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EVALUATING ESG SUSTAINABILITY PERFORMANCE IN THE TURKISH BANKING INDUSTRY: A GREY LOPCOW–MSD–PIV APPROACH

Türk Bankacılık Sektöründe ESG Sürdürülebilirlik Performansının Değerlendirilmesi: Gri LOPCOW–MSD–PIV Yaklaşımı

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Keywords:
ESG Sustainability, G-LOPCOW, G-MSD, G-PIV, Grey System Theory, Turkish banks

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Abstract

This study introduces a novel grey-based multi-criteria decision-making (MCDM) framework designed to assess the Environmental, Social, and Governance (ESG) sustainability performance of banks listed on Borsa İstanbul (BIST). The suggested hybrid grey-based model integrates two objective weighting techniques—Grey Logarithmic Percentage Change-Driven Objective Weighting (G-LOPCOW) and Grey Modified Standard Deviation (G-MSD)—with the Grey Preference Index Value (G-PIV) ranking procedure to effectively manage epistemic uncertainty inherent in sustainability data. Ten ESG indicators obtained from the Refinitiv Eikon database for the 2021–2023 period form the analytical foundation of the sustainability assessment. The integrated weighting process identifies community engagement, product responsibility, and shareholder relations as the most influential determinants shaping banks' sustainability profiles. Based on the G-PIV results, İşbank, Yapı Kredi, and TSKB rank as the top-performing institutions. The empirical findings not only provide valuable insights into the ESG positioning of Turkish banks but also offer a replicable methodological framework for practitioners and policymakers seeking data-driven sustainability benchmarking. Furthermore, the study contributes to the growing body of literature on grey system-based decision models, reinforcing their utility in addressing ambiguity and partial information in complex financial and sustainability evaluations.

Anahtar Kelimeler:
ESG Sürdürülebilirliği, G-LOPCOW, G-MSD, G-PIV, Gri Sistem Teorisi, Türk Bankaları.

JEL Kodları:
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Öz

Bu çalışma, Borsa İstanbul'da (BIST) işlem gören bankaların Çevresel, Sosyal ve Yönetişim (ESG) sürdürülebilirlik performansını değerlendirmek üzere tasarlanmış yeni bir gri tabanlı çok kriterli karar verme (ÇKKV) çerçevesi sunmaktadır. Önerilen hibrit gri tabanlı model, sürdürülebilirlik verilerinde bulunan epistemik belirsizliği etkin bir şekilde yönetmek için iki nesnel ağırlıklandırma tekniği olan Gri Logaritmik Yüzde Değişim Odaklı Nesnel Ağırlıklandırma (G-LOPCOW) ve Gri Değiştirilmiş Standart Sapma'yı (G-MSD) Gri Tercih Endeksi Değeri (G-PIV) sıralama prosedürüyle birleştirir. Refinitiv Eikon veri tabanından 2021-2023 dönemi için elde edilen on ESG göstergesi, sürdürülebilirlik değerlendirmesinin analitik temelini oluşturmaktadır. Entegre ağırlıklandırma süreci, topluluk katılımını, ürün sorumluluğunu ve hissedar ilişkilerini bankaların sürdürülebilirlik profillerini şekillendiren en etkili belirleyiciler olarak belirlemiştir. G-PIV sonuçlarına göre, İş Bankası, Yapı Kredi ve TSKB en iyi performans gösteren kurumlar olarak sıralanmaktadır. Ampirik bulgular, Türk bankalarının ESG konumlandırmasına dair değerli bilgiler sağlamanın yanı sıra, veri odaklı sürdürülebilirlik kıyaslamasına odaklanan uygulayıcılar ve politika yapıcılar için tekrarlanabilir bir metodolojik çerçeve de sunmaktadır. Ayrıca, çalışma, gri sistem tabanlı karar modelleri hakkındaki giderek artan literatüre katkıda bulunarak, karmaşık finansal ve sürdürülebilirlik değerlendirmelerinde belirsizlik ve kısmi bilginin ele alınmasındaki faydalarını pekiştirmektedir.

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1. Introduction

In recent years, Environmental, Social, and Governance (ESG) considerations have become a central pillar of financial and corporate strategy, shaping how institutions create value, manage risk, and interact with society (Akbulut, 2024; Işık and Adalar, 2025; Manta et al., 2025). As global markets shift toward sustainability-oriented growth, banks—acting as the primary channels of financial intermediation—are expected to align their operations with ESG principles to strengthen ethical accountability and long-term resilience (Karki et al., 2025; Mirza et al., 2025).

ESG performance captures how effectively financial institutions internalize sustainability values through environmental stewardship, social responsibility, and governance transparency. Strong ESG practices enhance financial resilience, reinforce market credibility, and mitigate exposure to reputational and regulatory risks (Buallay, 2019; Broadstock et al., 2021; Ersoy et al., 2022; López-Penabad et al., 2023; Dou et al., 2025). Assessing ESG performance in the banking sector is not only a compliance requirement but also a strategic necessity. Financial institutions play a key role in financing low-carbon transitions, fostering financial inclusion, and ensuring responsible corporate conduct throughout the economy (Işık et al., 2025a; Ünlü and Çıtak, 2025; Akbulut and Aydın, 2024). Consequently, a reliable evaluation mechanism enables banks to identify sustainability strengths and weaknesses, guide improvement strategies, and enhance alignment with global initiatives such as the United Nations Sustainable Development Goals (SDGs) and the Principles for Responsible Banking (PRB) (Ecer and Pamucar, 2022).

From a theoretical standpoint, the quantification of ESG performance in banking extends beyond measurement—it reflects the interplay of economic, ethical, and institutional dynamics (Azmi et al., 2021, Ersoy et al., 2022; Işık, 2023; Dohrmann et al., 2024). Stakeholder theory (Freeman, 1984) offers the ethical foundation by asserting that firms sustain long-term value by balancing the interests of all stakeholders—shareholders, employees, customers, regulators, and communities. Within this framework, ESG measurement allows banks to evaluate how effectively they fulfill multi-stakeholder responsibilities and sustain social legitimacy. The resource-based view (Russo and Fouts, 1997) complements this reasoning by interpreting ESG capabilities as strategic resources that can generate enduring competitive advantages. Objective ESG evaluation helps identify which sustainability practices translate into distinctive, inimitable, and value-creating organizational capabilities. Stewardship theory (van Puyvelde et al., 2012) further strengthens this perspective by portraying managers as custodians of corporate value, implying that systematic ESG assessment serves as a governance mechanism that aligns managerial actions with long-term sustainability goals. Finally, legitimacy theory (Suchman, 1995) provides the institutional rationale, arguing that transparent ESG measurement and disclosure reinforce organizational legitimacy in a regulatory environment where social responsibility and compliance expectations continue to intensify. Collectively, these theories justify the need for rigorous and objective ESG performance measurement in banking.

Despite its growing importance, ESG performance assessment remains analytically challenging. ESG frameworks consist of multiple heterogeneous indicators—ranging from emissions and resource efficiency to workforce diversity and board accountability (Işık and Adalar, 2025; Demir, 2025; Yang et al., 2025). These indicators differ in scale, completeness, and precision, complicating their integration into a single composite framework. Furthermore, interdependencies among the three ESG pillars often lead to trade-offs between dimensions, such as when environmental investments temporarily affect social or governance outcomes.

Traditional linear or statistical models fail to fully capture these interactions and the epistemic uncertainty inherent in ESG data, emphasizing the need for a more flexible and uncertainty-tolerant decision framework (Reig-Mullor and Brotons-Martinez, 2021; Hoang et al., 2024; Yu et al., 2024; da Cunha et al., 2025; Lombardi Netto et al., 2025).

To systematically address the epistemic uncertainty inherent in ESG evaluations and to construct a robust and reliable decision-support mechanism tailored to the banking sector, this study develops a novel Multi-Criteria Decision-Making (MCDM) approach grounded in grey system theory. Grey theory, developed by Deng (1982), provides a mathematically consistent structure for analyzing systems with incomplete, imprecise, or uncertain information (Akbulut, 2024; Ulutaş et al., 2024; Durdu et al., 2025). It enables robust evaluation even when data are partially disclosed or inconsistent—conditions typical of sustainability datasets (Karadağ Albayrak, 2021). Building upon this theoretical basis, the present research develops an integrated grey-based MCDM framework for the systematic evaluation of ESG sustainability performance among banks.

To empirically validate the proposed grey-based decision framework, a case study was conducted comparing the ESG sustainability performance of nine banks listed on Borsa İstanbul (BIST) over the 2021–2023 period. This timeframe was strategically selected, as it coincides with the institutionalization of sustainability reporting practices in the Turkish banking sector—driven by intensified regulatory focus on climate-related risk disclosures and the broader adoption of sustainable finance principles. ESG data were retrieved from the Refinitiv Eikon database, which offers standardized and internationally comparable indicators suitable for cross-institutional benchmarking. The selected period represents a critical transition phase during which ESG integration progressed from voluntary disclosure to formalized compliance, thereby providing a robust and policy-relevant context for evaluating sustainability performance across banking institutions.

Accordingly, the research questions addressed in the present manuscript are as follows:

RQ1. Which ESG criteria exert the most significant influence on the overall sustainability performance of Turkish banks?

RQ2. How do BIST-listed banks perform in terms of ESG sustainability between 2021 and 2023 when evaluated through an objective, grey-based MCDM framework?

RQ3. Can the proposed Grey LOPCOW–MSD–PIV model serve as a reliable and replicable decision-support mechanism for ESG assessment under uncertainty?

To address the outlined research questions, this work introduces a novel grey-based MCDM framework specifically designed for ESG performance assessment in banking institutions. Within this structure, two objective weighting techniques—Grey LOgarithmic Percentage Change-driven Objective Weighting (G-LOPCOW) and Grey Modified Standard Deviation (G-MSD)—are employed to quantify the informational contribution of each ESG criterion from distinct statistical standpoints. G-LOPCOW captures logarithmic sensitivity to proportional changes in grey data, while G-MSD reflects the degree of dispersion across grey interval values, offering a robust measure of variability under uncertainty. The resulting weight vectors are subsequently synthesized using a linear aggregation operator to ensure consistency and minimize potential weighting bias. Finally, the Grey Proximity Indexed Value (G-PIV) integrates the aggregated weights to produce a composite ranking of banks, yielding a decision-support framework that is interpretable, resilient to data uncertainty, and analytically coherent for ESG sustainability assessment.

This study adds new insights to the MCDM literature and advances empirical approaches to ESG performance assessment in the banking sector from various perspectives. First, the present work introduces a comprehensive and theoretically grounded grey-based MCDM framework for assessing the ESG sustainability performance of banks. Its principal novelty arises from the methodological integration of grey system theory with three complementary analytical components—G-LOPCOW, G-MSD, and G-PIV. This hybrid structure enables a coherent and uncertainty-tolerant assessment process that surpasses the limitations of traditional linear or purely statistical ESG evaluation models. By incorporating grey interval numbers, the suggested approach provides a mathematically consistent foundation for handling epistemic uncertainty, thereby ensuring reliable decision outcomes even when the available data are incomplete, imprecise, or partially known. Second, from a methodological standpoint, the integration of G-LOPCOW and G-MSD represents a dual-objective weighting scheme that combines logarithmic sensitivity and dispersion-based variability under epistemic uncertainty. The linear aggregation of these two weighting schemes produces a balanced and bias-free vector of criterion weights, thus enhancing the objectivity and stability of the decision-making process. The subsequent application of the Grey PIV tool offers a transparent and computationally efficient ranking procedure, which is particularly suitable for sustainability assessments that require interpretability and reproducibility. Third, empirically, this manuscript applies this integrated framework to nine banks listed on BIST for the period 2021–2023, a time frame that marks the institutionalization of sustainability reporting practices in the Turkish banking sector. The use of ESG data from the Refinitiv Eikon database allows for internationally standardized comparison and enhances the external validity of the findings. The results not only shed light on the relative sustainability performance of leading financial institutions but also capture the structural transformation of the sector as it transitions from voluntary ESG disclosure to mandatory sustainability compliance. This empirical validation provides policy-relevant insights for regulators and financial authorities seeking to promote sustainable finance within emerging markets. Finally, theoretically, the developed grey-based hybrid framework contributes to the growing body of MCDM literature by bridging two fundamental logics of objective weighting—information theory and variance-based reasoning—within a unified grey environment. This dual-statistical perspective enriches the methodological toolkit available for researchers dealing with uncertain, heterogeneous, or interval-valued data. Practically, the model provides a decision-support mechanism that is both flexible and generalizable, allowing its application beyond ESG performance analysis to other domains such as corporate governance evaluation, financial resilience measurement, or innovation efficiency assessment.

2. Literature Review

In recent years, the integration of MCDM procedures into performance assessment frameworks has gained substantial momentum, particularly within the domains of banking, finance, and sustainability. These techniques offer a structured and transparent means of assessing organizational performance across both quantitative financial indicators and qualitative non-financial dimensions, such as ESG criteria.

Within the context of banking industry research, MCDM approaches have been increasingly adopted to address the limitations of traditional single-criterion evaluations. By incorporating diverse weighting structure and ranking algorithms, scholars have developed robust models that capture the multi-dimensional nature of bank performance, including profitability, operational efficiency, and sustainability. Notably, recent studies have adopted a diverse range of hybrid and fuzzy-augmented MCDM techniques to evaluate banking performance across multiple dimensions. These applications not only enhance decision transparency but also support comparative benchmarking across institutions and regions.

Table 1 provides a comprehensive synthesis of recent empirical studies that utilize MCDM methodologies to assess firm-level performance in the banking sector, highlighting the diversity of methodological configurations and evaluation scopes.

Table 1. Multidimensional Firm Performance Assessments via MCDM Approaches

Study	Bank	Weighting Methodology	Ranking Procedure	Scope
Akbulut (2019)	İşbank	CRITIC	EDAS	Assessment of financial performance
Reig-Mullor and Brotons-Martinez (2021)	Spanish commercial banks	IF-AHP	IF-TOPSIS	Evaluating sustainability and financial health
Abdel-Basset et al. (2021)	Egyptian commercial banks	PF-AHP	PF-TOPSIS, PF-VIKOR, and PF-COPRAS	Multidimensional performance measurement
Gupta et al. (2021a)	Indian commercial banks	CRITIC	TOPSIS	Financial performance assessment
Gupta et al. (2021b)	Indian commercial banks	AHP	interval-valued TOPSIS	Financial performance evaluation
Ecer and Pamucar (2022)	Turkish commercial banks	LOPCOW	DOBI	Sustainability performance measurement
Ünlü et al. (2022)	Turkish commercial banks	SWARA II and MEREC	MARCOS	Analysis of productivity and efficiency performance
Ünlü and Yalçın (2023)	Turkish commercial banks	CRITIC	WASPAS	Financial performance evaluation
Akbulut (2024)	Turkish deposit banks	G-LOPCOW	G-PIV	Analysis of environmental sustainability performance
Akbulut and Aydın (2024)	Turkish deposit banks	MSD and MPSI	RAWEC	Multidimensional performance measurement
Trung et al. (2024)	Vietnamese banks	Equal weights	SRP, PSI, and RAM	Financial performance evaluation
Goel et al. (2024)	Indian banks	Equal weights	GRA	Sustainability performance measurement
Hussain et al. (2024)	Emerging markets banks (China, Pakistan, India, and Thailand)	AHP	TOPSIS and GRA	Financial performance assessment
Ünlü and Çıtak (2025)	Turkish deposit banks	MEREC, CILOS, and CCSD	WASPAS and ARAS	Sustainability performance measurement
Işık et al. (2025a)	Turkish participation banks	SF-SPC and SF-SWARA	SF-AROMAN	Evaluating sustainability, efficiency, and productivity

Table 1. Continued

Işık et al. (2025b)	Turkish deposit banks	G-SPC and G-MSD	G-SRP	ESG performance comparison
Işık et al. (2025c)	Pakistani commercial banks	F-LBWA and F-LMAW	MARCOS	Analysis of the performance of service network, market performance, and financial health
Karki et al. (2025)	Indian deposit banks	R-SWARA	CoCoSo	ESG performance assessment
Durmuş et al. (2025)	Commercial banks operating in the Balkans	Type-2 NF-PSI	Type-2 NF-CODAS	Financial performance evaluation
Yang et al. (2025)	Chinese commercial banks	ISF method	ISF-TOPSIS	Operational performance evaluation
Peci et al. (2025)	Albanian banks	F-AHP	F-TOPSIS	Financial performance assessment
Karadağ Ak et al. (2025)	Turkish development and investment banks	Entropy	ARAS	Financial performance assessment

As summarized in Table 1, recent studies have employed a diverse range of hybrid MCDM techniques to evaluate bank performance across financial, operational, and sustainability dimensions. These models reflect growing methodological sophistication, incorporating traditional methods, fuzzy logic, and interval-valued data to enhance decision transparency and benchmarking accuracy.

However, a critical conceptual gap remains in the ESG-focused literature. Prior papers have largely treated ESG indicators as isolated metrics, without systematically linking them to underlying sustainability theories. In particular, the theoretical foundations—such as stakeholder theory, legitimacy theory, stewardship theory, and the resource-based view—have not been explicitly mapped to the ESG criteria used in performance evaluation. This omission limits the interpretability and strategic relevance of existing models, especially in regulatory and institutional contexts where ESG disclosure is increasingly mandated.

The present manuscript addresses this gap by integrating ten ESG sustainability criteria across ESG dimensions with four complementary theoretical anchors. Each criterion is conceptually aligned with one or more theories, as detailed in Table 3.

By embedding these theoretical linkages into the analytical structure, the proposed grey-based MCDM framework offers not only methodological novelty but also conceptual depth. It enables a more meaningful interpretation of ESG performance, grounded in institutional accountability, stakeholder legitimacy, and strategic resource utilization. This dual contribution—bridging theory and method—positions the model as a robust decision-support tool for sustainability evaluation in banking.

3. Methodology

This research assesses the ESG performance of publicly listed Turkish banks using an integrated grey-based MCDM framework. The analytical structure combines G-LOPCOW, G-MSD, and G-PIV to ensure methodological diversity and enhance decision robustness under epistemic uncertainty. Figure 1 presents the schematic flow of the proposed model, while the following section outlines the theoretical foundations of each grey-oriented component.

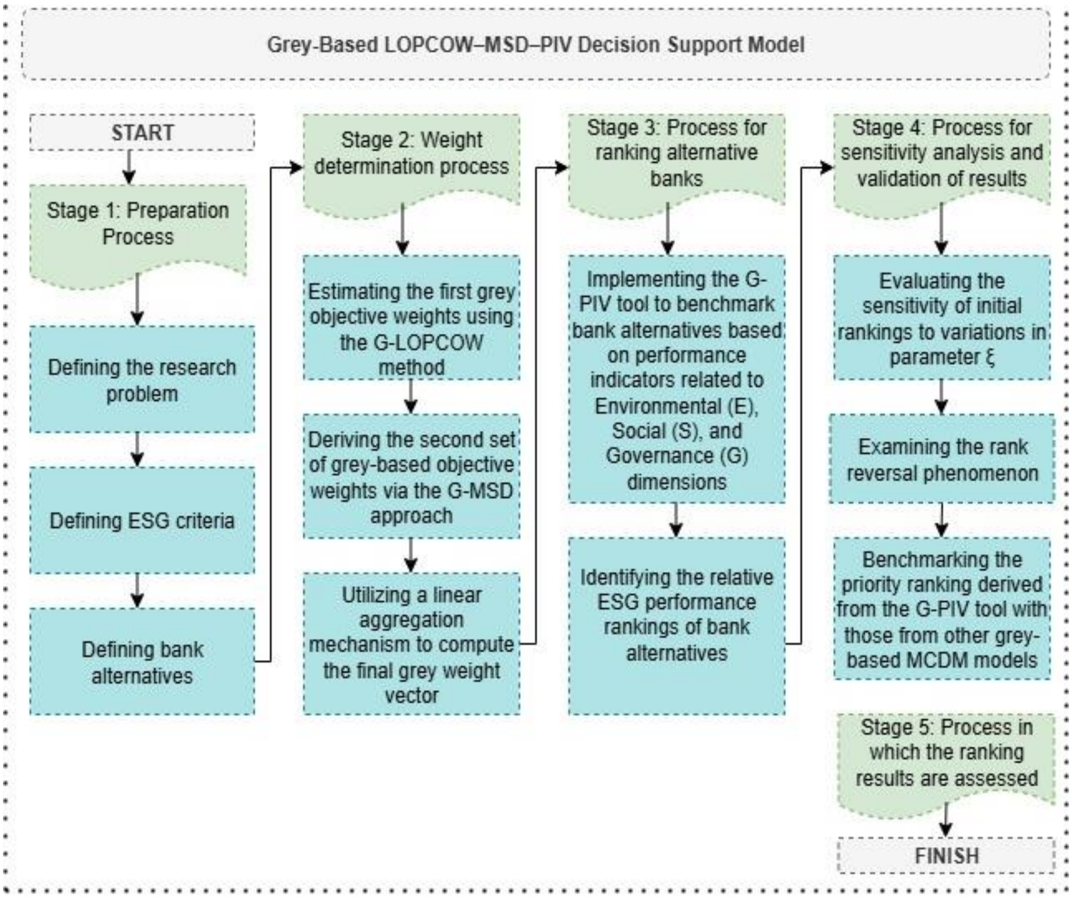

Figure 1. Methodological Framework

3.1. Grey LOPCOW (G-LOPCOW) Methodology

The classical LOPCOW weighting algorithm was originally introduced by Ecer and Pamucar (2022) as a computationally efficient and interpretable method for objective criterion weighting. From a methodological standpoint, it has gained considerable attention across various decision-making domains due to its ability to handle negative data and its straightforward implementation. As an extension of the original model, Ulutaş et al. (2024) subsequently developed a grey interval-based version, referred to as G-LOPCOW, to enhance its applicability under uncertainty and incomplete information. This enhancement allows the technique to more effectively address epistemic uncertainty by integrating grey numbers into the weighting process. As a result, its applicability is significantly improved in decision-making environments characterized by incomplete or ambiguous information. The computational framework of the G-LOPCOW procedure is structured as follows:

Step 1. The grey decision matrix ⊗A, comprising the set of alternatives and evaluation criteria, is constructed. This matrix is provided in Eq. (1).

$$\otimes A = \left[\otimes a_{ij}\right]_{m\times n} = \begin{bmatrix} \left[a_{11}^{l}, a_{11}^{u}\right] & \left[a_{12}^{l}, a_{12}^{u}\right] & \cdots & \left[a_{1n}^{l}, a_{1n}^{u}\right] \\ \left[a_{21}^{l}, a_{21}^{u}\right] & \left[a_{22}^{l}, a_{22}^{u}\right] & \cdots & \left[a_{2n}^{l}, a_{2n}^{u}\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[a_{m1}^{l}, a_{m1}^{u}\right] & \left[a_{m2}^{l}, a_{m2}^{u}\right] & \cdots & \left[a_{mn}^{l}, a_{mn}^{u}\right] \end{bmatrix}_{m\times n} \tag{1}$$

In Eq. (1), $\otimes \mathrm{a}_{\mathrm{ij}}$, defined as $\otimes \mathrm{a}_{\mathrm{ij}} = \left[\mathrm{a}_{\mathrm{ij}}^{\mathrm{l}}, \mathrm{a}_{\mathrm{ij}}^{\mathrm{u}}\right]$, represents the grey performance value of the ith alternative with respect to the jth assessment criterion. Here, $\mathrm{a}_{\mathrm{ij}}^{\mathrm{l}}$ and $\mathrm{a}_{\mathrm{ij}}^{\mathrm{u}}$ denote the lower and upper bounds of the grey interval, respectively.

Step 2. The grey decision matrix presented in Eq. (1) is normalized employing Eq. (2) for beneficial criteria and Eq. (3) for non-beneficial criteria.

$$\otimes b_{ij} = \frac{\otimes a_{ij} - min\left\{\otimes a_{ij} \middle| 1 \leq i \leq m\right\}}{max\left\{\otimes a_{ij} \middle| 1 \leq i \leq m\right\} - min\left\{\otimes a_{ij} \middle| 1 \leq i \leq m\right\}} \tag{2}$$

$$\otimes b_{ij} = \frac{max\left\{\otimes a_{ij} \middle| 1 \leq i \leq m\right\} - \otimes a_{ij}}{max\left\{\otimes a_{ij} \middle| 1 \leq i \leq m\right\} - min\left\{\otimes a_{ij} \middle| 1 \leq i \leq m\right\}} \tag{3}$$

Step 3. The grey percentage values PV_j corresponding to each criterion are computed according to the following formulation.

$$\otimes PV_j = \left[PV_j^l, PV_j^u\right] = \left[\left| ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m}\left(b_{ij}^{l}\right)^2}{m}}}{\sigma_j^l}\right) \times 100\right|, \left| ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m}\left(b_{ij}^{u}\right)^2}{m}}}{\sigma_j^u}\right) \times 100\right|\right] \tag{4}$$

In Equation (4), σ_j^l and σ_j^u denote the lower and upper bounds of the standard deviation scores corresponding to each assessment criterion.

Step 4. The final step of the G-LOPCOW weighting procedure entails the computation of grey weight scores for the selected criteria using Eq. (5)

$$\otimes \mathrm{w}_{\mathrm{j,lop}} = \left[w_{j,lop}^{l}, w_{j,lop}^{u}\right] = \left[min\left(\frac{PV_j^l}{\sum_{j=1}^{n} PV_j^l}, \frac{PV_j^u}{\sum_{j=1}^{n} PV_j^u}\right), max\left(\frac{PV_j^l}{\sum_{j=1}^{n} PV_j^l}, \frac{PV_j^u}{\sum_{j=1}^{n} PV_j^u}\right)\right] \tag{5}$$

3.2. Grey Modified Standard Deviation (G-MSD) Procedure

The Standard Deviation (SD) technique, originally recommended by Diakoulaki et al. (1995), has been widely employed in MCDM to derive objective coefficient weights by capturing the dispersion of criterion values across alternatives. To enhance its sensitivity to data magnitude, Puška et al. (2022) introduced the MSD variant, which incorporates two additional steps: computing the column-wise totals and adjusting the standard deviation accordingly. More recently, Işık et al. (2025b) extended this structure into the grey environment by developing the G-MSD model, which integrates grey interval numbers to better handle epistemic uncertainty and incomplete information. This methodological progression reflects a shift toward more robust and uncertainty-resilient weighting procedures in complex decision-making contexts. The implementation of the G-MSD weighting procedure comprises the following steps:

Step 1. The initial grey decision matrix is constructed as shown in Eq. (1).

Step 2. As specified in Eq. (1), the initial grey decision matrix is subjected to normalization, where Eq. (6) is applied to benefit-type criteria and Eq. (7) to cost-type criteria.

$$\otimes b_{ij} = \begin{cases} \otimes b_{ij}^{+} = \frac{\otimes b_{ij}}{max\{\otimes b_{ij} | 1 \leq i \leq m\}} = \left[\frac{b_{ij}^{l}}{max\{b_{ij}^{u} | 1 \leq i \leq m\}}, \frac{b_{ij}^{u}}{max\{b_{ij}^{u} | 1 \leq i \leq m\}}\right] & (6) \\ \otimes b_{ij}^{-} = \frac{min\{\otimes b_{ij} | 1 \leq i \leq m\}}{\otimes b_{ij}} = \left[\frac{min\{b_{ij}^{l} | 1 \leq i \leq m\}}{(b_{ij}^{u})}, \frac{min\{b_{ij}^{l} | 1 \leq i \leq m\}}{(b_{ij}^{l})}\right] & (7) \end{cases}$$

Step 3. The modified values of the standard deviation scores for each performance measure are obtained through Eq. (8).

$$\otimes t_j = [t_j^l, t_j^u] = \left[min\left(\frac{\sigma^l}{\sum_{i=1}^{m}(b_{ij}^l)}\right), \left(\frac{\sigma^u}{\sum_{i=1}^{m}(b_{ij}^u)}\right), max\left(\frac{\sigma^l}{\sum_{i=1}^{m}(b_{ij}^l)}\right), \left(\frac{\sigma^u}{\sum_{i=1}^{m}(b_{ij}^u)}\right)\right] \quad (8)$$

Step 4. The last phase of the MSD-G procedure involves computing the objective significance weights of each performance criterion using Eq. (9).

$$\otimes \mathrm{w}_{\mathrm{j,msd}} = [w_{j,msd}^l, w_{j,msd}^u] = \left[\frac{\otimes t_j}{\sum_{j=1}^{n} \otimes t_j}\right] \left[min\left(\frac{t_j^l}{\sum_{j=1}^{n}(t_j^l)}, \frac{t_j^u}{\sum_{j=1}^{n}(t_j^u)}\right), max\left(\frac{t_j^l}{\sum_{j=1}^{n}(t_j^l)}, \frac{t_j^u}{\sum_{j=1}^{n}(t_j^u)}\right)\right] \quad (9)$$

3.3. Aggregation of Criterion Weights

In MCDM, employing diverse weighting techniques often yields slight variations in the computed criterion weights owing to the inherent differences in their evaluative mechanisms. To reconcile these discrepancies and leverage the complementary strengths of each tool, a linear aggregation operator was utilized to integrate the outputs of the G-LOPCOW and G-MSD procedures. This integration enables a more balanced and epistemically resilient weighting structure. The resulting composite weights offer enhanced interpretability, methodological neutrality, and improved robustness in performance assessment. By synthesizing multiple weighting schemes, the final weights more accurately reflect the relative significance of criteria across uncertain decision environments, thereby strengthening the reliability and analytical depth of the overall assessment. The combined weights are computed employing the following linear integration formula.

$$\otimes \mathrm{w}_{\mathrm{j,com}} = [\mathrm{w}_{\mathrm{j,com}}^{\mathrm{l}}, \mathrm{w}_{\mathrm{j,com}}^{\mathrm{u}}] = [\xi \otimes \mathrm{w}_{\mathrm{j,lop}} + (1-\xi) \otimes \mathrm{w}_{\mathrm{j,msd}}] = [\min(\xi w_{j,lop}^l + (1-\xi) w_{j,msd}^l), \max(\xi w_{j,lop}^u + (1-\xi) w_{j,msd}^u)] \quad (10)$$

Here, $\mathrm{w}_{\mathrm{j,com}}$ (j = 1, 2,..., n) represents the integrated weight coefficient corresponding to the j^{th} ESG criterion. In the current manuscript, the individual weight coefficients of criteria derived from G-LOPCOW and G-MSD are represented as $\otimes \mathrm{w}_{\mathrm{j,lop}}$ and $\otimes \mathrm{w}_{\mathrm{j,msd}}$, respectively. In Eq. (10), the parameter $\xi \in [0, 1]$ denotes the proportional coefficient employed to balance the contribution of individual weighting approaches in the aggregation process. For the initial solution, its value was set to 0.5, implying equal influence from both G-MSD and G-LOPCOW-derived weights. Hence, the applicability and consistency of the proposed aggregation strategy can be empirically validated in different settings.

3.4. Grey PIV Method

The Proximity Indexed Value (PIV) technique, developed by Mufazzal and Muzakkir (2018), is a ranking-oriented MCDM tool designed to minimize the rank reversal phenomenon commonly observed in traditional models. Next, to extend its applicability under uncertainty, Ulutaş et al. (2021) introduced the Grey PIV (G-PIV) approach, which integrates grey system theory into the original PIV structure. G-PIV replaces crisp performance values with grey interval numbers, allowing the technique to handle epistemic uncertainty and incomplete information more effectively. The procedural implementation of the G-PIV consists of five systematic steps.

Step 1. The initial grey decision matrix is formulated in accordance with Eq. (1).

Step 2. Normalization of the values in the initial grey decision matrix is performed via Eq. (11).

$$\otimes k_{ij} = \left[k_{ij}^{l}, k_{ij}^{u}\right] = \frac{\otimes a_{ij}}{\sqrt{\sum_{i=1}^{m}(\otimes a_{ij})^{2}}} = \left[\frac{a_{ij}^{l}}{\sqrt{\sum_{i=1}^{m}\left(a_{ij}^{u}\right)^{2} + \sum_{i=1}^{m}\left(a_{ij}^{l}\right)^{2}}}, \frac{a_{ij}^{u}}{\sqrt{\sum_{i=1}^{m}\left(a_{ij}^{u}\right)^{2} + \sum_{i=1}^{m}\left(a_{ij}^{l}\right)^{2}}}\right] \quad (11)$$

Step 3. The values of the weighted normalized grey decision matrix are obtained by applying Eq. (12).

$$\otimes z_{ij} = \left[z_{ij}^{l}, z_{ij}^{u}\right] = \otimes w_{j,com} \times \otimes k_{ij} = \left[w_{j,com}^{l} \times k_{ij}^{l}, w_{j,com}^{u} \times k_{ij}^{u}\right] \quad (12)$$

Step 4. The grey weighted proximity index $\left(\otimes f_{ij} = \left[f_{ij}^{l}, f_{ij}^{u}\right]\right)$ is obtained for benefit-type criteria using Eq. (13) and for cost-type criteria using Eq. (14).

$$\otimes f_{ij} = max\left(\otimes z_{ij}\right) - \otimes z_{ij} = \left[max(z_{ij}^{l}) - z_{ij}^{u}, max(z_{ij}^{u}) - z_{ij}^{l}\right] \quad (13)$$

$$\otimes f_{ij} = \otimes z_{ij} - min\left(\otimes z_{ij}\right) = \left[z_{ij}^{l} - min\left(z_{ij}^{u}\right), z_{ij}^{u} - min\left(z_{ij}^{l}\right)\right] \quad (14)$$

Step 5. In the final step of the G-PIV procedure, the overall proximity values—grey $\left(\otimes v_i = \left[v_i^{l}, v_i^{u}\right]\right)$ and crisp v_i—are computed by applying Eqs. (15) and (16), respectively.

$$\otimes v_i = \left[v_i^{l}, v_i^{u}\right] = \sum_{j=1}^{n} \otimes f_{ij} = \left[\sum_{j=1}^{n} f_{ij}^{l}, \sum_{j=1}^{n} f_{ij}^{u}\right] \quad (15)$$

$$\mathrm{v_i} = \frac{\mathrm{d_i^l} + \mathrm{d_i^u}}{2} \quad (16)$$

3.5. Rationale for Choosing the LOPCOW-MSD-PIV Hybrid Combination in Grey Environment and Its Advantages Over Alternative MCDM Frameworks

The selection of the G-LOPCOW–G-MSD–G-PIV combination is driven by both theoretical coherence and practical suitability to the complex data structure underlying ESG performance assessment in the banking industry. ESG assessment demands a methodological framework capable of accommodating epistemic uncertainty, indicator heterogeneity, and incomplete disclosure—characteristics that frequently define sustainability-related datasets. Conventional deterministic MCDM techniques (e.g., Entropy, CRITIC, CRISUS, MEREC, TOPSIS, VIKOR, WASPAS) presuppose complete and precise data, a condition rarely satisfied in ESG reporting. Likewise, although fuzzy-based MCDM models (such as F-AHP, F-BWM, F-TOPSIS, or F-MARCOS) can address linguistic vagueness, they rely extensively on expert elicitation for defining membership functions and constructing pairwise comparison matrices. This dependence on subjective judgment may introduce cognitive bias and reduce reproducibility—an especially critical limitation in regulated sectors such as banking, where methodological transparency and data objectivity are paramount.

In contrast, the present study employs a fully data-driven grey-based hybrid framework that unites three complementary models within a unified theoretical structure. The weighting phase integrates G-LOPCOW and G-MSD, which collectively capture both information sensitivity and dispersion-based variability through objective statistical computation. G-LOPCOW, through its logarithmic mechanism, measures the proportional responsiveness of each criterion to marginal performance changes within grey intervals, thereby detecting subtle ESG performance differences across banks. G-MSD, in turn, quantifies the magnitude of dispersion and asymmetry within these intervals, accurately representing volatility in sustainability outcomes. The linear aggregation of these two tools creates a dual-objective weighting equilibrium between sensitivity and stability, generating weight vectors that are statistically coherent and free from expert bias.

The ranking stage, conducted through G-PIV, complements this weighting design by offering a transparent, rank-reversal-resistant decision procedure. Unlike conventional distance-based methods, G-PIV employs a proximity indexing logic that preserves ranking consistency under interval-valued data and avoids distortions arising from deterministic normalization. Its analytical robustness makes it particularly effective for ESG applications, where the indicators—often drawn from third-party databases such as Refinitiv Eikon or Bloomberg ESG—are inherently incomplete or partially disclosed. The G-PIV's simplicity and interpretability further enhance its value to finance practitioners, risk managers, and regulatory stakeholders who need reliable sustainability rankings without resorting to subjective expert opinions.

Compared with fuzzy-based or expert-dependent grey MCDM approaches, the proposed grey-based framework is entirely empirical and evidence-driven. All parameters are derived directly from observed data, ensuring methodological neutrality and compliance with the evidence-based evaluation principles increasingly emphasized by financial regulators and sustainable-finance institutions. This structure minimizes cognitive subjectivity, enhances reproducibility over time, and ensures that the assessment remains stable even as new ESG data emerge.

From an epistemological perspective, integrating G-LOPCOW, G-MSD, and G-PIV yields a mathematically robust and uncertainty-resilient decision-support system tailored for decision makers and practitioners in the banking industry. All three components operate within the same grey-system logic, ensuring internal consistency throughout the weighting and ranking stages. Consequently, the Grey LOPCOW–MSD-PIV hybrid method provides a unified, transparent, and replicable analytical environment that is empirically rigorous, statistically robust, and conceptually aligned with the uncertainty-laden structure of ESG performance assessment in modern banking.

4. Data Set and Sample

The empirical analysis employs a dataset specifically designed to assess the sustainability performance of Turkish publicly listed banks through a novel grey-based hybrid method. The recommended model integrates epistemic uncertainty into the ESG evaluation process, ensuring a robust and comprehensive comparison of institutional sustainability capacities across the domestic banking industry.

A total of nine commercial banks listed on BIST constitute the decision alternatives under investigation. These banks were chosen based on the availability of consistent ESG data over the 2021–2023 period, ensuring comparability and data reliability. The corresponding codes and rankings of the bank alternatives are presented in Table 2. The assessment framework rests upon a three-dimensional ESG structure, comprising ten measurable indicators that collectively capture the ESG pillars of sustainability. As detailed in Table 3, the environmental dimension (E1–E3) encompasses resource use, emissions management, and environmental innovation, reflecting the extent to which banks utilize their tangible and intangible resources to achieve environmental efficiency. The social dimension (S1–S4) covers workforce management, human rights practices, community engagement, and product responsibility, which jointly express how financial institutions align their social policies with stakeholder expectations and ethical standards. Finally, the governance dimension (G1–G3) integrates management effectiveness, shareholder relations, and corporate social responsibility (CSR) performance, representing the internal governance quality and strategic commitment to long-term value creation. Each of the ten ESG indicators was formulated under the maximization criterion, indicating that higher scores correspond to superior sustainability performance. This optimization direction aligns with the MCDM principle of utility maximization, wherein greater values reflect improved environmental efficiency, stronger social responsibility, and more transparent governance structures.

Furthermore, the inclusion of theoretical linkages for each ESG criterion ensures conceptual validity and interpretive depth. Specifically, the Resource-Based View (RBV) underpins indicators related to environmental innovation and resource efficiency, positioning sustainability-oriented capabilities as strategic assets. The Stakeholder Theory provides the foundation for criteria emphasizing social and relational responsibilities, such as community engagement and shareholder relations. The Stewardship Theory justifies management- and workforce-related criteria by emphasizing long-term institutional commitment and ethical leadership. Finally, the Legitimacy Theory explains indicators like emissions control, human rights, and CSR by framing sustainability as a mechanism to maintain social acceptance and regulatory conformity. In this context, the selected ESG criteria are not arbitrary performance measures but represent theoretically grounded constructs that collectively portray the multidimensional sustainability posture of the Turkish banking sector. Their maximization ensures that the proposed grey-based hybrid MCDM model effectively captures the most desirable outcomes across all ESG fronts.

Table 2. Bank Alternatives

Rank	Firm	Code
1	Akbank	A1
2	Garanti	A2
3	Vakıfbank	A3
4	Halkbank	A4
5	İşbank	A5
6	Yapı Kredi	A6
7	Albaraka	A7
8	Şekerbank	A8
9	Türkiye Sınai Kalkınma Bankası (TSKB)	A9

Table 3. ESG Sustainability Indicators

Dimension	Assessment Criteria	Code	Relevant Theory
Environmental Performance Indicators	Resource Use	E1	Recourse-Based Theory
	Emissions	E2	Legitimacy Theory
	Innovation	E3	Recourse-Based Theory/ Stakeholder Theory
Social Performance Indicators	Workforce	S1	Stewardship Theory
	Human Rights	S2	Legitimacy Theory/ Stakeholder Theory
	Community	S3	Stakeholder Theory
	Product Responsibility	S4	Stewardship Theory/ Legitimacy Theory
Governance Performance Indicators	Management	G1	Stewardship Theory
	Shareholders	G2	Legitimacy Theory/ Stakeholder Theory
	Corporate Social Responsibility	G3	Legitimacy Theory/ Recourse-Based Theory

5. Application Outcomes

This section outlines the empirical outcomes of the grey-based decision model developed for assessing the multidimensional ESG sustainability performance of nine banks traded on BIST. To implement the three grey-based models, the required ESG data were retrieved from the Refinitiv Eikon database. The dataset covers the period from 2021 to 2023. For each technique, the initial grey decision matrix was constructed after the minimum and maximum values for every criterion were determined across the three-year span. These values define the lower and upper bounds of the grey numbers, respectively. Table 4 presents the resulting matrix structure.

5.1. Empirical Findings of G-LOPCOW Algorithm

As outlined earlier, the first phase of the G-LOPCOW algorithm entails the construction of the grey initial decision matrix. As presented in Table 4, the smallest value in this grey matrix defines the lower bound of the corresponding grey number, whereas the largest value determines its upper bound.

Table 4. Initial Grey Decision Matrix

	E1	E2	E3	S1	S2
A1	[89.54, 93.14]	[91.14, 99.60]	[66.80, 81.76]	[82.07, 90.39]	[51.75, 55.50]
A2	[92.03, 97.55]	[98.53, 98.84]	[79.40, 97.54]	[81.42, 96.87]	[95.45, 96.68]
A3	[80.44, 98.56]	[97.76, 98.70]	[96.48, 96.80]	[84.69, 86.54]	[95.45, 95.70]
A4	[80.13, 85.66]	[80.95, 91.35]	[49.46, 55.33]	[82.45, 90.96]	[78.76, 80.13]
A5	[97.60, 99.85]	[99.19, 99.60]	[96.48, 97.54]	[98.68, 99.58]	[95.45, 96.17]
A6	[67.72, 70.92]	[66.46, 71.56]	[49.46, 60.45]	[73.49, 74.58]	[56.59, 96.54]
A7	[47.35, 80.52]	[74.87, 99.25]	[96.48, 97.14]	[98.10, 99.02]	[78.76, 79.69]
A8	[91.46, 96.77]	[94.58, 95.97]	[49.46, 55.78]	[94.99, 96.45]	[95.45, 96.47]
A9	[90.25, 94.34]	[82.92, 97.64]	[90.38, 91.09]	[89.01, 95.55]	[95.45, 96.25]

Table 4. Continued

	S3	S4	G1	G2	G3
A1	[40.22, 51.15]	[87.56, 90.46]	[34.66, 43.25]	[43.63, 48.30]	[81.38, 90.24]
A2	[88.55, 91.66]	[96.40, 98.55]	[25.57, 76.81]	[60.78, 71.59]	[96.28, 97.57]
A3	[98.08, 98.68]	[96.40, 98.11]	[46.02, 51.66]	[84.66, 89.69]	[56.91, 82.93]
A4	[88.90, 99.48]	[98.11, 99.20]	[44.61, 51.70]	[25.98, 34.66]	[56.91, 58.54]
A5	[98.87, 99.14]	[99.57, 99.80]	[42.56, 82.39]	[60.78, 71.59]	[80.58, 82.93]
A6	[23.88, 27.15]	[60.56, 63.67]	[30.11, 35.44]	[53.43, 66.48]	[68.90, 83.14]
A7	[83.72, 85.72]	[96.40, 98.25]	[62.25, 67.61]	[34.80, 40.34]	[80.52, 82.93]
A8	[99.39, 99.83]	[96.40, 98.96]	[28.92, 33.52]	[35.80, 78.85]	[90.43, 96.95]
A9	[89.93, 95.55]	[29.63, 79.15]	[47.16, 48.85]	[76.58, 82.39]	[58.54, 83.44]

Since the ten ESG criteria included in the initial grey decision matrix are benefit-oriented, normalization was performed with the help of Eq. (2). The resulting normalized grey matrix is presented in Table 5.

Table 5. Grey-Based Normalized Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.80, 0.87]	[0.74, 1.00]	[0.36, 0.67]	[0.33, 0.65]	[0.00, 0.08]
A2	[0.85, 0.96]	[0.97, 0.98]	[0.62, 1.00]	[0.30, 0.90]	[0.97, 1.00]
A3	[0.63, 0.98]	[0.94, 0.97]	[0.98, 0.98]	[0.43, 0.50]	[0.97, 0.98]
A4	[0.62, 0.73]	[0.44, 0.75]	[0.00, 0.12]	[0.34, 0.67]	[0.60, 0.63]
A5	[0.96, 1.00]	[0.99, 1.00]	[0.98, 1.00]	[0.97, 1.00]	[0.97, 0.99]
A6	[0.39, 0.45]	[0.00, 0.15]	[0.00, 0.23]	[0.00, 0.04]	[0.11, 1.00]
A7	[0.00, 0.63]	[0.25, 0.99]	[0.98, 0.99]	[0.94, 0.98]	[0.60, 0.62]
A8	[0.84, 0.94]	[0.85, 0.89]	[0.00, 0.13]	[0.82, 0.88]	[0.97, 1.00]
A9	[0.82, 0.90]	[0.50, 0.94]	[0.85, 0.87]	[0.59, 0.85]	[0.97, 0.99]
	S3	**S4**	**G1**	**G2**	**G3**
A1	[0.22, 0.36]	[0.83, 0.87]	[0.16, 0.31]	[0.28, 0.35]	[0.60, 0.82]
A2	[0.85, 0.89]	[0.95, 0.98]	[0.00, 0.90]	[0.55, 0.72]	[0.97, 1.00]
A3	[0.98, 0.98]	[0.95, 0.98]	[0.36, 0.46]	[0.92, 1.00]	[0.00, 0.64]
A4	[0.86, 1.00]	[0.98, 0.99]	[0.34, 0.46]	[0.00, 0.14]	[0.00, 0.04]
A5	[0.99, 0.99]	[1.00, 1.00]	[0.30, 1.00]	[0.55, 0.72]	[0.58, 0.64]
A6	[0.00, 0.04]	[0.44, 0.49]	[0.08, 0.17]	[0.43, 0.64]	[0.29, 0.65]
A7	[0.79, 0.81]	[0.95, 0.98]	[0.65, 0.74]	[0.14, 0.23]	[0.58, 0.64]
A8	[0.99, 1.00]	[0.95, 0.99]	[0.06, 0.14]	[0.15, 0.83]	[0.82, 0.98]
A9	[0.87, 0.94]	[0.00, 0.71]	[0.38, 0.41]	[0.79, 0.89]	[0.04, 0.65]

At the concluding stage of the analysis, the grey objective weights were derived through the application of Eqs. (4) and (5). As shown in Table 6, the crisp weight of each criterion was computed by taking the arithmetic mean of its lower and upper grey bounds.

Table 6. G-LOPCOW Results

	E1	E2	E3	S1	S2
$\otimes PV_j$	[104.12, 134,24]	[92.68, 95.76]	[53.88, 53.90]	[70.16, 85.21]	[78.80, 90.61]
$\otimes w_{j,lop}$	[0.139, 0.147]	[0.105, 0.124]	[0.059, 0.072]	[0.093, 0.094]	[0.099, 0.105]
$w_{j,lop}$	0.143	0.114	0.066	0.094	0.102
Rank	2	3	10	6	5
	S3	**S4**	**G1**	**G2**	**G3**
$\otimes PV_j$	[84.74, 84.98]	[97.33, 155.81]	[45.71, 64.94]	[52.60, 77.67]	[67.63, 68.69]
$\otimes w_{j,lop}$	[0.093, 0.113]	[0.130, 0.171]	[0.061, 0.071]	[0.070, 0.085]	[0.075, 0.090]
$w_{j,lop}$	0.103	0.151	0.066	0.078	0.083
Rank	4	1	9	8	7

5.2. Empirical Findings Based on the G-MSD Algorithm

In this section, the second set of objective importance weights—based on grey numbers—is computed via the G-MSD procedure. To initiate the process, the initial grey decision matrix—presented in Table 4—is constructed. Subsequently, each element in the matrix is normalized via Eq. (6), taking into account the nature of the corresponding criterion. The resulting normalized grey decision matrix is reported in Table 7. Next, Table 8 summarizes the final results of the G-MSD procedure, which were computed based on Eqs. (8) and (9). As illustrated in Table 8, the crisp weight of each criterion was obtained by calculating the arithmetic mean of its corresponding lower and upper grey bounds.

Table 7. Grey-Based Normalized Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.90, 0.93]	[0.92, 1.00]	[0.68, 0.84]	[0.82, 0.91]	[0.54, 0.57]
A2	[0.92, 0.98]	[0.99, 0.99]	[0.81, 1.00]	[0.82, 0.97]	[0.99, 1.00]
A3	[0.81, 0.99]	[0.98, 0.99]	[0.99, 0.99]	[0.85, 0.87]	[0.99, 0.99]
A4	[0.80, 0.86]	[0.81, 0.92]	[0.51, 0.57]	[0.83, 0.91]	[0.81, 0.83]
A5	[0.98, 1.00]	[1.00, 1.00]	[0.99, 1.00]	[0.99, 1.00]	[0.99, 0.99]
A6	[0.68, 0.71]	[0.67, 0.72]	[0.51, 0.62]	[0.74, 0.75]	[0.59, 1.00]
A7	[0.47, 0.81]	[0.75, 1.00]	[0.99, 1.00]	[0.99, 0.99]	[0.81, 0.82]
A8	[0.92, 0.97]	[0.95, 0.96]	[0.51, 0.57]	[0.95, 0.97]	[0.99, 1.00]
A9	[0.90, 0.94]	[0.83, 0.98]	[0.93, 0.93]	[0.89, 0.96]	[0.99, 1.00]
	S3	**S4**	**G1**	**G2**	**G3**
A1	[0.40, 0.51]	[0.88, 0.91]	[0.42, 0.52]	[0.49, 0.54]	[0.83, 0.92]
A2	[0.89, 0.92]	[0.97, 0.99]	[0.31, 0.93]	[0.68, 0.80]	[0.99, 1.00]
A3	[0.98, 0.99]	[0.97, 0.98]	[0.56, 0.63]	[0.94, 1.00]	[0.58, 0.85]
A4	[0.89, 1.00]	[0.98, 0.99]	[0.54, 0.63]	[0.29, 0.39]	[0.58, 0.60]
A5	[0.99, 0.99]	[1.00, 1.00]	[0.52, 1.00]	[0.68, 0.80]	[0.83, 0.85]
A6	[0.24, 0.27]	[0.61, 0.64]	[0.37, 0.43]	[0.60, 0.74]	[0.71, 0.85]
A7	[0.84, 0.86]	[0.97, 0.98]	[0.76, 0.82]	[0.39, 0.45]	[0.83, 0.85]
A8	[1.00, 1.00]	[0.97, 0.99]	[0.35, 0.41]	[0.40, 0.88]	[0.93, 0.99]
A9	[0.90, 0.96]	[0.30, 0.79]	[0.57, 0.59]	[0.85, 0.92]	[0.60, 0.86]

Table 8. Results of the G-MSD Procedure

	$\sum_{j=1}^{n}\otimes b_j$	$\otimes\sigma_j$	$\otimes t_j$	$\otimes w_{j,msd}$	$w_{j,msd}$	Rank
E1	[7.38, 8.19]	[0.10, 0.16]	[0.01, 0.02]	[0.06, 0.08]	0.068	8
E2	[7.90, 8.56]	[0.09, 0.12]	[0.01, 0.01]	[0.05, 0.05]	0.053	9
E3	[6.91, 7.52]	[0.19, 0.22]	[0.03, 0.03]	[0.12, 0.13]	0.121	4
S1	[7.88, 8.33]	[0.08, 0.09]	[0.01, 0.01]	[0.04, 0.05]	0.043	10
S2	[7.69, 8.20]	[0.15, 0.18]	[0.02, 0.02]	[0.09, 0.09]	0.087	6
S3	[7.13, 7.50]	[0.26, 0.28]	[0.03, 0.04]	[0.14, 0.17]	0.156	2
S4	[7.63, 8.28]	[0.13, 0.24]	[0.02, 0.03]	[0.07, 0.12]	0.095	5
G1	[4.39, 5.96]	[0.14, 0.21]	[0.03, 0.04]	[0.13, 0.15]	0.143	3
G2	[5.31, 6.51]	[0.22, 0.22]	[0.03, 0.04]	[0.15, 0.16]	0.157	1
G3	[6.87, 7.78]	[0.12, 0.15]	[0.02, 0.02]	[0.07, 0.08]	0.077	7

5.3. Final Results Regarding the Criterion Weight Coefficients

The final step of the weight estimation procedure involves integrating the grey weight values obtained from the G-LOPCOW and G-MSD methods, as formulated in Eq. (10). The resulting combined grey weights are presented in Table 9. These grey weights are subsequently converted into crisp coefficients by computing the arithmetic mean of their respective lower and upper bounds. A detailed analysis of the results in Table 9 indicates that the three most influential determinants of banks' ESG sustainable performance are Community (S3), Product Responsibility (S4), and Shareholders (G2), respectively.

Table 9. Aggregated Grey Weights

	$\otimes w_{j,lop}$	$\otimes w_{j,msd}$	$\otimes w_{j,com}$	$w_{j,com}$	Rank
E1	[0.139, 0.147]	[0.058, 0.078]	[0.099, 0.113]	[0.106]	4
E2	[0.105, 0.124]	[0.052, 0.055]	[0.078, 0.089]	[0.084]	8
E3	[0.059, 0.072]	[0.117, 0.126]	[0.088, 0.099]	[0.093]	7
S1	[0.093, 0.094]	[0.040, 0.046]	[0.067, 0.070]	[0.068]	10
S2	[0.099, 0.105]	[0.087, 0.087]	[0.093, 0.096]	[0.095]	6
S3	[0.093, 0.113]	[0.142, 0.169]	[0.118, 0.141]	[0.129]	1
S4	[0.130, 0.171]	[0.073, 0.116]	[0.102, 0.143]	[0.123]	2
G1	[0.061, 0.071]	[0.130, 0.155]	[0.096, 0.113]	[0.104]	5
G2	[0.070, 0.085]	[0.153, 0.161]	[0.112, 0.123]	[0.117]	3
G3	[0.075, 0.090]	[0.073, 0.081]	[0.074, 0.086]	[0.080]	9

5.4. Findings from G-PIV Procedure

Following the determination of the final grey-based importance weights for the evaluation criteria, this section advances to the ranking of banks according to their ESG performance through the application of the G-PIV approach. In this regard, the initial grey decision matrix—constructed in accordance with Eq. (1) and presented in Table 4—serves as the analytical foundation. In the subsequent stage of the G-PIV procedure, all elements of the decision matrix were normalized via Eq. (11), yielding the normalized grey decision matrix reported in Table 10. Thereafter, the weighted normalized grey decision matrix—obtained by applying Eq. (12)—is presented in Table 11. The grey weighted proximity index for benefit-type criteria was then obtained based on Eq. (13), and the results are summarized in Table 12. In the final stage of the G-PIV methodology, the overall grey proximity index values—representing the aggregate ESG performance scores of the evaluated banks—were derived with the aid of Eqs. (15) and (16). The computed grey proximity index values are displayed in Table 13. From Table 13

Table 10. Grey-Based Normalized Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.23, 0.33]	[0.07, 0.68]	[0.06, 0.27]	[0.07, 0.26]	[0.02, 0.16]
A2	[0.13, 0.13]	[0.08, 0.09]	[0.16, 0.32]	[0.09, 0.18]	[0.23, 0.29]
A3	[0.22, 0.28]	[0.06, 0.07]	[0.11, 0.28]	[0.10, 0.32]	[0.22, 0.32]
A4	[0.28, 0.31]	[0.07, 0.07]	[0.20, 0.33]	[0.26, 0.39]	[0.18, 0.27]
A5	[0.16, 0.18]	[0.06, 0.06]	[0.04, 0.24]	[0.03, 0.18]	[0.25, 0.28]
A6	[0.16, 0.20]	[0.06, 0.06]	[0.10, 0.39]	[0.07, 0.33]	[0.18, 0.24]
A7	[0.22, 0.31]	[0.05, 0.06]	[0.09, 0.31]	[0.09, 0.40]	[0.15, 0.35]
A8	[0.23, 0.32]	[0.06, 0.68]	[0.11, 0.34]	[0.12, 0.39]	[0.19, 0.33]
A9	[0.19, 0.22]	[0.06, 0.06]	[0.10, 0.30]	[0.10, 0.27]	[0.15, 0.23]

	S3	S4	G1	G2	G3
A1	[0.23, 0.26]	[0.25, 0.33]	[0.02, 0.12]	[0.15, 0.21]	[0.02, 0.23]
A2	[0.05, 0.08]	[0.08, 0.10]	[0.38, 0.41]	[0.08, 0.12]	[0.07, 0.09]
A3	[0.19, 0.23]	[0.14, 0.23]	[0.16, 0.22]	[0.17, 0.21]	[0.25, 0.26]
A4	[0.15, 0.20]	[0.08, 0.17]	[0.14, 0.16]	[0.11, 0.15]	[0.23, 0.25]
A5	[0.28, 0.38]	[0.19, 0.31]	[0.28, 0.31]	[0.36, 0.45]	[0.28, 0.28]
A6	[0.22, 0.29]	[0.28, 0.39]	[0.24, 0.30]	[0.23, 0.35]	[0.26, 0.27]
A7	[0.16, 0.21]	[0.23, 0.30]	[0.14, 0.21]	[0.11, 0.14]	[0.24, 0.27]
A8	[0.14, 0.25]	[0.13, 0.18]	[0.13, 0.20]	[0.09, 0.22]	[0.24, 0.26]
A9	[0.29, 0.35]	[0.25, 0.30]	[0.21, 0.26]	[0.27, 0.37]	[0.26, 0.27]

Table 11. Weighted Normalized Grey Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.02, 0.04]	[0.01, 0.06]	[0.01, 0.03]	[0.00, 0.02]	[0.00, 0.02]
A2	[0.01, 0.02]	[0.01, 0.01]	[0.01, 0.03]	[0.01, 0.01]	[0.02, 0.03]
A3	[0.02, 0.03]	[0.00, 0.01]	[0.01, 0.03]	[0.01, 0.02]	[0.02, 0.03]
A4	[0.03, 0.03]	[0.01, 0.01]	[0.02, 0.03]	[0.02, 0.03]	[0.02, 0.03]
A5	[0.02, 0.02]	[0.00, 0.01]	[0.00, 0.02]	[0.00, 0.01]	[0.02, 0.03]
A6	[0.02, 0.02]	[0.00, 0.01]	[0.01, 0.04]	[0.00, 0.02]	[0.02, 0.02]
A7	[0.02, 0.04]	[0.00, 0.01]	[0.01, 0.03]	[0.01, 0.03]	[0.01, 0.03]
A8	[0.02, 0.04]	[0.01, 0.06]	[0.01, 0.03]	[0.01, 0.03]	[0.02, 0.03]
A9	[0.02, 0.02]	[0.00, 0.01]	[0.01, 0.03]	[0.01, 0.02]	[0.01, 0.02]

	S3	S4	G1	G2	G3
A1	[0.03, 0.04]	[0.02, 0.05]	[0.00, 0.01]	[0.02, 0.03]	[0.00, 0.02]
A2	[0.01, 0.01]	[0.01, 0.01]	[0.04, 0.05]	[0.01, 0.01]	[0.01, 0.01]
A3	[0.02, 0.03]	[0.01, 0.03]	[0.02, 0.02]	[0.02, 0.03]	[0.02, 0.02]
A4	[0.02, 0.03]	[0.01, 0.02]	[0.01, 0.02]	[0.01, 0.02]	[0.02, 0.02]
A5	[0.03, 0.05]	[0.02, 0.04]	[0.03, 0.03]	[0.04, 0.06]	[0.02, 0.02]
A6	[0.03, 0.04]	[0.03, 0.06]	[0.02, 0.03]	[0.03, 0.04]	[0.02, 0.02]
A7	[0.02, 0.03]	[0.02, 0.04]	[0.01, 0.02]	[0.01, 0.02]	[0.02, 0.02]
A8	[0.02, 0.04]	[0.01, 0.03]	[0.01, 0.02]	[0.01, 0.03]	[0.02, 0.02]
A9	[0.03, 0.05]	[0.03, 0.04]	[0.02, 0.03]	[0.03, 0.05]	[0.02, 0.02]

Table 12. Grey Weighted Proximity Index Matrix

	E1	E2	E3	S1	S2
A1	[-0.01, 0.02]	[-0.05, 0.06]	[-0.01, 0.03]	[0.00, 0.02]	[0.01, 0.03]
A2	[0.01, 0.03]	[0.00, 0.05]	[-0.01, 0.02]	[0.00, 0.02]	[0.00, 0.01]
A3	[0.00, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[-0.01, 0.02]	[-0.01, 0.01]
A4	[-0.01, 0.01]	[0.00, 0.06]	[-0.01, 0.02]	[-0.01, 0.01]	[0.00, 0.02]
A5	[0.01, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[0.00, 0.03]	[0.00, 0.01]
A6	[0.00, 0.02]	[0.00, 0.06]	[-0.02, 0.03]	[-0.01, 0.02]	[0.00, 0.02]
A7	[-0.01, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[-0.01, 0.02]	[-0.01, 0.02]
A8	[-0.01, 0.01]	[-0.05, 0.06]	[-0.02, 0.03]	[-0.01, 0.02]	[-0.01, 0.02]
A9	[0.00, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[0.00, 0.02]	[-0.02, 0.02]
	S3	**S4**	**G1**	**G2**	**G3**
A1	[0.00, 0.03]	[-0.02, 0.03]	[0.02, 0.04]	[0.01, 0.04]	[0.00, 0.02]
A2	[0.02, 0.05]	[0.01, 0.05]	[-0.01, 0.01]	[0.02, 0.05]	[0.01, 0.02]
A3	[0.00, 0.03]	[0.00, 0.04]	[0.01, 0.03]	[0.01, 0.04]	[0.00, 0.01]
A4	[0.01, 0.04]	[0.00, 0.05]	[0.02, 0.03]	[0.02, 0.04]	[0.00, 0.01]
A5	[-0.02, 0.02]	[-0.02, 0.04]	[0.00, 0.02]	[-0.02, 0.02]	[0.00, 0.00]
A6	[-0.01, 0.03]	[-0.03, 0.03]	[0.00, 0.02]	[0.00, 0.03]	[0.00, 0.00]
A7	[0.00, 0.04]	[-0.01, 0.03]	[0.01, 0.03]	[0.02, 0.04]	[0.00, 0.01]
A8	[0.00, 0.04]	[0.00, 0.04]	[0.01, 0.03]	[0.01, 0.04]	[0.00, 0.01]
A9	[-0.01, 0.02]	[-0.01, 0.03]	[0.01, 0.03]	[-0.01, 0.02]	[0.00, 0.01]

Table 13. G-PIV-Based ESG Performance Evaluation Results

	$\otimes v_i$	v_i	Rank
A1	[-0.051, 0.323]	0.136	5
A2	[0.063, 0.307]	0.185	9
A3	[-0.005, 0.282]	0.138	6
A4	[0.013, 0.281]	0.147	8
A5	[-0.050, 0.245]	0.098	1
A6	[-0.060, 0.261]	0.100	2
A7	[-0.018, 0.295]	0.138	7
A8	[-0.072, 0.301]	0.114	4
A9	[-0.040, 0.252]	0.106	3

According to the ranking results presented in Table 13, the top three performing banks are A5 (İşbank), A6 (Yapı kredi), and A9 (TSKB). These alternatives exhibit the lowest proximity scores, indicating a strong alignment with the ideal ESG profile and suggesting robust sustainability practices across multiple dimensions. In contrast, the lowest-ranked banks—A2 (Garanti), A4 (Halkbank), and A7 (Albaraka)—demonstrate relatively higher proximity scores, reflecting a greater distance from the ideal benchmark and signaling potential weaknesses in their ESG performance.

6. Robustness and Sensitivity Analyses

In this section, a comprehensive three-stage sensitivity analysis was carried out to assess the reliability, stability, and parametric robustness of the introduced grey-based framework. In the first stage, the ranking results obtained through the G-PIV methodology—based on the integrated weighting of the G-LOPCOW and G-MSD techniques—were compared with those derived from alternative grey MCDM tools. This comparison aimed to assess inter-method consistency and validate the correlative soundness of the proposed model. In the second stage, the potential occurrence of rank reversal was examined to test the structural stability of the grey decision-making approach. In this context, the effect of varying the number of alternatives on the final rankings was systematically analyzed. Finally, in the third stage, the impact of varying the parameter ξ —employed in determining the final criterion weights—on the resulting bank rankings was analyzed to examine the grey model's sensitivity to parameter changes.

6.1. Comparative Analysis

In the first stage of the robustness analysis, the reliability and consistency of the ranking results obtained through the proposed G-PIV methodology—based on the integrated weighting of G-LOPCOW and G-MSD—were thoroughly examined. For this purpose, several widely recognized grey-based decision-making approaches from the literature were employed for comparative evaluation, including G-RAWEC (Ulutaş et al., 2025), G-SAW (Churchman and Ackoff, 1954), G-MARCOS (Torkayesh et al., 2021), and G-COPRAS (Zavadskas et al., 2008). The findings of these comparisons are illustrated in Figure 2. Notably, no changes were observed in the rankings of alternatives A5, A6, A9, A4, and A2, while only minor shifts were detected in the rankings of the remaining alternatives. These results collectively indicate that the proposed grey hybrid model yields stable and reliable outcomes, reinforcing its methodological soundness and practical applicability in ESG-based decision contexts.

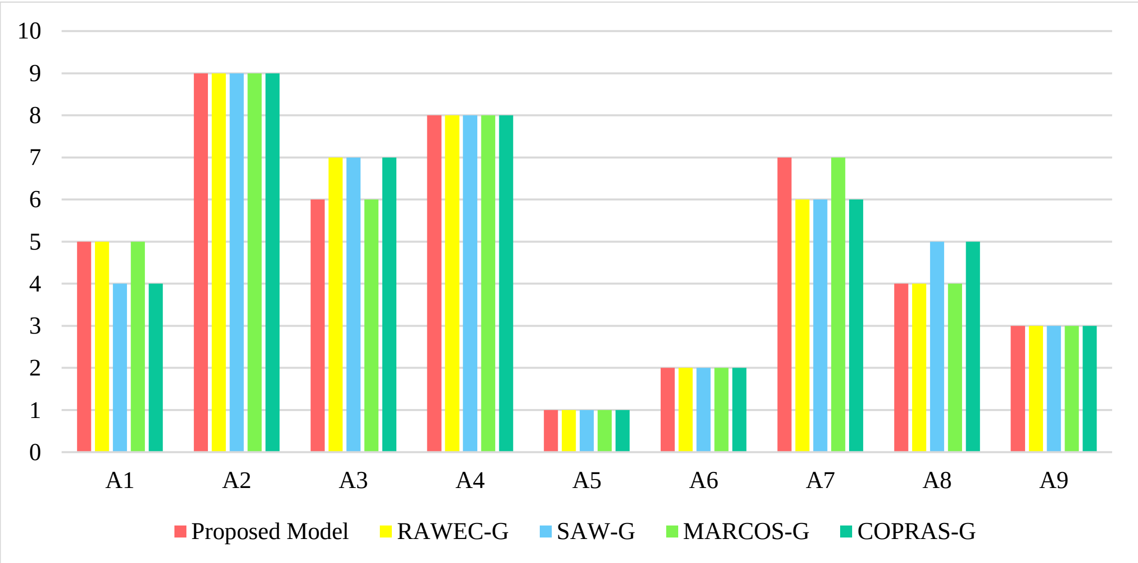

Figure 2. Comparative Rankings Across Grey MCDM Techniques

6.2. Investigation of the Rank Reversal Phenomenon

In the second stage of the robustness analysis, the reliability of the proposed integrated grey decision-making model and the stability of its ranking structure were examined through the lens of the rank reversal phenomenon. In this context, the lowest-performing bank was systematically removed from the analysis in each scenario, and the process was repeated iteratively until only the top-ranked bank remained. The empirical results obtained across nine distinct scenarios are presented in Figure 3. As illustrated, the exclusion of the least-performing alternative in each iteration did not lead to any changes in the final ranking order. This finding clearly demonstrates that the proposed model exhibits a high degree of robustness and consistency, even under structural modifications to the decision matrix.

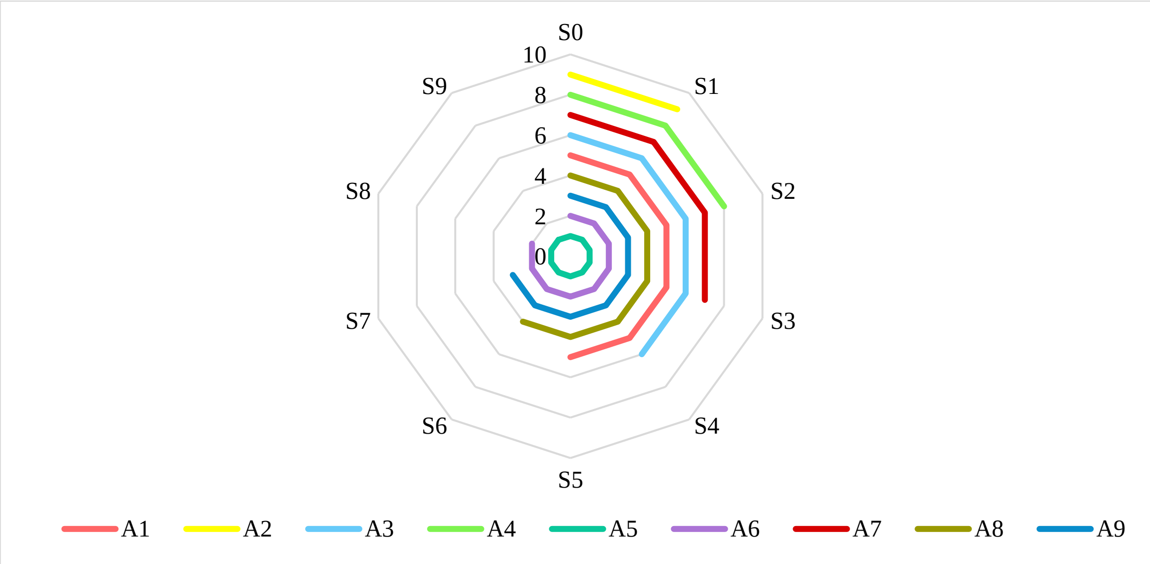

Figure 3. Rankings of Bank Alternatives Across Generated Scenarios

6.3. Parametric Robustness Analysis Based on the Parameter ξ

In the final stage of the robustness analysis, the influence of varying the parameter ξ —utilized in the final weighting process—on the bank rankings was systematically assessed. According to preceding studies in the MCDM literature, the parameter ξ is typically incorporated into calculations employing a fixed value of 0.5. However, ξ has the flexibility to assume different values within the [0, 1] interval. Therefore, the analysis was not limited to the conventional value of 0.5; instead, twenty distinct scenarios were formed by considering incremental ξ values ranging from 0 to 1 (i.e., 0, 0.05, 0.10, …, 1). The results of these analyses are provided in Figure 4.

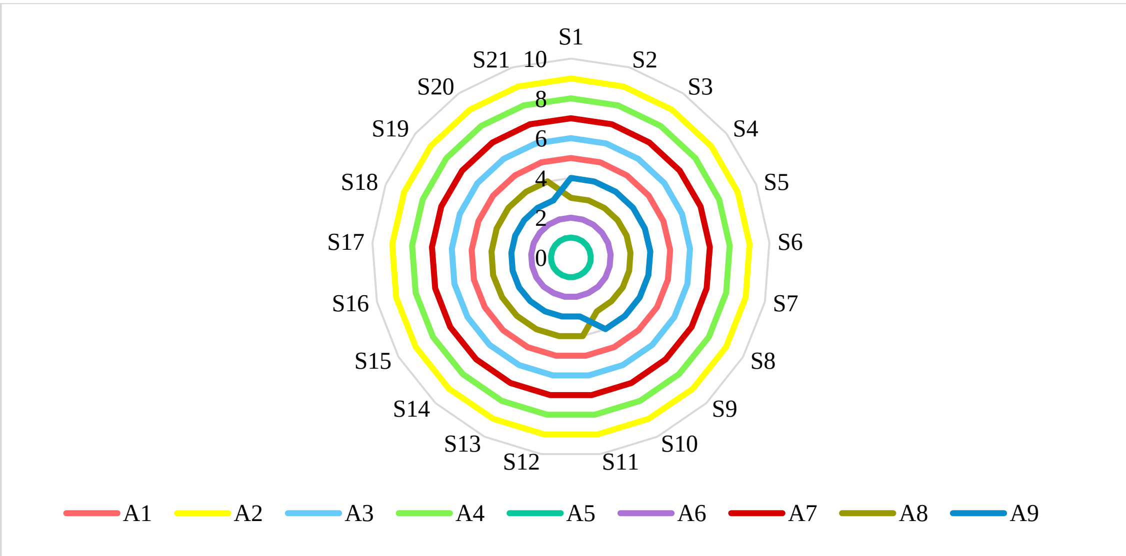

Figure 4. Bank Rankings Under Modified ξ-Based Weighting Scenario

From Figure 4, it is observed that changes in the ξ parameter do not significantly affect the ranking structure of the bank alternatives—except for two specific cases. This finding clearly demonstrates that the proposed grey-based methodological framework exhibits a high degree of stability and consistency, even under parametric variation.

7. Discussion and Managerial Implications

The aggregated criterion weights obtained via the integration of G-LOPCOW and G-MSD techniques provide a statistically grounded and epistemically resilient representation of ESG performance dimensions.

The weighting outputs reveal that the most influential criteria in shaping the sustainability profiles of BIST-listed banks are community engagement, product responsibility, and shareholder relations. These dimensions collectively reflect the strategic importance of stakeholder inclusivity, customer-centric accountability, and governance transparency in the Turkish banking industry. The prominence of community engagement and product responsibility suggests that banks are increasingly evaluated not only by their financial metrics but also by their capacity to generate social value and uphold ethical standards in service delivery. Shareholder relations, as a governance indicator, further underscores the role of participatory decision-making and transparent corporate oversight in enhancing ESG credibility.

The dominance of community engagement and product responsibility indicators within the ESG structure can be better understood within the institutional and market context of Türkiye's financial system. Historically, Turkish banks have acted as engines of socio-economic development, channeling resources toward regional growth, SME financing, and inclusive welfare initiatives. This developmental orientation—deeply embedded in national financial policy—has aligned banks' strategic missions with broader social objectives. In recent years, the Turkish Green Deal Action Plan (2021) and the Banking Regulation and Supervision Agency's (BRSA) sustainability guidelines have further formalized these expectations, urging banks to integrate community-oriented value creation and responsible lending practices into their core business models. Consequently, the strong weight of community engagement in the model mirrors not only social expectations but also the regulatory transition toward sustainability-linked accountability.

Similarly, the significant influence of product responsibility stems from increasing stakeholder attention to ethical finance and consumer protection in the post-2020 era. The rapid digitalization of banking services and expansion of retail financial products have elevated concerns regarding customer data security, transparency, and responsible product design. Turkish banks, responding to regulatory supervision and reputational pressures, have begun integrating consumer-focused sustainability measures into their ESG frameworks—such as transparent fee structures, responsible credit policies, and green financing instruments. Thus, product responsibility acts as a proxy for customer-oriented ethics and innovation capacity within a rapidly evolving digital financial ecosystem.

On the other hand, the high importance of shareholder relations underscores the growing role of corporate governance reforms and transparency norms in shaping sustainability practices across the Turkish financial sector. As the regulatory environment increasingly aligns with global disclosure frameworks—such as the UN Principles for Responsible Banking (PRB) and the IFRS

Sustainability Disclosure Standards (IFRS S1 and S2)—banks have prioritized board independence, shareholder inclusivity, and information symmetry as mechanisms to enhance credibility and investor confidence. In emerging markets like Türkiye, where ownership concentration and state participation remain relatively high, strong shareholder relations also signal effective accountability structures and balance between regulatory oversight and market discipline.

Taken together, these contextual explanations reveal that the dominance of social and governance-oriented criteria in the weighting results is not coincidental but reflects the institutional evolution of the Turkish banking system toward greater transparency, inclusion, and accountability. The grey-based analytical framework captures these structural shifts objectively, providing empirical evidence that ESG performance in emerging economies is shaped by both macro-level policy mandates and micro-level organizational adaptations. This contextual interpretation enriches the theoretical depth of the findings, bridging quantitative MCDM evidence with qualitative institutional economics perspectives.

Taken together, these contextual explanations reveal that the dominance of social and governance-oriented criteria in the weighting results is not coincidental but reflects the institutional evolution of the Turkish banking system toward greater transparency, inclusion, and accountability.

In contrast, the least influential criteria—workforce, corporate social responsibility, and emissions—exhibited relatively lower weight coefficients. While these criteria remain integral to ESG frameworks, their subdued influence may be attributed to limited data variability or the transitional nature of ESG reporting practices in emerging markets. Nevertheless, these criteria should not be disregarded, as their strategic relevance is expected to increase in alignment with global sustainability mandates and evolving stakeholder expectations.

The ranking outputs derived from the G-PIV methodology demonstrate a clear stratification among the assessed banks. Leading institutions such as İşbank, Yapı Kredi, and TSKB consistently outperformed their peers across multiple ESG dimensions. Their superior rankings may reflect a proactive integration of sustainability principles into core banking operations, robust stakeholder engagement mechanisms, and comprehensive ESG disclosure practices. Conversely, lower-ranked banks such as Garanti Bankası, Halkbank, and Albaraka Türk exhibited weaker alignment with the ideal ESG profile. Their performance gaps may stem from fragmented sustainability strategies, limited innovation in ESG practices, or underdeveloped reporting infrastructures. These institutions face strategic challenges in translating ESG commitments into measurable outcomes, which may hinder their ability to meet emerging regulatory standards and investor expectations.

From a managerial perspective, the findings offer actionable insights for both strategic planning and operational refinement. First, banks should prioritize high-impact ESG dimensions—particularly those related to social engagement and product accountability—by investing in inclusive financial services, community development programs, and transparent customer protection mechanisms. Second, governance structures must be strengthened to ensure shareholder inclusivity, ethical oversight, and ESG-linked performance incentives. Third, institutions that exhibit relatively lower ESG performance are advised to undertake a comprehensive review of their existing sustainability frameworks and, where appropriate, recalibrate their strategic orientation to better reflect evolving ESG imperatives. Leveraging the practices of sector-leading institutions may provide actionable insights into effective implementation models, disclosure mechanisms, and stakeholder engagement strategies. Such efforts may facilitate the identification of proven methodologies, strengthen institutional capacity, and support the progressive embedding of ESG principles into core banking functions—ultimately enhancing both reputational resilience and long-term value creation. Finally, aligning ESG strategies with global frameworks such as the United Nations SDGs and the PRB will enhance regulatory compliance, facilitate access to green financing instruments, and reinforce the legitimacy of banking institutions in the eyes of stakeholders. Overall, the proposed grey-based hybrid MCDM method not only enables a rigorous and uncertainty-tolerant assessment of ESG performance but also provides strategic guidance for banks seeking to enhance their sustainability profiles in a rapidly evolving financial landscape.

Beyond firm-level managerial considerations, our findings also carry significant policy relevance for regulators and supervisory authorities. In Türkiye, the BRSA has increasingly emphasized the integration of ESG considerations into prudential oversight. The BRSA's "Sustainability Principles in the Banking Sector" (2021) and the "ESG Disclosure Standards" (2023) mark a decisive shift toward mandatory transparency and sustainability-linked accountability. The high weights of social and governance-related indicators in this study empirically support these policy directions, suggesting that regulatory interventions have begun to shape banks' strategic priorities and disclosure practices.

At a broader level, the alignment of the Turkish banking framework with the European Green Deal and the EU Sustainable Finance Taxonomy reflects the country's efforts to harmonize financial regulation with international sustainability standards. These initiatives encourage banks to expand green lending portfolios, integrate climate-risk metrics into credit assessments, and adopt sustainability-linked financial instruments such as green bonds and ESG loans. The proposed grey-based model, by quantifying the performance outcomes of these policy shifts, offers a practical analytical tool that can assist policymakers and supervisors in monitoring compliance, benchmarking institutional progress, and identifying structural gaps in sustainability performance.

While the analytical findings provide valuable insights into the ESG sustainability performance of Turkish banks, it is necessary to recognize the empirical constraints arising from data availability. The study relies exclusively on the Refinitiv Eikon database, selected for its standardized, transparent, and internationally comparable ESG reporting framework. This choice ensures consistency in indicator construction and cross-institutional comparability—features essential for testing the methodological validity of the proposed grey-based model. Nevertheless, dependence on a single data source may introduce provider-specific bias, as ESG scoring methodologies differ across platforms such as Bloomberg ESG, MSCI, and Sustainalytics. Therefore, the obtained results should be interpreted as data-consistent but source-specific representations of ESG performance within the Refinitiv context.

Regarding temporal coverage, the study deliberately focuses on the 2021–2023 period, which corresponds to the institutionalization of ESG disclosure in Türkiye and the consolidation of sustainability reporting standards. Extending the analysis to pre-2021 years would significantly reduce the number of banks included in the sample because several banks exhibit missing or incomplete ESG indicators in earlier datasets. By contrast, the selected three-year window provides a complete and balanced dataset for all ten ESG criteria, enabling accurate determination of lower and upper grey bounds and ensuring the methodological validity of the grey modelling process. The grey system framework, by design, is particularly effective in handling limited, uncertain, or partially available data, allowing for reliable inference even within a short temporal horizon. Therefore, while the time span may appear limited, the use of grey interval modelling transforms this potential constraint into an analytical advantage—by capturing variability and uncertainty through the lower and upper bounds of each criterion rather than relying on extended historical observations.

8. Conclusion

Measuring ESG sustainability performance enables financial institutions to align their strategic operations with long-term ESG objectives, thereby fostering transparency, stakeholder trust, and organizational resilience. In this regard, the present work develops and empirically validates a comprehensive grey-based MCDM method for assessing the ESG performance of listed banks in Türkiye. The suggested grey model integrates two objective weighting techniques—G-LOPCOW and G-MSD—with the G-PIV ranking procedure. ESG sustainability data for the 2021–2023 period was obtained from the Refinitiv Eikon database and encompass ten performance criteria representing the ESG pillars.

The aggregated weighting results indicate that community engagement, product responsibility, and shareholder relations emerged as the most influential determinants of ESG performance. Additionally, based on the final rankings, İşbank, Yapı Kredi, and TSKB achieved the highest ESG performance, reflecting a strong strategic commitment to sustainability principles and alignment with stakeholder expectations.

The suggested grey-based framework offers several methodological advantages that enhance the robustness and applicability of ESG performance assessment. First, the most significant advantage of the introduced grey model is its epistemic robustness. This robustness is achieved through the integration of gray interval numbers. Because ESG performance data is often incomplete, uncertain, or partially available, this creates epistemic uncertainty, and traditional crisp approaches cannot adequately handle such data gaps. The developed gray-based approach, on the other hand, addresses these uncertainties directly at the data level, improving the analytical consistency and decision reliability of the assessment process. Thus, despite the information gaps frequently encountered in sustainability reporting, the hybrid model is able to produce robust and reliable results. Second, the dual-objective weighting structure, combining G-LOPCOW and G-MSD, captures both logarithmic sensitivity and dispersion-based variability, resulting in a balanced and bias-minimized representation of criterion importance. Third, the G-PIV algorithm introduces a proximity-based ranking mechanism that is inherently resistant to rank reversal, thereby supporting reproducibility and stakeholder accountability in decision-making. Finally, the framework’s computational efficiency—driven by the analytical tractability and scalability of its components—makes it suitable for larger datasets and cross-sectoral applications, reinforcing its value as a decision-support tool in complex evaluation environments.

In policy terms, the existing manuscript's implications extend beyond methodological contributions. The empirical findings align closely with Türkiye’s National Green Deal Action Plan and the BRSA’s ESG Disclosure Guidelines, both of which seek to integrate sustainability into the financial system through enhanced transparency, green credit allocation, and climate-risk management. The dominance of social and governance dimensions in the weighting structure underscores the regulatory shift toward stakeholder accountability, financial inclusivity, and ethical banking. This convergence with international frameworks—such as the EU Green Deal, IFRS Sustainability Disclosure Standards (IFRS S1–S2), and Task Force on Climate-related Financial Disclosures (TCFD)—indicates that Turkish banks are progressively aligning with the global sustainability architecture. For emerging market economies, where ESG institutionalization remains nascent, the presented framework provides actionable insights for balancing developmental priorities with sustainability mandates. Policymakers should leverage similar grey-based analytical systems to design incentive-compatible regulations that reward transparency, penalize greenwashing, and promote capacity development among smaller financial institutions.

While the proposed grey-based MCDM framework demonstrates high analytical integrity, it is important to acknowledge several inherent limitations that may inform future methodological enhancements. First, the temporal scope of the analysis is restricted to a three-year window (2021–2023), which may not sufficiently capture long-term ESG performance trajectories or structural transitions in sustainability practices within the banking sector. Second, the scope of the analysis is confined exclusively to ESG-related indicators, without incorporating financial performance variables that are critically linked to sustainability outcomes. While ESG metrics offer valuable insights into non-financial dimensions of corporate responsibility, the exclusion of financial data—such as profitability, capital adequacy, or risk-adjusted returns—limits the model's ability to capture the full spectrum of sustainable performance. Lastly, the framework is purely objective and does not incorporate expert judgment or stakeholder preferences, which could enrich the evaluative process in participatory or policy-sensitive settings.

Future research could extend the temporal coverage beyond the 2021–2023 period to capture long-term ESG performance trajectories, structural transformations in sustainability practices, and the dynamic responsiveness of banks to evolving regulatory and societal expectations. Moreover, while the current framework employs ten standardized ESG indicators sourced from the Refinitiv Eikon database, subsequent studies could enrich the analytical scope by integrating complementary financial variables—such as profitability ratios, capital adequacy metrics, and risk-adjusted performance measures—alongside sector-specific sustainability indicators. This expansion would facilitate a more comprehensive and multidimensional evaluation of institutional performance. Additionally, incorporating expert judgment through fuzzy logic, rough set theory, or advanced grey-based modeling approaches could enhance the framework's adaptability to qualitative insights, thereby improving its alignment with stakeholder priorities and policy objectives. Finally, applying the proposed grey-MCDM framework to other ESG-sensitive industries or across different national and regional contexts would enable a deeper understanding of its scalability, transferability, and comparative validity, yielding valuable insights for cross-sectoral benchmarking and international sustainability assessments.

Declaration of Research and Publication Ethics
This study, which does not require ethics committee approval and/or legal/specific permission, complies with the research and publication ethics.

Researcher's Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest
There are no potential conflicts of interest in this study.

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