practical decision-making approach for decision-makers [35]. The proposed approach consists of three implementation steps.

Step 9. Construction of the initial decision matrix: At this stage, since the decision matrix constructed in the first step of the entropy method is used as is, it is not shown here a second time in order to avoid repetition.

Step 10. Normalization of the matrix elements: In this second step, the values assigned to the decision matrix are placed, and then the best and worst values for each attribute are determined, assigning the value 1 to the best and 0 to the worst. The normalized values of the elements of the initial decision matrix are calculated using Equation (20).

$$f_{ij} = \frac{x_{ij} - x_{ij}^{\min}}{x_{ij}^{\max} - x_{ij}^{\min}} \quad (20)$$

Here denotes the normalized values of the matrix elements, while $x_{ij}^{\min}$ the smallest value in each vector, $x_{ij}^{\max}$ denotes the largest value.

Step 11. Determination of the utility value: After normalization, the utility values are calculated using Equation (21).

$$U_{ai} = \sum_{j=1}^n f_{ij} \cdot w_j \quad (21)$$

First, the normalized matrix elements are weighted by multiplying the normalized matrix value for each alternative by the weight value. Then, the utility value of the alternative is determined by summing the values in each row. The utility value also indicates the ranking score for the alternatives. In this context, the alternatives are ranked starting from the highest utility score.

4. Application of the Proposed Model

In this section, the proposed combination of T-spherical fuzzy set-based entropy and MAUT is applied to the decision problem concerning the determination and prioritization of digital-transformation strategies in public finance, and the results obtained are summarized and discussed. The proposed approach consists of four main phases. In the first phase, the processes prior to the computational steps of the model were designed, and this process was defined as the preparation phase.

4.1 Preparation Phase

At the beginning of the preparation process, the researchers first defined and formulated the decision problem in detail. Subsequently, the experts who would contribute to the evaluation process were determined, and a committee composed of these experts was formed. In the next stage of the process, the strategy alternatives and evaluation criteria were defined as a result of the comprehensive negotiation and evaluation work carried out with the experts.

Definition of the research problem: Today, digital transformation has increasing importance in terms of public finance and state administration. Digital technologies enable public-sector services to be delivered more effectively, efficiently and transparently. However, the integration of these technologies into public-finance systems also brings complex problems and challenges. In this context, the main purpose of the research is to examine the effects of the digital-transformation process on public finance and to evaluate the opportunities this transformation offers and the risks it faces in public financial management.

The focus of the research is to analyze the contributions of digital transformation to public-finance processes while at the same time identifying the factors that may hinder the applicability of this

transformation. In particular, answers will be sought to the following questions: i) Are the innovations that digital transformation brings to public-finance processes sustainable? ii) Are these innovations sufficient to ensure the more effective management of public resources? iii) How can the challenges that arise during the digitalization process be overcome? In light of these questions, the research has the potential to develop strategic recommendations that will facilitate digital transformation in the field of public finance.

By comprehensively evaluating the effects of the digital-transformation process on public finance, this study aims to guide public institutions. The research aims to define the problems encountered during the digitalization process and, by offering solutions to them, to determine the steps necessary to achieve a sustainable and effective transformation.

Digital transformation in public finance has critical importance not only in terms of increasing efficiency and transparency but also in terms of sustainability. In this context, by analyzing the opportunities and threats in the integration of digital technologies in a balanced way, the research aims to provide important contributions to the successful realization of digital transformation in the field of public finance.

Formation of the expert committee: The Expert Committee was carefully selected from among individuals with the technical and sectoral knowledge required by the study and with more than 15 years of experience. In determining the committee members, their competencies in evaluation methods in particular and their level of knowledge in multi-criteria decision-making processes were taken into account. A comprehensive preliminary assessment was made by considering the candidates' previous studies and their reputation in the sector. Members of a professionals group consisting of three people also took part in the process of determining the experts. In order to integrate the different characteristics and attributes of the experts into the evaluation process, the professionals carried out linguistic evaluations regarding the characteristics of the experts, and then, by taking these evaluations into account, the relative weight (reputation) degrees were calculated for each of the experts. During the selection process, the candidates' CVs were examined and their achievements in the relevant fields were analyzed. Care was taken to ensure that the experts had the capacity to provide methodological support appropriate to the objectives of the study and to offer solution-oriented approaches. At the end of this comprehensive evaluation process, the three experts with the most appropriate knowledge and experience for the study were appointed to the committee. The characteristics of the determined experts are presented in Table 1 below.

Table 1

Characteristics of the Experts and Members of the Professionals Group Involved in the Study

Expert Committee					
Code	Age	Experience	Expertise	Degree	Department
U1	61	28	Public finance	Bachelor's	Public Finance
U2	58	24	Taxation	Bachelor's	Economics
U3	55	21	Auditing	Master's	Economics
Professionals Committee					
P1	55	30	Public Finance	PhD	Economics
P2	64	28	Public Finance	PhD	Finance
P3	62	30	Tax Law	PhD	Public Finance

Determination of strategies and criteria: The strategy alternatives to be used in the evaluation process were determined by taking into account the objectives of the study and the characteristics of the field of application. First, applicable and effective strategies were defined by considering similar studies in the literature and expert opinions; then the most appropriate ones among these strategies

were determined as alternatives. A comprehensive analysis was carried out by considering the contribution and potential effects that each alternative could provide to the field of study.

The criteria to be used in evaluating the strategy alternatives were determined through negotiation methods such as meetings and face-to-face interviews held with the experts. In the selection of the criteria, elements such as the efficiency, cost, sustainability, applicability and long-term effects of the strategies were taken into account. By bringing together the main criteria in the literature and additional criteria based on expert opinions, a set of criteria was created that would enable the strategies to be evaluated in a comparable manner. Table 2 shows and explains the evaluation criteria and their definitions determined within the scope of this study, and Table 3 shows and explains the digital-transformation strategies in public finance. During the research process, the researchers, with the help of the experts, determined ten digital-transformation strategies together with ten evaluation criteria.

Table 2

Criteria Related to Digital Transformation Strategies in Public Finance

Code	Criterion	Definition.
C1	Alignment with Strategic Goals	How compatible the digital-transformation strategy is with the general strategic goals set for public finance
C2	Impact and Benefits Provided	The positive effects and benefits that the digital-transformation process provides in areas such as public services, cost savings and efficiency improvement
C3	Resource Requirements	The resource requirements, such as the manpower, financial resources and technological infrastructure needed for the implementation of digital transformation
C4	Risk Management and Control	The capacity to identify and manage the security, operational and financial risks that may arise during the digital-transformation process
C5	Stakeholder Participation Level	The participation of and contribution by public employees, citizens and other relevant stakeholders in the digital-transformation process
C6	Implementation Feasibility and Scalability	The applicability and sustainability of the digital-transformation strategy and whether it can be adapted to different levels in public finance
C7	Measurability of Objectives	The level to which the objectives determined within the scope of the digital-transformation strategy are traceable and evaluable
C8	Legal Compliance and Ethical Requirements	Whether the digital-transformation process complies with the legal regulations in force and meets ethical requirements
C9	Change Management Strategy	The effectiveness of the strategies implemented for stakeholders to adapt to the changes brought about by digital transformation.
C10	Continuous Improvement and Innovation	A criterion expressing the capacity of the digital-transformation strategy to be updated and developed with a continuous-improvement approach.

Table 3

Digital Transformation Strategies in Public Finance

Code	Criterion	Definition.
A1	Digital Automation of Financial Processes	Providing automation to accelerate financial processes and reduce error rates.
A2	Digital Payment and Transaction Systems	Providing easy access for citizens and businesses by digitalizing public payments.
A3	Open Data Management and Transparency Strategy	Increasing transparency through the accessibility of data and ensuring accountability.
A4	Cloud-Based Data Management Systems	Storing data securely in the cloud and facilitating access to it.

Table 3

Continued

Code	Criterion	Definition.
A5	Data Analytics and Business Intelligence Applications	Using data analytics and business intelligence to improve decision-making processes.
A6	Advanced Cybersecurity Measures	Protecting public data against cyberattacks and ensuring data security.
A7	Digital Skills Training for Public Employees	Enabling public employees to adapt to digital transformation by giving them technology skills.
A8	Strategic Partnerships with the Private Sector	Developing innovative solutions in digital transformation through public-private-sector cooperation.
A9	Citizen Participation and Feedback Mechanisms	Improving service quality by obtaining citizen feedback through digital platforms.
A10	Digital Regulatory and Policy Frameworks	Creating legal regulations and policies appropriate to the digital-transformation process.

4.2 Determination of the Reputation Degrees of the Experts

At this stage, the professionals evaluated the experts by taking into account characteristics of the three experts such as age, experience, expertise, degree and graduated department. When making their linguistic evaluations of the experts, the professionals took into account the linguistic-evaluation scale shown in Table 4.

Table 4

Linguistic Evaluation Scale Used in the Study

Linguistic Terms	Notation	μ	η	ς
Extremely high importance	EG	0,9	0,1	0,1
Very high importance	VG	0,8	0,2	0,2
High importance	G	0,7	0,3	0,3
Medium-high importance	MG	0,6	0,4	0,4
Medium importance	M	0,5	0,5	0,5
Medium-low importance	MP	0,4	0,6	0,4
Low importance	P	0,3	0,7	0,3
Very low importance	VP	0,2	0,8	0,2
Extremely low importance	EP	0,1	0,9	0,1

Step 1. In the first step of the application, linguistic evaluations regarding the characteristics of the experts were collected and converted into T-spherical fuzzy number values. Then, these values were aggregated using Equation (11). In the evaluation process, the weight values of the professionals were taken as equal ($1/3 = 0.333$). Table 5 shows the evaluations of the professionals regarding the characteristics of the experts.

Table 6 shows the values converted into T-spherical number values.

Step 2. -3: In the next step, the evaluations regarding the experts are aggregated as shown in Equation 12. Table 7 shows the aggregated evaluations.

Then, the reputation degrees of the experts are determined using Equation 13. Finally, after the score values for each expert are calculated with the help of Equation (9), the score values of the experts are normalized as shown in Equation (14), and the relative weight (reputation) degrees of each expert are calculated. Table 8 shows the aggregated T-spherical number values, the score values and the final weights of the experts.

According to their relative weight values, the experts are ranked as $U3 > U2 > U1$. According to the results obtained, $U3$ was determined as the most influential expert.

Table 5

Linguistic Evaluations of the Professionals Regarding the Characteristics of the Experts

	Code	Age	Experience	Expertise	Degree	Department
		γ_1	γ_2	γ_3	γ_4	γ_5
P1	U1	VG	VG	VG	G	VG
	U2	G	G	G	G	G
	U3	MG	G	M	VG	G
P2	U1	G	G	VG	MG	VG
	U2	MG	MG	MG	MG	G
	U3	M	MG	MG	G	G
P3	U1	VG	VG	G	G	G
	U2	G	MG	MG	G	MG
	U3	G	MG	MG	VG	MG

Table 6

T-Spherical Fuzzy Number Equivalent of the Evaluations

	Code	γ_1			γ_2			γ_3			γ_4			γ_5		
		μ	η	ς	μ	η	ς	μ	η	ς	μ	η	ς	μ	η	ς
P1	U1	0.01	0.01	0.9	0.01	0.01	0.90	0.01	0.0	0.90	0.20	0.30	0.90	0.01	0.01	0.90
	U2	0.30	0.30	0.90	0.20	0.30	0.90	0.20	0.30	0.90	0.20	0.30	0.90	0.20	0.30	0.90
	U3	0.20	0.20	0.80	0.20	0.30	0.90	0.60	0.20	0.60	0.01	0.01	0.90	0.20	0.30	0.90
P2	U1	0.30	0.30	0.90	0.20	0.30	0.90	0.01	0.01	0.90	0.40	0.20	0.80	0.01	0.01	0.90
	U2	0.20	0.20	0.80	0.40	0.20	0.80	0.40	0.20	0.80	0.40	0.20	0.80	0.20	0.30	0.90
	U3	0.20	0.20	0.60	0.40	0.20	0.80	0.40	0.20	0.80	0.20	0.30	0.90	0.20	0.30	0.90
P3	U1	0.01	0.01	0.90	0.01	0.01	0.90	0.20	0.30	0.90	0.20	0.30	0.90	0.20	0.30	0.90
	U2	0.30	0.30	0.90	0.40	0.20	0.80	0.40	0.20	0.80	0.20	0.30	0.90	0.40	0.20	0.80
	U3	0.30	0.30	0.90	0.40	0.20	0.80	0.40	0.20	0.80	0.01	0.01	0.90	0.40	0.20	0.80

Table 7

Aggregated Values for the Experts

Code	γ_1			γ_2			γ_3		
	μ	η	ς	μ	η	ς	μ	η	ς
U1	0.176	0.214	0.930	0.117	0.211	0.908	0.117	0.124	0.908
U2	0.271	0.214	0.906	0.349	0.211	0.841	0.349	0.269	0.841
U3	0.239	0.240	0.877	0.349	0.236	0.841	0.482	0.201	0.737
Code	γ_4			γ_5					
	μ	η	ς	μ	η	ς			
U1	0.286	0.269	0.873	0.117	0.179	0.908			
U2	0.286	0.269	0.873	0.286	0.300	0.873			
U3	0.117	0.249	0.908	0.286	0.269	0.873			

Table 8

Aggregated Values, Score Values and Final Weights of the Experts

	Aggregated			Score value	Weight value
	μ	η	ς	$Sc(\lambda_p)$	ψ_p
U1	0.1763	0.2128	0.0000	0.4929	0.3249
U2	0.3105	0.2839	0.0000	0.5079	0.3348
U3	0.3234	0.2692	0.0000	0.5161	0.3402

4.3 Determination of the Relative Weights of the Criteria

At this stage, the T-spherical fuzzy set-based entropy method used for weighting the criteria of the proposed model was applied.

Step 4. In this step, the experts first made linguistic evaluations by considering the criteria for each alternative. The linguistic-evaluation matrix in which the experts evaluated the ten strategy alternatives with respect to the ten evaluation criteria using linguistic terms is presented in Appendix: Table A. Then, these evaluations were converted into T-spherical fuzzy number values, and these T-SFS-based evaluations were aggregated using the aggregation operators shown in Equations (6) and (7). *Appendix:* Table A2 shows the aggregated T-SFSs for the evaluations. Finally, the score values were calculated with the help of Equation (9), and the initial decision matrix was constructed. Table 9 shows the initial decision matrix.

Table 9

Initial Decision Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.662	0.746	0.617	0.713	0.541	0.647	0.662	0.758	0.616	0.616
A2	0.128	0.157	0.045	0.097	0.042	0.088	0.143	0.159	0.072	0.139
A3	0.689	0.660	0.557	0.630	0.712	0.602	0.602	0.689	0.662	0.602
A4	0.602	0.662	0.616	0.662	0.563	0.616	0.698	0.662	0.616	0.712
A5	0.712	0.712	0.616	0.602	0.586	0.602	0.758	0.602	0.712	0.712
A6	0.780	0.780	0.633	0.780	0.580	0.780	0.780	0.780	0.662	0.780
A7	0.575	0.530	0.530	0.530	0.616	0.530	0.530	0.530	0.530	0.552
A8	0.662	0.616	0.647	0.586	0.712	0.662	0.586	0.616	0.586	0.552
A9	0.647	0.758	0.586	0.541	0.712	0.586	0.586	0.586	0.586	0.586
A10	0.780	0.689	0.633	0.738	0.632	0.662	0.780	0.780	0.662	0.662

Step 5. In this step, the elements of the decision matrix shown in Table 7 were normalized with the help of Equation (16), and the normalized decision matrix was constructed using the obtained normalized values. Table 10 shows the normalized decision matrix.

Table 10

Normalized Decision Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.106	0.118	0.113	0.121	0.095	0.112	0.108	0.123	0.108	0.104
A2	0.021	0.025	0.008	0.017	0.007	0.015	0.023	0.026	0.013	0.024
A3	0.110	0.105	0.102	0.107	0.125	0.104	0.098	0.112	0.116	0.102
A4	0.096	0.105	0.112	0.113	0.099	0.107	0.114	0.107	0.108	0.120
A5	0.114	0.113	0.112	0.102	0.103	0.104	0.124	0.098	0.125	0.120
A6	0.125	0.124	0.115	0.133	0.102	0.135	0.127	0.127	0.116	0.132
A7	0.092	0.084	0.097	0.090	0.108	0.092	0.086	0.086	0.093	0.093
A8	0.106	0.098	0.118	0.100	0.125	0.115	0.096	0.100	0.103	0.093
A9	0.104	0.120	0.107	0.092	0.125	0.101	0.096	0.095	0.103	0.099
A10	0.125	0.109	0.115	0.125	0.111	0.115	0.127	0.127	0.116	0.112

Step 6. In the next steps, the entropy value, divergence value and final weight values for the criteria were calculated using Equations 17, 18 and 19, respectively. Table 11 shows the values obtained for these parameters.

According to the results obtained, when the relative weights of the criteria considered for evaluating digital-transformation strategies in public finance are taken into account, criterion C5 “Stakeholder Participation Level” was determined as the most important and influential criterion, with an importance score of 0.1339. This is followed by criteria C3 “Resource Requirements” (0.1251) and C9 “Change Management Strategy” (0.1109). The other criteria are ranked, respectively, as C4

“Risk Management and Control” (0.1054) > C6 “Implementation Feasibility and Scalability” (0.1045) > C7 “Measurability of Objectives” (0.0876) > C10 “Continuous Improvement and Innovation” (0.0839) > C8 “Legal Compliance and Ethical Requirements” (0.0809) > C2 “Impact and Benefits Provided” (0.0795).

Table 11

Entropy Value, Divergence Value and Final Weight Values

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
e_j	0.976	0.979	0.966	0.972	0.964	0.972	0.976	0.978	0.970	0.977
d_j	0.024	0.021	0.034	0.028	0.036	0.028	0.024	0.022	0.030	0.023
w_j	0.088	0.080	0.125	0.105	0.134	0.104	0.088	0.081	0.111	0.084

4.4 Evaluation and Ranking of the Strategy Alternatives

In this section, the implementation steps of the MAUT method were followed to prioritize digital-transformation strategies in public finance.

Steps 9 and 10. At this stage, the decision matrix constructed in the first step of the entropy method was used as is. In the tenth step of the proposed model, the elements of the initial decision matrix were normalized using Equation (20). Table 12 shows the constructed normalized matrix.

Table 12

Normalized Decision Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.820	0.054	0.950	0.097	0.255	0.192	0.816	0.966	0.850	0.745
A2	0.000	1.000	0.000	1.000	1.000	1.000	0.000	0.000	0.000	0.000
A3	0.860	0.192	0.850	0.220	0.000	0.257	0.720	0.854	0.922	0.722
A4	0.727	0.188	0.949	0.172	0.222	0.236	0.871	0.811	0.850	0.894
A5	0.896	0.109	0.949	0.261	0.188	0.257	0.966	0.713	1.000	0.894
A6	1.000	0.000	0.977	0.000	0.197	0.000	1.000	1.000	0.922	1.000
A7	0.685	0.401	0.805	0.366	0.143	0.362	0.607	0.597	0.715	0.644
A8	0.820	0.262	1.000	0.284	0.000	0.170	0.696	0.737	0.803	0.644
A9	0.796	0.034	0.899	0.349	0.000	0.280	0.696	0.688	0.803	0.698
A10	1.000	0.146	0.977	0.062	0.119	0.170	1.000	1.000	0.922	0.817

Step 11. In the final step, the utility value of each alternative was calculated using Equation (21), and the relative preferability values of the alternatives were determined. Table 13 shows the weighted normalized values, the utility value and the ranking performance of the alternatives for each alternative.

Table 13

Weighted Normalized Values, Utility Values and Ranking Results

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	U_{ai}	Rank
A1	0.072	0.004	0.119	0.010	0.034	0.020	0.071	0.078	0.094	0.063	0.566	5
A2	0.000	0.080	0.000	0.105	0.134	0.104	0.000	0.000	0.000	0.000	0.423	10
A3	0.076	0.015	0.106	0.023	0.000	0.027	0.063	0.069	0.102	0.061	0.543	6
A4	0.064	0.015	0.119	0.018	0.030	0.025	0.076	0.066	0.094	0.075	0.582	4
A5	0.079	0.009	0.119	0.027	0.025	0.027	0.085	0.058	0.111	0.075	0.614	1
A6	0.088	0.000	0.122	0.000	0.026	0.000	0.088	0.081	0.102	0.084	0.592	3
A7	0.061	0.032	0.101	0.039	0.019	0.038	0.053	0.048	0.079	0.054	0.524	8
A8	0.072	0.021	0.125	0.030	0.000	0.018	0.061	0.060	0.089	0.054	0.530	7
A9	0.070	0.003	0.112	0.037	0.000	0.029	0.061	0.056	0.089	0.059	0.516	9
A10	0.088	0.012	0.122	0.006	0.016	0.018	0.088	0.081	0.102	0.069	0.602	2

When the ranking results regarding the prioritization of the strategy alternatives are examined, the A5 Data Analytics and Business Intelligence strategy was determined as the most important and influential strategy. This is followed, respectively, by the A10 Regulatory and Policy Frameworks and A6 Advanced Cybersecurity Measures strategies. The other strategies are ranked as A4 Cloud-Based Data Management Systems > A1 Digital Automation of Financial Processes > A3 Open Data Management and Transparency Strategy > A8 Strategic Partnerships with the Private Sector > A7 Digital Skills Training for Public Employees > A9 Citizen Participation and Feedback Mechanisms > A2 Digital Payment and Transaction Systems.

5. Robustness and Validity Tests

5.1 Sensitivity Analysis

To test the validity and robustness of the proposed model, the researchers applied sensitivity and comparison tests. First, the expert weights were changed and the effects of these changes on the overall ranking results were examined. Within this scope the basic procedure proposed by Görçün *et al.*, [36] was followed. Accordingly, starting from the most important expert, the weight value of each expert was gradually reduced by 10% in each scenario until it reached 0, and the difference arising in between was added to the other criteria to satisfy the condition that the total value of the criteria equals one. When the results obtained according to the scenarios are examined, it is observed that owing to the limited number of decision-makers, namely three experts in the study-although the positions of the highest-priority and second-highest-priority strategies in the ranking changed in only five scenarios, they retained their positions in twenty-five scenarios. The ranking performances of the remaining strategy alternatives stayed the same for each scenario. Figure 1 shows the changes in the ranking results for the thirty scenarios constructed according to the modified expert weights. According to the original ranking and the ranking results determined for the scenarios, the average similarity value was calculated as 0.9667.

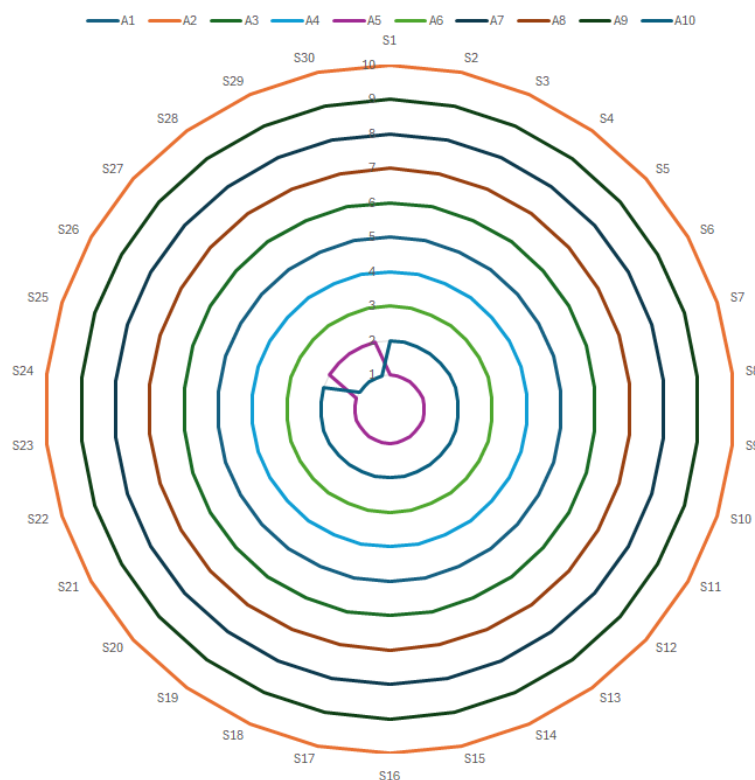


Fig. 1. Changes in the Ranking Results According to the Variations in Expert Weights

In the second stage of the analysis, the weights of the criteria were changed with a similar approach, the proposed model was re-applied for 100 different scenarios that were constructed, and the changes in the ranking results were recorded. In general, small differences that would not change the overall results were detected in the rankings of the strategies. As can be seen in Figure 2, certain changes occurred in the ranking results of all strategies. However, it was observed that these changes generally occurred in cases where the criterion weights were changed by 70% or more. Under real-life conditions, changes of this magnitude in the weights of the selection and evaluation criteria carry a fairly low probability. In addition, the changes in the ranking results of the alternatives are not at a level that could affect the overall ranking order. According to the analysis results, the similarity coefficient between the original ranking and the ranking in the 100 scenarios in which the criterion weights were changed was calculated as 0.8550. This proves that the proposed combination of T-spherical fuzzy set-based entropy and MAUT (Multi-Attribute Utility Theory) is an extremely robust, consistent and reliable model.

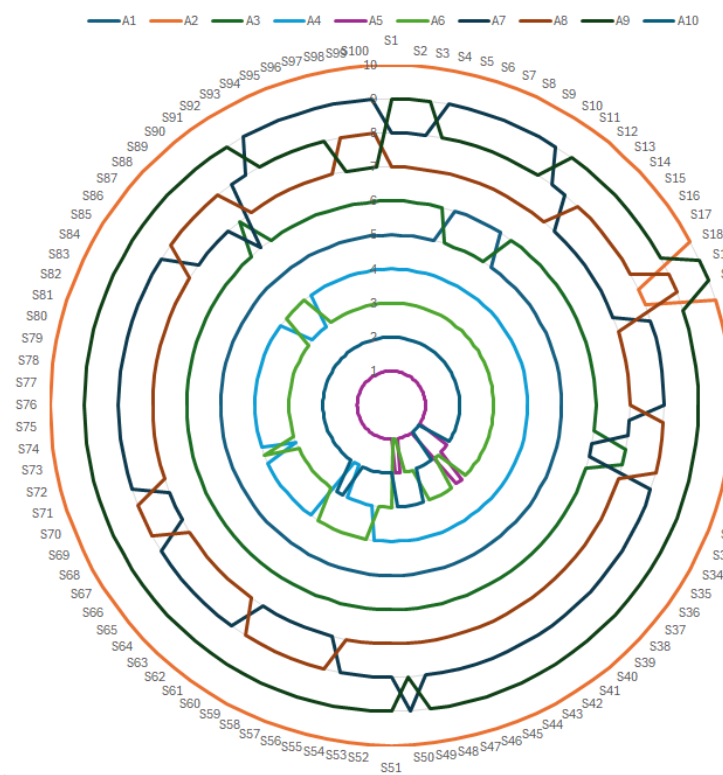


Fig. 2. Changes in the Ranking Results According to the Variations in Criterion Weights

Despite changes in expert opinions and criterion weights that could be considered extreme, the consistency and reliability levels of the model are remarkable. The average similarity ratios were determined as 0.9667 for the changes in expert opinions and 0.8550 for the changes in criterion weights. These values clearly demonstrate the reliability of the model.

The similarity ratios obtained within the scope of this study exceed the consistency standards widely accepted in the literature. In important studies such as Saaty [37] and Belton & Stewart [38], it is recommended that consistency and similarity values be above the 85-90% level, and it is emphasized that these levels indicate that multi-criteria decision-making methods produce reliable results. The similarity ratios calculated in this study show that the results of the model both meet and exceed the reliability standards accepted in the literature. The results of the sensitivity analysis support the conclusion that the proposed model is consistent, robust and reliable. The high similarity ratios

obtained demonstrate the applicability of the model under real-life conditions and that it offers a reliable solution in decision-making processes.

5.2 Monte Carlo Simulation

Although the one-at-a-time sensitivity analysis presented above confirms the local stability of the ranking, it perturbs a single input at a time and therefore cannot capture the simultaneous and stochastic variation of all parameters that characterizes real decision environments. To address this, a Monte Carlo simulation was carried out in which the criterion weights and the aggregated performance scores were perturbed simultaneously and repeatedly. In each of the $N = 10,000$ independent replications, the entropy-based criterion weights were multiplied by a Gaussian noise term with a standard deviation of 10% and renormalized to sum to one, while every element of the normalized decision matrix was independently perturbed by a Gaussian noise term with a standard deviation of 5% and truncated to the admissible between 0 and 1 interval. The MAUT utility scores were then recomputed and the alternatives re-ranked in each replication, and the resulting rankings were compared with the baseline ranking obtained in Section 4.

The simulation produced a mean Spearman rank-correlation coefficient of 0.9624 and a mean Kendall tau of 0.8940 between the perturbed rankings and the baseline ranking, indicating that the overall ranking structure is preserved under substantial simultaneous noise. The Rank Acceptability Index, defined as the relative frequency with which each alternative occupies each rank position across the 10,000 replications, is presented in Figure 3. The strongly diagonal structure of the index confirms the robustness of the model: the best strategy, A5 (Data Analytics and Business Intelligence), retained the first rank in 86.61% of the replications, while A10 (Regulatory and Policy Frameworks) accounted for 11.49% of the first-rank occurrences. The worst-performing alternative, A2 (Digital Payment and Transaction Systems), retained the last rank in 100% of the replications. These findings demonstrate that the prioritization obtained by the proposed model is highly resistant to random co-variation in the input parameters.

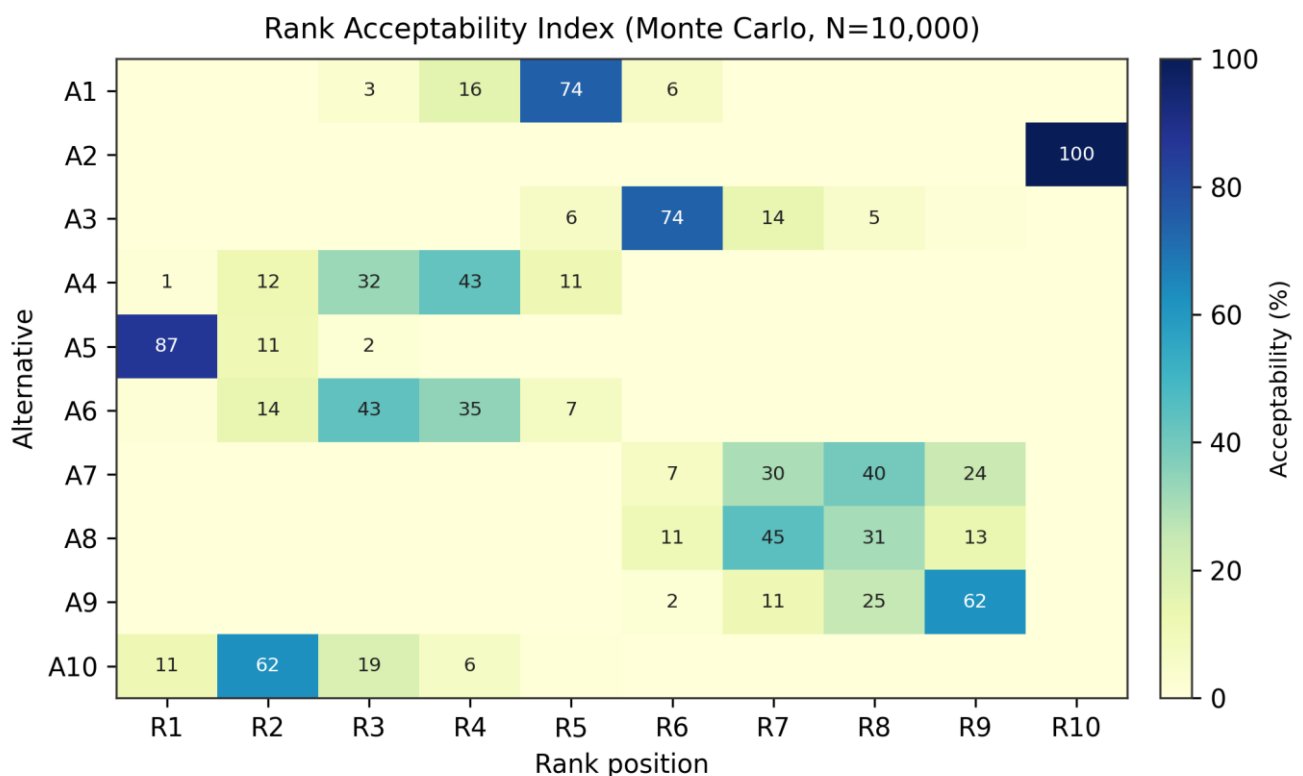


Fig. 3. Rank Acceptability Index Obtained from the Monte Carlo Simulation (N = 10,000)

5.3 Markov Chain Analysis

To examine the stability of the leading alternative as a stochastic process rather than as a set of independent draws, the sequence of first-ranked alternatives generated by the Monte Carlo replications was modelled as a discrete-time Markov chain. The states of the chain correspond to the alternatives that attain the first rank, and the one-step transition matrix was estimated empirically from the relative frequencies with which the first-ranked alternative in one replication is followed by each alternative in the next. The stationary distribution of the chain, which describes the long-run probability of each alternative occupying the leading position, was obtained as the normalized left eigenvector of the transition matrix associated with the unit eigenvalue.

As shown in Figure 4, the stationary distribution is strongly concentrated on alternative A5, which carries a long-run probability of 0.8661, followed by A10 with 0.1149; the remaining alternatives carry negligible stationary probabilities. Because the stationary distribution is independent of the initial state, this result confirms that A5 constitutes a stable attractor of the ranking process and that the leadership of A5 is not an artefact of any particular parameter configuration. The Markov-chain analysis therefore reinforces the conclusions of both the sensitivity and the Monte Carlo analyses regarding the robustness of the proposed prioritization.

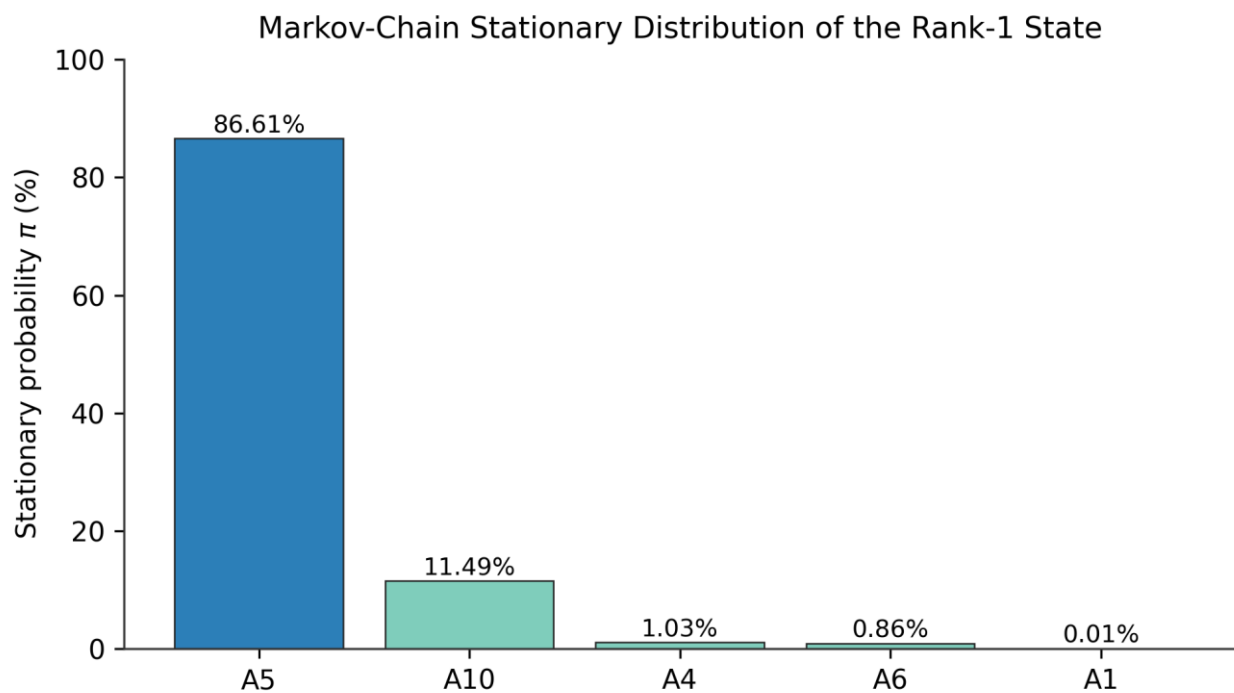


Fig. 4. Markov-Chain Stationary Distribution of the First-Rank State

5.4 Internal Consistency Analysis

Beyond the robustness of the ranking, the reliability of the judgemental inputs that drive the model was assessed through a battery of internal-consistency and inter-rater agreement statistics computed on the experts' linguistic evaluations reported in Appendix Table A. First, Cronbach's alpha was calculated over the aggregated performance scores, treating the ten criteria as items and the ten alternatives as cases, in order to quantify the internal consistency of the criterion set. The coefficient obtained, $\alpha = 0.9203$, lies well above the conventional 0.70 threshold and indicates an excellent level of internal consistency among the evaluation criteria.

Second, the agreement among the three experts on the 100 alternative–criterion linguistic ratings was evaluated using Fleiss' kappa, which yielded $\kappa = 0.4513$, corresponding to a moderate level of agreement once the agreement expected by chance is removed—an entirely plausible value given

the nine-level linguistic scale and the independent judgement of the experts. Third, the concordance among the experts' implied rankings of the ten alternatives was measured by Kendall's coefficient of concordance, which produced $W = 0.8364$, denoting a strong and statistically meaningful consensus on the relative ordering of the strategies. Finally, the pairwise Spearman rank-correlation coefficients between the experts were 0.7530 (U1-U2), 0.6982 (U1-U3) and 0.8354 (U2-U3), giving a mean inter-expert correlation of 0.7622. Taken together, and summarized in Figure 5, these coefficients confirm that the linguistic assessments underpinning the model are internally consistent and reflect a reliable expert consensus, thereby strengthening the credibility of the results obtained.

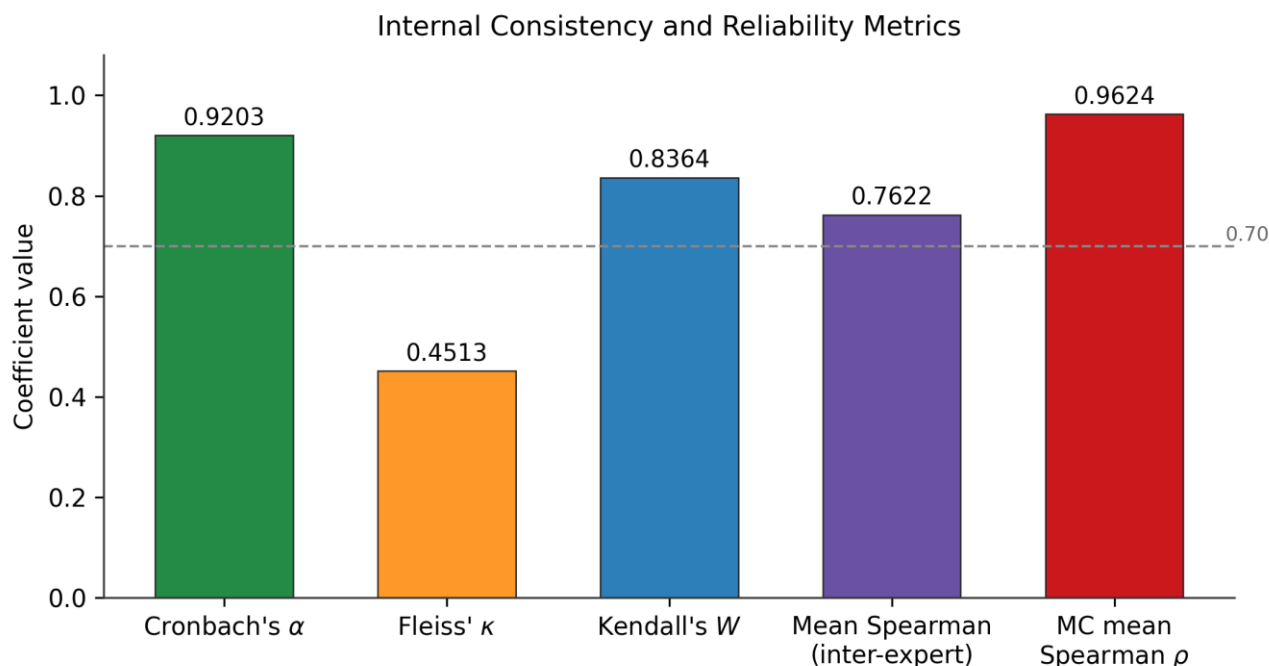


Fig. 5. Internal-Consistency and Reliability Coefficients

6. Conclusions and Discussion

In this study, the effects of digital transformation on public finance were examined comprehensively. The research focused on the effects of digitalization on public-finance processes and budget management, addressing elements such as efficiency, transparency and accountability, as well as contributions such as cost reduction, the accessibility of services and the improvement of budget processes. It was observed that digital transformation increases tax collection, the traceability of public expenditures and budget transparency.

In the research, A5 - Data Analytics and Business Intelligence was determined as the most critical digitalization priority. While this strategy emphasizes the importance of data-driven decision-making processes, it was found that big-data analyses increase predictability and risk management. A10 - Regulatory and Policy Frameworks, which ranks second, points to the necessity of strengthening the legal and institutional infrastructure of digitalization processes. A6 - Advanced Cybersecurity Measures, in third place, reveals the critical importance of data security and the management of cyber threats.

The other strategies are ranked, respectively, as A4 - Cloud-Based Data Management, A1 - Digital Automation of Financial Processes, A3 - Open Data Management, A8 - Private-Sector Partnerships, A7 - Digital Training for Public Employees, A9 - Citizen Participation and A2 - Digital Payment Systems. This ranking shows that strategies supporting operational sustainability were also taken into account.

The analysis of strategic priorities reveals that data analytics and business intelligence together with regulatory frameworks are critical to the success of digital transformation in public finance. For policymakers, this ranking emphasizes that investments in data security and business intelligence

should be increased and stresses the importance of evaluating public-private partnership opportunities. By offering a theoretical framework that addresses the effects of digital transformation on public finance, this study contributes to the literature. The proposed model establishes a basis for future research and offers insights to public administrators and policymakers on developing more effective and efficient policies.

Although recent studies in the relevant literature state that digital transformation and the adoption of innovative technologies will give rise to certain challenges and opportunities in public finance, the literature on this subject has not yet reached sufficient saturation, and owing to the dynamic and changing nature of the field more research and more analytical and experimental studies are needed. Accordingly, while sustainability, transparency and adaptation to technological transformation in public finance increasingly become prominent themes, they have begun to attract the interest of a larger number of researchers. In the future, in order to measure more clearly and to understand better the effects of digital transformation and the integration of technologies into the field on public finance, there is a need to conduct empirical studies that include more comprehensive and multidimensional analyses and to create strategic roadmaps that will guide decision-makers in this technological-transformation process.

Acknowledgement

This research was not funded by any grant.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Gupta, S., Keen, M., Shah, I., & Verdier G. (2017). Reshaping Public Finance. Digital Revolutions in Public Finance International Monetary Fund. <https://doi.org/10.5089/9781484315224.071>
- [2] Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Company.
- [3] Kotina, H., Stepura, M. & Kondro, P. (2022). How Does Active Digital Transformation Affect the Efficiency of Governance and the Sustainability of Public Finance? The Ukrainian Case", *Baltic Journal of Economic Studies*, 8(1), 75-82. <https://doi.org/10.30525/2256-0742/2022-8-1-75-82>.
- [4] Vovchenko, N. G., Ivanova, O. B., Kostoglodova, E. D., Nerovnya, Y. V., & Rykina, S.N. (2020). Digital Transformation of the System of Public Finances Management. In: *Digital Economy: Complexity and Variety vs. Rationality 9* (pp. 940-949), Part of the book series: *Lecture Notes in Networks and Systems*, Springer International Publishing. https://doi.org/10.1007/978-3-030-29586-8_107
- [5] Laposha, D. (2022). Implementation of Digital Technologies When Executing Control of Public Finances in the Territorial Community. *Management of Development of Complex Systems*, 51, 58-68.
- [6] Molchanova, N. (2017). Transformation of Financial Relations in the Conditions of Formation of the Digital Economy. *Scientific Research of Faculty of Economics. Electronic Journal*, 9(3), 7-16.
- [7] Blizkiy, R. S., & Lebedinskaya, Y. S. (2023). Transformation of Accounting and Reporting of State Finances of Digital Environment of National Project Digital Economy. *Vestnik of Astrakhan State Technical University. Series: Economics. Vestnik of Astrakhan State Technical University*, 1.
- [8] Pantieliieva, N., Krynytsia, S., Zhezherun, Y., Rebryk, M., & Potapenko, L. (2018). Digitization of the Economy of Ukraine: Strategic Challenges and Implementation Technologies. *Proceedings of 2018 IEEE 9th International Conference on Dependable Systems, Services and Technologies, DESSERT 2018*. <https://doi.org/10.1109/DESSERT.2018.8409186>
- [9] Lima, D., Zego, E.P. & Rodrigues, J. (2022). Digital Transformation in Public Finance: A Paradigm That Has Contributed to Cabo Verde's Growth. In *Proceedings of the 15th International Conference on Theory and Practice of Electronic Governance* (pp. 570-572). ICEGOV '22. <https://doi.org/10.1145/3560107.3560198>
- [10] Mosteanu, N. R., & Faccia, A. (2020). Digital Systems and New Challenges of Financial Management- Fintech, XBRL, Blockchain and Cryptocurrencies. *Quality - Access to Success*, 21(174), 159-166.

- [11] Vovchenko, N. G., Ivanova, O. B., Kostoglodova, E. D., Khapilin, A. F., & Khapilin, S.A. (2023). Issues of Using Artificial Intelligence in the Framework of Public Finance. In *Technological Trends in the AI Economy. International Review and Ways of Adaptation* (pp. 329-335). Part of the book series: Smart Innovation, Systems and Technologies, Springer.
- [12] Pudryk, D., Bohiv, Y., & Shpak, N. (2020). Anti-Corruption Agenda for State Geo-Cadastre of Ukraine By 2030 in the Context of Transparency of Public Finance. *Baltic Journal of Economic Studies*, 6(1), 113-117.
- [13] Matviienko, H. (2021). Digital Transformation of Public Finance in Ukraine. *Odessa National University Herald. Economy*, 1(86), 135-140. <https://doi.org/10.32782/2304-0920/1-86-21>
- [14] Tsindeliiani, I., Kot, S., Vasilyeva, E., & Narinyan, L. (2019). Tax System of The Russian Federation: Current State and Steps Towards Financial Sustainability. *Sustainability*, 11(24), 1-18.
- [15] Volkova, O. H. (2021). The Financial Policy of Developed Countries: Current Challenges. *Socio-Economic Problems of the Modern Period of Ukraine*, 3(149), 42-46. <https://doi.org/10.36818/2071-4653-2021-3-7>
- [16] Mulendeeva, L. N. (2022). Strategy for Public Finance Development Under the Digital Transformation of Russian Economy. In: *International Scientific Conference Digital Transformation of the Economy: Challenges, Trends, New Opportunities* (pp. 739-744), Part of the book series: Lecture Notes in Networks and Systems, 304, Springer International Publishing.
- [17] El-Manaseer, S. A., Al-Kayid, J. H., Al Khawatreh, A. M., & Shamim, M. (2023). The Impact of Digital Transformation on Combating Tax Evasion (Electronic Billing System as a Model). In: *Artificial Intelligence (AI) and Finance* (pp. 679-690), Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-39158-3_63
- [18] Shichanin M. (2021). On the Place of Digital Technologies in the System of Public Financial Control. *Gosudarstvo i pravo*, 5, 154-158.
- [19] Efremova, T. A. (2024). Digital Technologies are a New Vector for the Development of Public Finance. *Теория и практика общественного развития*, 2, 72-78. <https://doi.org/10.24158/tipor.2024.2.9>
- [20] Senturk, O. (2021). Türkiye’de Kamu İç Denetim Faaliyetlerinin Dijital Dönüşümüne Yönelik Uygulamalar. *TIDE Academia Research*, 3(1), 157-186.
- [21] Garg, H., Munir, M., Ullah, K., Mahmood, T., & Jan, N. (2018). Algorithm for T-spherical Fuzzy Multi-Attribute Decision Making Based on Improved Interactive Aggregation Operators. *Symmetry*, 10(12), 1-23.
- [22] Huang, G., Xiao, L., Pedrycz, W., Zhang, G., & Martinez, L. (2022). bFailure Mode and Effect Analysis Using T-Spherical Fuzzy Maximizing Deviation and Combined Comparison Solution Methods. *IEEE Transactions on Reliability*. 72(2), 552-573. <https://doi.org/10.1109/TR.2022.3194057>
- [23] Ju, Y., Liang, Y., Luo, C., Dong, P., Gonzalez, E. D. R. S., & Wang, A. (2021). T-Spherical Fuzzy TODIM Method for Multi-Criteria Group Decision-Making Problem with Incomplete Weight Information. *Soft Computing*, 25(4), 2981-3001. <https://doi.org/10.1007/s00500-020-05357-x>
- [24] Mahmood, T., Ullah, K., Khan, Q., & Jan, N. (2019). An Approach Toward Decision-Making and Medical Diagnosis Problems Using the Concept of Spherical Fuzzy Sets. *Neural Computing and Applications*, 31(11), 7041-7053. <https://doi.org/10.1007/s00521-018-3521-2>
- [25] Gurmani, S. H., Chen, H., & Bai, Y. (2023). An extended MABAC method for multiple-attribute group decision making under probabilistic T-spherical hesitant fuzzy environment. *Kybernetes*, 52(10), 4041-4060. <https://doi.org/10.1108/K-01-2022-0137>
- [26] Shannon, C. E., & Weaver, W. (1964). *The Mathematical Theory of Communication*. The University of Illinois.
- [27] Aytekin, A., Görçün, Ö. F., Ecer, F., Pamucar, D., & Karamaşa, Ç. (2022). Evaluation of the Pharmaceutical Distribution and Warehousing Companies Through an Integrated Fermatean Fuzzy Entropy-WASPAS Approach. *Kybernetes*, 52(11), 5561-5592. <https://doi.org/10.1108/K-04-2022-0508>
- [28] Yi, Y. U. N. (2006). Entropy method for determination of weight of evaluating indicators in fuzzy synthetic evaluation for water quality assessment. *Journal of Environmental sciences*, 18(5), 1020-1023. [https://doi.org/10.1016/S1001-0742\(06\)60032-6](https://doi.org/10.1016/S1001-0742(06)60032-6)
- [29] Görçün, Ö. F., Mishra, A.R., Aytekin, A., Simic, V., & Korucuk, S. (2024). Evaluation of Industry 4.0 Strategies for Digital Transformation in the Automotive Manufacturing Industry Using an Integrated Fuzzy Decision-Making Model. *Journal of Manufacturing Systems*, 74, 922-948.
- [30] Rao, A. V. A. R. R., Sai, N. V. & Babu, K. P. (2017). An Integrated Approach Using VIKOR and ENTROPY Methods for a Supplier Selection Problem. *International Journal of Innovations in Engineering and Technology*, 8(3), 1-9. <https://doi.org/10.21172/ijiet.83.001>
- [31] Görçün, Ö. F. (2020). Efficiency Analysis of Black Sea Container Seaports: Application of an Integrated MCDM Approach. *Maritime Policy and Management*, 48(5), 672-699.
- [32] Løken, E. (2007). Use of Multicriteria Decision Analysis Methods for Energy Planning Problems. *Renewable and Sustainable Energy Reviews*, 11(7), 1584-1595.

- [33] Gül, Ş. & Fırat, M. (2021). bTOPSIS & MAUT Yöntemleri ile İçmesuyu Dağıtım Sistemlerinde Rehabilitasyon Önceliğinin Belirlenmesi. *Fırat Üniversitesi Mühendislik Bilimleri Dergisi*, 33(1), 27-38. <https://doi.org/10.35234/fumbd.691241>
- [34] Ömürbek, N., Karaatlı, M., & Balci, H.F. (2016). Entropi Temelli MAUT & SAW Yöntemleri ile Otomotiv Firmalarının Performans Değerlemesi. *Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 31(1), 227-255.
- [35] Çanakçıoğlu, M. (2019). Bağımsız Mali Müşavirlerin Müşteri Seçimine Etki Eden Faktörlerin & Karar Alternatiflerinin AHP & MAUT Yöntemleri Çerçevesinde Değerlendirilmesi: İstanbul Kentine İlişkin Bir Uygulama. *Muhasebe Ve Denetime Bakış*, 19(57), 165-194.
- [36] Görçün, Ö. F., Senthil, S., & Küçükönder, H. (2021). Evaluation of Tanker Vehicle Selection Using A Novel Hybrid Fuzzy MCDM Technique. *Decision Making: Applications in Management and Engineering*, 4(2), 140-162. <https://doi.org/10.31181/dmame210402140g>
- [37] Saaty, T. (1980). *The Analytic Hierarchy Process*. McGraw Hill, New York.
- [38] Belton, V., & Stewart, T. (2012). *Multiple criteria decision analysis: an integrated approach*. Springer Science & Business Media. <https://doi.org/10.1007/978-1-4615-1495-4>