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ORIGINAL ARTICLE

EVALUATION OF ESG RISKS IN THE BANKING INDUSTRY THROUGH AN INTEGRATED DECISION-MAKING FRAMEWORK

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Abstract
This manuscript develops and applies a hybrid multi-criteria decision-making (MCDM) framework for the systematic assessment of Environmental, Social, and Governance (ESG) risks within the Turkish banking industry. The recommended framework combines the CRISUS objective weighting technique, which quantifies the relative importance of ESG risk criteria, with the Proximity Indexed Value (PIV) ranking algorithm, which enables stable and rank-reversal-free prioritization of bank alternatives. The empirical analysis is conducted on major commercial banks included in the Borsa İstanbul Sustainability Index. The outcomes derived from the CRISUS procedure indicate that environmental and governance-related risks dominate the ESG risk structure of Turkish banks, reflecting heightened regulatory requirements and systemic exposure, whereas social risk criteria display relatively weaker discriminatory capacity. The application of the PIV algorithm yields a clear and interpretable ranking of bank alternatives, with Yapı Kredi identified as the most resilient institution, followed by Halkbank and İş Bank, all of which exhibit close proximity to the ideal ESG risk profile. Additional sensitivity and comparative analyses confirm the robustness and reliability of the proposed hybrid framework. Overall, this research contributes to the existing literature by introducing one of the limited number of integrated ESG risk assessment models tailored to an emerging market setting. Beyond its methodological contribution, the framework offers practical decision-support insights for regulators, investors, and bank managers seeking to benchmark ESG risk exposure and enhance resilience within the banking industry.

Keywords
ESG risk assessment, Turkish banking industry, Risk management, Sustainable finance, MCDM.

JEL Classification
C54, G17, G22, G32, G41.

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1. INTRODUCTION

In recent years, Environmental, Social, and Governance (ESG) considerations have come to be recognized as fundamental determinants of strategic orientation, competitive positioning, and long-term value creation in the global banking industry. As sustainability principles have been progressively integrated into financial systems, banks have been expected not only to maintain sound credit and liquidity structures but also to ensure that their activities are conducted in a responsible, transparent, and socially accountable manner (Işık et al., 2025a). Consequently, ESG-related performance has increasingly been treated as a key differentiating factor influencing banks' reputational standing, regulatory alignment, investor confidence, access to international funding, and consistency with sustainable finance standards. Under these conditions, the incorporation of ESG considerations into banking operations has evolved from a voluntary strategic preference into a structural requirement for institutional resilience within a rapidly transforming financial ecosystem (Tekgün, 2025).

From this perspective, ESG risk has emerged as a complementary but distinct concept, referring to the potential vulnerabilities that may undermine banks' financial soundness when sustainability-related challenges are not effectively managed. Such risks originate from environmental stressors such as climate change, social pressures associated with labor practices and stakeholder relations, and governance deficiencies related to weak transparency and oversight mechanisms. These vulnerabilities may materialize in the form of tangible financial losses, most notably through the deterioration of asset quality and the escalation of non-performing loans, thereby weakening balance-sheet resilience. Accordingly, the establishment of robust ESG risk management frameworks has been widely acknowledged as essential for safeguarding financial stability and mitigating credit risk exposure (Yudaruddin & Yudaruddin, 2025).

The banking industry is inherently characterized by high risk intensity, stemming from exposure to credit market volatility, macroeconomic shocks, regulatory pressure, operational fragilities, and reputational sensitivities. Within this already complex risk environment, ESG-related dimensions introduce an additional and increasingly material layer of uncertainty (Ahmed et al., 2018; Pyka & Nocoń, 2024). Although ESG factors were initially perceived as largely qualitative and peripheral considerations, they are now recognized as financially material risk drivers capable of influencing banks' asset quality, operational continuity, compliance capacity, and long-term financial stability. Climate-induced physical disruptions, cybersecurity threats associated with digitalization, governance failures, and weaknesses in disclosure practices collectively constitute what is now widely defined as ESG risk (Yudaruddin et al., 2025; Erhemjamts et al., 2024).

The growing salience of ESG risks has reinforced the need for banks to systematically assess their exposure to sustainability-related vulnerabilities. However, ESG risk assessment remains methodologically challenging, as it involves multiple interrelated dimensions, heterogeneous indicators, and expert-dependent judgments that cannot be adequately captured through a single financial metric. Consequently, ESG risk evaluation is best conceptualized as a multi-criteria and multidimensional decision-making problem, requiring the adoption of structured, transparent, and analytically rigorous assessment frameworks capable of integrating diverse sources of information into a coherent analytical structure. Within this analytical landscape, Multi-Criteria Decision-Making (MCDM) methods offer powerful tools for addressing the complexity of ESG risk evaluation. MCDM techniques allow for the integration of heterogeneous qualitative and quantitative criteria, facilitate expert-based assessment, and provide systematic weighting mechanisms that enhance objectivity and comparability across decision alternatives. They are particularly well-suited for ESG analyses because sustainability dimensions are intrinsically multi-attribute, interdependent, and difficult to evaluate using conventional statistical models alone.

In the current paper, the criterion weight coefficients are derived via the CRISUS (CRiterion Importance Based on SUm of Squares) objective weighting technique, whereas the prioritization of bank alternatives is performed using the Proximity Indexed Value (PIV) method. The CRISUS is employed owing to its transparent computational structure, its independence from inter-criterion correlation effects, and its capacity to capture the discriminative contribution of each criterion through variance-based calculations. The PIV technique, in turn, is adopted as it produces a linear, easily interpretable, and stable ranking structure, while effectively eliminating rank-reversal problems and enhancing robustness in comparative evaluations. The joint implementation of CRISUS and PIV therefore facilitates the development of a consistent, replicable, and decision-oriented framework for ESG risk assessment.

Within this methodological setting, the study seeks to address three central research questions. First, it examines which ESG risk dimensions exert the strongest influence on the overall risk exposure of Turkish commercial banks. Second, it investigates how banks included in the Borsa İstanbul Sustainability Index differ with respect to their ESG risk profiles. Third, it evaluates whether an integrated CRISUS–PIV framework can deliver a stable and rank-reversal-free prioritization of banks under ESG risk considerations.

By responding to these questions, our paper contributes to the existing literature in several important ways. It introduces one of the relatively limited number of integrated ESG risk assessment frameworks applied specifically to the Turkish banking sector using a hybrid MCDM structure. In addition, ESG risks are systematically operationalized through a structured set of environmental, social, and governance criteria that explicitly reflect the risk characteristics of commercial banks. From an empirical perspective, the focus on major banks listed in the Borsa İstanbul Sustainability Index provides a context-specific and policy-relevant comparison of ESG risk exposure. From a methodological standpoint, the combined use of CRISUS and PIV represents a novel and effective approach for addressing the multidimensional and complex nature of ESG risk evaluation. Accordingly, the study aims to make both methodological and empirical contributions to the growing body of research on ESG risk-oriented decision-making in the banking industry.

The remainder of the manuscript is organized as follows. Section 2 reviews the relevant literature and establishes the theoretical and empirical background of the study. Section 3 describes the proposed research methodology and the integrated MCDM framework. Section 4 presents the case study on ESG risk assessment for commercial banks, while Section 5 reports the empirical application and results. Section 6 discusses the validation and robustness analyses, and Section 7 concludes with policy implications, study limitations, and directions for future research.

2. RELATED LITERATURE

In recent years, a growing body of research has applied multi-criteria decision-making (MCDM) approaches to assess corporate sustainability and ESG performance across different industries. Scholars have introduced hybrid models that combine classical techniques such as AHP, TOPSIS, VIKOR, and MAUT with advanced extensions including fuzzy sets, intuitionistic fuzzy sets, spherical fuzzy sets, neutrosophic sets, and grey systems theory. These methodological innovations have been employed to assess sustainability in diverse contexts such as banking, insurance, manufacturing, energy, and electronics industries, offering structured tools to capture uncertainty, subjectivity, and data limitations. Case studies from Spain, Turkey, India, China, and global industries demonstrate how integrated MCDM frameworks can benchmark firms, prioritize ESG criteria, and provide robust rankings of corporate performance. The following section presents a concise overview of these recent contributions, highlighting the methodological configurations and sectoral applications that inform the design of our study.

Aktaş and Demirel (2021) introduced a hybrid MCDM tool to estimate corporate sustainability performance across the economic, environmental, and social dimensions of the triple bottom line. The methodology integrates the Entropy method for objective criteria weighting with three ranking techniques—VIKOR, TOPSIS, and MAUT—to assess sustainability reports. To consolidate results and avoid inconsistencies across methods, the Borda count data fusion technique was applied to generate a final robust ranking. A case study was conducted on a leading Turkish furniture company, where sustainability performance was evaluated over multiple years.

Reig-Mullor and Brotons-Martinez (2021) developed a novel performance assessment model for Spanish commercial banks by integrating financial and non-financial indicators within an expanded CAMELS-ESG rating system. To address uncertainty and subjectivity in decision-making, the study employed intuitionistic fuzzy sets (IFS) combined with the Analytic Hierarchy Process (IFAHP) for weighting criteria and intuitionistic fuzzy TOPSIS (IFTOPSIS) for ranking alternatives.

Reig-Mullor et al. (2022) proposed a novel hybrid methodology to evaluate corporate ESG performance by integrating the AHP and the TOPSIS within a neutrosophic environment. The approach employs single-valued triangular neutrosophic numbers to capture uncertainty, indeterminacy, and subjectivity in sustainability reporting. Leveraging single-valued triangular neutrosophic numbers, the model effectively addressed uncertainty, indeterminacy, and subjectivity inherent in sustainability reporting. Its applicability was demonstrated through a case study assessing the ESG performance of leading global oil and gas firms.

Li et al. (2023) examined the role of ESG factors and policy options in shaping green finance investment decisions for sustainable development in China. To address the complexity and uncertainty inherent in ESG evaluation, the study applied two fuzzy MCDM techniques: the fuzzy AHP to identify and prioritize ESG factors and sub-factors, and the fuzzy DEMATEL to analyze causal relationships and rank policy options.

Sharma and Kumar (2024) investigated the sustainable performance of banking institutions using a multidimensional framework that incorporates ESG, and financial dimensions, supported by 52 sustainability indicators. The authors used data for the period 2021–2022 to examine banks' responsiveness to sustainability dimensions. A hybrid MCDM approach was then employed, integrating Entropy, TOPSIS, and VIKOR to assign relative weights to indicators and prioritize banks based on their sustainable performance.

Akbulut and Aydın (2024) recommended a hybrid multidimensional performance measurement model for Turkish banks by integrating the MSD, MPSI, and RAWEC approaches. Their framework evaluated banks' sustainability performance across financial, environmental, social, and corporate governance dimensions, employing 21 indicators derived from the CAMELS rating system and ESG practices to ensure a holistic assessment. Within this model, MSD and MPSI were utilized to generate objective and reliable weights for the criteria, while RAWEC was implemented to provide a robust ranking of banks according to their overall sustainability performance. To validate the applicability of the recommended methodology, a comprehensive case study was conducted on six major Turkish commercial banks representing significant market shares in the sector.

Yu et al. (2024) developed an integrated MCDM framework to assess the ESG sustainable performance of companies by combining the interval type-2 (IT2) fuzzy set, AHP, and CoCoSo. In this approach, IT2 fuzzy sets were employed to transform qualitative linguistic judgments into quantitative values, IT2FAHP was applied to derive the weights of ESG criteria, and IT2F-CoCoSo was employed to rank the alternatives. The framework was tested through a case study of five listed medical companies, evaluated across 14 ESG sub-criteria under environmental, social, and governance dimensions.

Hoang et al. (2024) introduced a combined MCDM methodology to assess the ESG performance of the global electronics industry under uncertainty. The study combined the AHP and WASPAS within a spherical fuzzy environment, resulting in the SF-AHP–SF-WASPAS approach. In this framework, SF-AHP was utilized to determine the relative importance of ESG criteria, while SF-WASPAS provided the final rankings of companies. The methodology was applied to leading electronics firms' ESG sustainability indicators.

Akbulut (2024) developed an integrated grey MCDM tool to evaluate the environmental sustainability performance of Turkish banks. The proposed model combines the Grey LOPCOW method for objective weighting of criteria with the Grey PIV ranking procedure, enabling robust analysis under conditions of uncertainty and limited data. A case study was conducted with six commercial banks, thirteen environmental performance indicators, and assessments from seven experts.

Demir (2025) developed a new decision-making framework for evaluating the sustainability performance of banks traded on the BIST by integrating the MPSI and RAWEC methods. In the 2022 case study, the MPSI objectively determined the weights of the indicators, and RAWEC provided the multi-criteria ranking of the banks. The findings revealed that ROE was the most decisive indicator, and according to RAWEC results, Akbank demonstrated the highest sustainability performance.

Işık and Adalar (2025) evaluated the sustainability performance of 10 Turkish non-life insurance companies through ESG criteria derived from the Refinitiv Eikon database, reflecting the triple bottom line of sustainability. The authors extended the classical CRADIS technique with intuitionistic fuzzy sets, resulting in the IF-CRADIS approach, which more effectively captured uncertainty, hesitation, and subjectivity in expert evaluations.

Adalar and Işık (2025) proposed a novel hybrid multi-criteria decision-making framework by introducing CRISUS, an objective weighting method, and integrating it with the RAM to rank decision alternatives for assessing corporate sustainability performance. The proposed methodology was applied to seven BIST-listed food and beverage firms, utilizing seven performance criteria that encompassed both ESG and financial indicators.

Işık et al. (2025b) introduced a grey-based hybrid decision support framework to evaluate the sustainability performance of Turkish banks. The study developed an integrated model that incorporated extended versions of the MSD, SPC, and PIV methods within the grey system theory. A case study was conducted on seven banks using ten ESG indicators, with assessments provided by five experts.

Tekgün (2025) developed a novel MCDM framework to assess the ESG sustainability performance of banks listed on Borsa İstanbul. The proposed hybrid model combined two objective weighting techniques—Grey LOPCOW and Grey MSD—with the Grey PIV ranking procedure to effectively manage epistemic uncertainty in sustainability data, incorporating ten ESG indicators from the Refinitiv Eikon database for the 2021–2023 period.

Karki et al. (2025) conducted an ESG performance assessment of Indian deposit banks using a hybrid multi-criteria decision-making framework. The study applied the R-SWARA technique to determine the weights of ESG criteria and then employed the CoCoSo approach to rank the banks according to their sustainability performance.

In spite of the fact that recent studies have significantly advanced the application of hybrid MCDM approaches for evaluating corporate sustainability and ESG performance across a wide range of sectors—including banking, insurance, manufacturing, and energy—important conceptual and methodological limitations remain. First, the prevailing focus of the existing literature is largely oriented toward ex post ESG performance measurement and corporate sustainability ranking, rather than the structured assessment of ESG-related risks, which represent forward-looking vulnerabilities with direct implications for financial stability and risk management. This limitation is particularly pronounced in the banking sector, where ESG risks are closely intertwined with credit risk, regulatory exposure, and systemic resilience, yet remain insufficiently operationalized within dedicated risk assessment frameworks. Second, although several studies rely on standardized ESG databases or broad indicator sets, these approaches often fail to translate ESG dimensions into risk-sensitive criteria that reflect the specific operational, regulatory, and portfolio-related characteristics of commercial banks. As a result, existing models may overlook the channels through which ESG risks materialize and propagate within banking systems. Third, from an empirical perspective, while MCDM-based ESG assessments have been widely applied to banks operating in developed markets or global samples, empirically grounded ESG risk comparisons for major Turkish banks listed in the Borsa İstanbul Sustainability Index remain scarce, limiting the relevance of prior findings for regulators, investors, and policymakers in emerging market contexts.

From a methodological standpoint, previous research has introduced a variety of hybrid MCDM configurations combining Entropy, TOPSIS, VIKOR, fuzzy AHP, DEMATEL, and grey-based approaches. However, these models often suffer from either instability in ranking outcomes, sensitivity to normalization procedures, or limited transparency in weight derivation. Notably, the joint application of the CRISUS objective weighting method and the PIV ranking algorithm has not yet been explored in the context of ESG risk evaluation, despite their complementary strengths in capturing criterion discriminative power and ensuring rank-reversal-free prioritization.

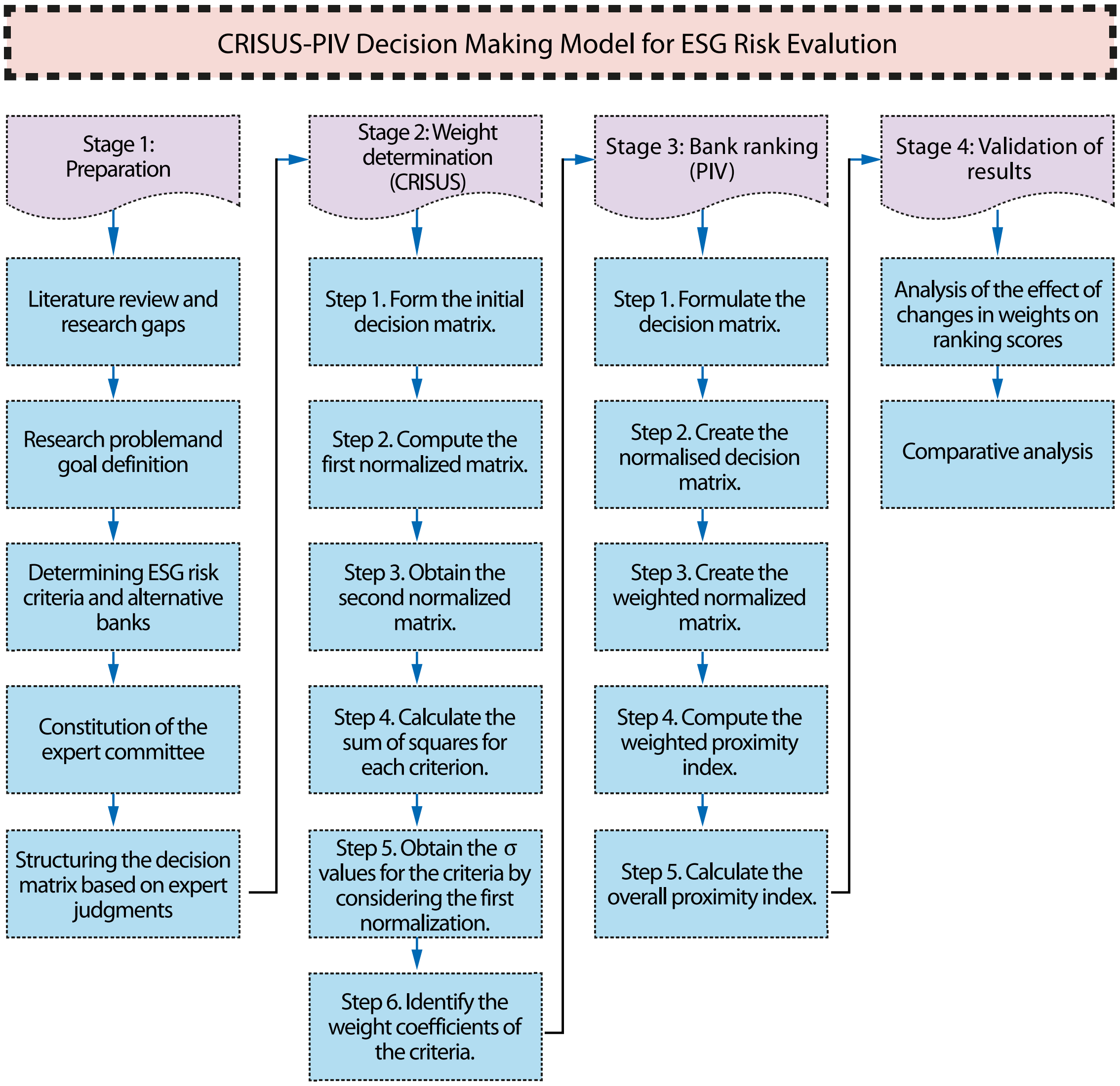
By addressing these gaps, the present work makes several contributions. It shifts the analytical focus from ESG performance to ESG risk assessment, offering a decision-oriented framework that is directly applicable to banking risk management. It operationalizes ESG risks through a bank-specific and risk-sensitive criterion structure, enhancing the interpretability and practical relevance of the evaluation. Empirically, it provides one of the first comprehensive ESG risk comparisons for Turkish banks listed in the BIST Sustainability Index. Methodologically, the integrated CRISUS–PIV framework delivers transparent weighting, stable rankings, and high robustness, thereby offering decision makers, regulators, and practitioners a reliable tool for benchmarking ESG risk exposure, supporting supervisory oversight, strategic planning, and ESG-informed investment decisions.

3. RESEARCH METHODOLOGY

This section elaborates on the core algorithmic structure of the proposed integrated MCDM framework. The ESG risk performance of Turkish commercial banks was systematically assessed through a sequence of methodological stages, as depicted in Figure 1. In the initial stage, a comprehensive decision matrix was constructed to capture the environmental, social, and governance risk dimensions across the selected bank alternatives. Subsequently, the objective weights of the criteria were derived employing the CRISUS weighting procedure, which ensures methodological rigor by minimizing subjectivity and enhancing the robustness of the weighting process. Once the criterion weights were established, the prioritization of bank alternatives was performed through the SPR ranking algorithm.

Figure 1

The methodological framework



3.1. The CRISUS-PIV Methodology

3.1.1. Stage 1: CRISUS algorithm for criterion weighting

The CRISUS approach was introduced into the decision-making literature by Adalar and Işık (2025) with the aim of calculating the objective weight coefficients of evaluation criteria in the process of solving decision problems. This method constitutes an analytical weighting technique developed by drawing upon the fundamental principles of the Statistical Variance (SV) approach proposed by Rao and Patel (2010) and the Entropy approach introduced by Shannon (1948). The CRISUS methodology estimates objective weights through a two-stage normalization procedure, employing the sum-of-squares operator. The rationale underlying the preference for this weighting algorithm, together with its methodological advantages, can be summarized as follows: (i) the computational steps of the CRISUS approach are straightforward, offering decision-makers an easy-to-use algorithm that does not require specialized software or advanced user expertise; (ii) the method is not affected by the number of alternatives considered in the decision problem; (iii) the normalization procedure is implemented in two stages, explicitly accounting for the benefit–cost characteristics of the evaluation criteria; (iv) the approach is immune to inconsistencies inherent in expert judgments that typically affect subjective weighting models; and (v) compared with alternative weighting methodologies, the sum-of-squares operation specific to the CRISUS method provides a simpler mechanism for weight estimation. The application procedure of the CRISUS methodology consists of the six steps outlined below (Adalar and Işık, 2025).

Step 1. To address the decision problem, the decision matrix—consisting of the set of bank alternatives and ESG risk-based criteria—is formulated in accordance with Equation (1).

$$\tilde{X} = \left(\begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \right) \tag{1}$$

Step 2. The first normalization procedure is carried out through vector normalization based on the sum of Euclidean distances, as developed by Van Delft and Nijkamp (1977). Accordingly, Equation (2) is applied to beneficial criteria, whereas Equation (3) is employed for non-beneficial criteria.

$$x_{ij} = \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^{m} \tilde{x}_{ij}^2}} \tag{2}$$

$$x_{ij} = 1 - \frac{\tilde{x}_{ij}}{\sqrt{\sum_{i=1}^{m} \tilde{x}_{ij}^2}} \tag{3}$$

Step 3. In the second normalization procedure, all elements of the matrix normalized in the previous step are transformed into the interval [0,1] with the help of Equation (4). In other words, all values are adjusted to conform to a standard distribution.

$$s_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{4}$$

Step 4. For each assessment criterion, the sum of squares is computed by means of Equation (5).

$$\rho_j = \sum_{i=1}^{m} s_{ij}^2 \tag{5}$$

Step 5. Following the first normalization procedure, the standard deviation value corresponding to each criterion $(\sigma_j,\ j = 1,2,\dots,n)$ is computed.

Step 6. The objective importance weights of the assessment criteria are derived in the final stage of the CRISUS approach via Equation (6).

$$w_j = \frac{\sigma_j \rho_j}{\sum_{j=1}^{n} \sigma_j \rho_j} \tag{6}$$

Here, the criterion associated with the highest importance weight is identified as exerting the most significant impact on performance.

3.1.2. Stage 2: Proximity Indexed Value (PIV) procedure for bank ranking

The Proximity Indexed Value (PIV) method is a relatively recent addition to the family of MCDM techniques, designed to provide decision makers with a simple yet reliable tool for ranking alternatives (Mufazzal and Muzakkir, 2018). Unlike more complex approaches, PIV relies on straightforward normalization and aggregation procedures, which makes it easy to implement and interpret. One of its key advantages is robustness against the rank reversal problem, ensuring that the inclusion or exclusion of irrelevant alternatives does not distort the final ordering. Moreover, the method is flexible enough to handle both benefit and cost criteria, as well as datasets containing negative values, by transforming them into a comparable scale. The PIV approach proceeds through the following steps:

Step 1. The initial decision matrix, as presented in Equation (1), is constructed

Step 2. The decision matrix constructed in the previous step is normalized using Equation (7).

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{7}$$

Step 3. The weighted normalized matrix is constructed. This matrix shown below is obtained through the application of Equation (8).

$$z_{ij} = R_{ij}.w_j \tag{8}$$

Step 4. The Weighted Proximity Index, denoted as k_i, is evaluated via Equation (9).

$$k_i = \begin{cases} z_{max} - z_{ij}; \text{for beneficial criteria} \\ z_{ij} - z_{min}; \text{for cost criteria} \end{cases} \tag{9}$$

Step 5. The Overall Proximity Value (μ_i) is obtained by applying Equation (10)

$$\mu_i = \sum_{j=1}^{n} k_i \tag{10}$$

Alternatives are ranked according to their μ_i values. The alternative with the smallest μ_i indicates the minimum deviation from the ideal solution and is therefore placed first, followed by alternatives with progressively larger μ_i values.

4. CASE STUDY FOR COMMERCIAL BANKS' ESG RISK ASSESSMENT

In order to demonstrate the applicability of the proposed methodology, a case study was conducted on commercial banks operating in Turkey. The objective of this case study is to evaluate the Environmental, Social, and Governance (ESG) risk exposure of banks listed in the BIST Sustainability Index, thereby providing a comparative framework for assessing their resilience and sustainability performance. The study follows a structured MCDM approach, beginning with the construction of an expert panel, the definition of ESG risk criteria, and the identification of bank alternatives.

4.1. Construction of a team of experts

To ensure methodological rigor and sectoral relevance, an expert panel was established to guide the ESG risk assessment process. The panel consisted of three senior professionals with extensive experience in sustainability and corporate governance within the banking industry. The first expert was a member of a bank's sustainability committee with 5 years of ESG experience, the second expert served as an independent board member with 7 years of ESG expertise, and the third expert was a member of a corporate governance committee with 6 years of ESG experience.

4.2. Definition of criteria

The evaluation framework was structured around a comprehensive set of ESG risk criteria, categorized into environmental, social, and governance dimensions. The set of criteria defined in the study was established through expert opinions and constructed within a consensus-based framework.

Carbon Emission Risk (E1): This criterion reflects the bank's direct (Scope 1) and indirect (Scope 2 and 3) carbon emissions generated through its branches, data centers, ATM networks, and financed activities. Higher carbon intensity elevates regulatory exposure to carbon pricing mechanisms, increases transition-related financial losses, and weakens sustainability performance in global ESG benchmarking frameworks.

Carbon-Intensive Portfolio Risk (E2): This criterion evaluates the proportion of loans and investments allocated to carbon-intensive industries such as fossil fuels, heavy manufacturing, cement, mining, and transportation. A higher share of carbon-intensive assets increases transition risk, elevates default probabilities for high-emission borrowers, and creates stranded asset exposure that threatens long-term portfolio stability.

Climate-Related Physical Damage Risk (E3): This criterion captures the vulnerability of the bank's physical infrastructure and loan collateral to climate-induced hazards such as floods, heatwaves, storms, wildfires, and rising sea levels. Physical climate stressors directly threaten operational continuity and reduce the recoverable value of collateral.

Environmental Compliance Risk (E4): This risk reflects the bank's level of alignment with environmental regulations, green taxonomy requirements, sustainability reporting standards, and environmental due-diligence obligations. Non-compliance increases the likelihood of regulatory penalties, legal action, financial sanctions, and reputational losses.

Customer Protection Risk (S1): This criterion measures the bank's exposure to customer complaints, misselling behavior, product suitability issues, and consumer protection breaches. Poor customer protection weakens social credibility, lowers stakeholder trust, and increases supervisory scrutiny.

Financial Inclusion Risk (S2): This risk assesses the bank's performance in providing accessible financial services to underserved groups, low-income individuals, SMEs, and disadvantaged regions. Low inclusion levels indicate social vulnerability and limit the bank's alignment with sustainable development goals and inclusive finance principles.

Cybersecurity Risk (S3): Cybersecurity risk refers to the vulnerability of the bank's information systems to data breaches, ransomware attacks, system outages, and unauthorized access. As digitalization expands, cyber risks have become a critical operational and reputational threat, directly affecting customer trust and regulatory compliance.

Human Capital Risk (S4): This risk captures challenges related to employee turnover, insufficient training, low engagement, weak workplace well-being, and inadequate skill development. Strong human capital is essential for sustainable transformation, effective ESG governance, and long-term operational resilience.

Board Independence Risk (G1): This criterion measures the independence, diversity, and objectivity of the board of directors, as well as the existence of potential conflicts of interest. Low independence undermines governance quality, weakens oversight, and increases the likelihood of biased strategic decisions.

Corruption and Ethical Misconduct Risk (G2): This risk captures exposure to bribery, fraud, money laundering, and ethical misconduct. Weaknesses in ethical systems threaten the bank's regulatory standing, public trust, and long-term legitimacy.

Regulatory Compliance Risk (G3): Regulatory compliance risk reflects the bank's adherence to BDDK, MASAK, Basel III–IV, AML/KYC obligations, and international sustainability frameworks. Higher non-compliance increases operational losses, penalties, and supervisory intervention.

Transparency and ESG Disclosure Risk (G4): This criterion evaluates the quality, depth, and accuracy of ESG reporting practices aligned with TCFD, GRI, SASB, and other disclosure frameworks.

Insufficient transparency undermines investor confidence, weakens ESG scoring, and restricts access to sustainable finance instruments.

4.3. Definition of bank alternatives

The case study focused on commercial banks listed in the BIST Sustainability Index, representing key players in the Turkish financial system. These institutions were chosen due to their significant market presence and active participation in sustainability initiatives. By evaluating these banks against the defined ESG risk criteria, the study aimed to provide a comparative analysis of their risk exposure and resilience, thereby offering valuable insights for both academic research and managerial decision-making.The selected alternatives are Akbank (A1), Garanti BBVA (A2), Halkbank (A3), İş Bank (A4), Şekerbank (A5), Vakıfbank (A6), and Yapı Kredi (A7).

5. APPLICATION AND RESULTS

In the final stage of the evaluation process, each decision-maker was requested to assign an importance score ranging from 1 (least important) to 9 (most important) for every criterion under consideration. These individual judgments were then aggregated by computing the arithmetic mean of the assigned values, thereby yielding a consolidated initial decision matrix.

The evaluations of the alternatives with respect to each criterion, provided by the experts selected from the banking sector, are presented in Tables 1, 2, and 3, respectively. Subsequently, by averaging these matrices, the initial decision matrix shown in Table 4 was constructed.

Table 1

The first expert's evaluation of the alternatives with respect to the criteria

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	8	8	8	9	8	8	9	8	8	7	6	9
A2	9	9	8	9	8	8	9	8	9	9	9	9
A3	6	5	6	7	6	5	7	7	6	6	7	7
A4	5	6	6	7	6	7	5	7	6	6	7	7
A5	9	9	8	7	8	7	9	8	8	8	9	9
A6	8	8	7	8	7	7	8	8	7	8	9	8
A7	5	6	4	6	6	4	4	6	6	6	4	6

Table 2

The second expert's assessment of the banks with respect to the criteria

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	8	8	8	8	8	8	8	8	9	8	9	9
A2	9	9	8	9	8	9	9	8	9	8	9	9
A3	6	4	6	4	6	4	7	7	6	6	6	6
A4	4	6	4	6	6	6	7	7	6	5	6	6
A5	9	8	8	9	8	9	9	8	9	9	8	9
A6	8	8	7	8	7	8	8	8	8	9	8	9
A7	5	4	5	5	4	5	6	6	6	4	5	5

Table 3

The third expert's evaluation of the bank alternatives based on the criteria

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	8	8	8	8	8	8	9	8	8	8	8	9
A2	9	9	8	9	8	9	9	8	9	9	9	9
A3	4	3	3	3	6	6	7	7	6	6	6	6
A4	6	4	3	3	6	6	7	7	6	6	6	6
A5	9	9	8	9	8	8	9	8	9	8	9	9
A6	8	8	7	8	7	8	8	8	9	8	8	9
A7	5	4	5	4	5	5	6	6	5	4	4	5

Table 4
The initial decision matrix

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	8.00	8.00	8.00	8.33	8.00	8.00	8.67	8.00	8.33	7.67	7.67	9.00
A2	9.00	9.00	8.00	9.00	8.00	8.67	9.00	8.00	9.00	8.67	9.00	9.00
A3	5.33	4.00	5.00	4.67	6.00	5.00	7.00	7.00	6.00	6.00	6.33	6.33
A4	5.00	5.33	4.33	5.33	6.00	6.33	6.33	7.00	6.00	5.67	6.33	6.33
A5	9.00	8.67	8.00	8.33	8.00	8.00	9.00	8.00	8.67	8.33	8.67	9.00
A6	8.00	8.00	7.00	8.00	7.00	7.67	8.00	8.00	8.00	8.33	8.33	8.67
A7	5.00	4.67	4.67	5.00	5.00	4.67	5.33	6.00	5.67	4.67	4.33	5.33

5.1. The results obtained from the CRISUS methodology

By applying Equations (2) and (3), the decision matrix presented in Table 4 was normalized, and the resulting initial normalized decision matrix is reported in Table 5. Next, by means of Equation (4), the second normalized decision matrix was determined, as illustrated in Table 6. Finally, Table 7 displays the outcomes produced employing the CRISUS objective weighting approach.

Table 5
The first normalised matrix

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	0.583	0.573	0.543	0.560	0.565	0.572	0.576	0.595	0.580	0.597	0.608	0.564
A2	0.531	0.519	0.543	0.525	0.565	0.536	0.560	0.595	0.546	0.545	0.540	0.564
A3	0.722	0.786	0.714	0.754	0.674	0.732	0.658	0.646	0.698	0.685	0.677	0.693
A4	0.740	0.715	0.753	0.719	0.674	0.661	0.690	0.646	0.698	0.702	0.677	0.693
A5	0.531	0.537	0.543	0.560	0.565	0.572	0.560	0.595	0.563	0.562	0.557	0.564
A6	0.583	0.573	0.600	0.578	0.619	0.589	0.609	0.595	0.597	0.562	0.574	0.580
A7	0.740	0.751	0.733	0.736	0.728	0.750	0.739	0.696	0.714	0.755	0.779	0.742

Table 6
The second normalised matrix

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	0.132	0.129	0.123	0.126	0.129	0.130	0.131	0.136	0.132	0.135	0.138	0.128
A2	0.120	0.117	0.123	0.118	0.129	0.121	0.127	0.136	0.124	0.124	0.122	0.128
A3	0.163	0.177	0.161	0.170	0.153	0.166	0.150	0.148	0.159	0.155	0.153	0.158
A4	0.167	0.161	0.170	0.162	0.153	0.150	0.157	0.148	0.159	0.159	0.153	0.158
A5	0.120	0.121	0.123	0.126	0.129	0.130	0.127	0.136	0.128	0.128	0.126	0.128
A6	0.132	0.129	0.135	0.130	0.141	0.134	0.139	0.136	0.136	0.128	0.130	0.132
A7	0.167	0.169	0.166	0.166	0.166	0.170	0.168	0.159	0.163	0.171	0.176	0.169

Table 7
The results of CRISUS approach

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
ρ_j	0.146	0.147	0.146	0.146	0.144	0.145	0.144	0.143	0.144	0.145	0.145	0.145
σ_j	0.097	0.111	0.097	0.098	0.066	0.085	0.070	0.040	0.072	0.083	0.085	0.077
$\sigma_j \rho_j$	0.014	0.016	0.014	0.014	0.01	0.012	0.01	0.006	0.01	0.012	0.012	0.011
w	0.099	0.114	0.099	0.100	0.067	0.086	0.071	0.040	0.073	0.084	0.087	0.079
rank	3	1	4	2	11	6	10	12	9	7	5	8

The CRISUS analysis indicates that E2 (Carbon-Intensive Portfolio Risk), E4 (Environmental Compliance Risk), and E1 (Carbon Emission Risk) are the most critical determinants of banks' ESG risk performance, while S4 (Human Capital Risk), S1 (Customer Protection Risk), and S3 (Cybersecurity Risk) emerge as the least influential factors. The overall importance ranking of the criteria is as follows: E2 > E4 > E1 > E3 > G3 > S2 > G2 > G4 > G1 > S3 > S1 > S4.

5.2. The results obtained from the PIV methodology

The normalized decision matrix was calculated using Equation (7) and presented in Table 8. Subsequently, the weighted ranking matrix was obtained with the help of Equation (8) and reported in Table 9. The Weighted Proximity Index was derived through Equation (9), while the Overall Proximity Value was determined using Equation (10). Finally, the Weighted Proximity Index, the Overall Proximity Value, and the corresponding ranking results are summarized in Table 10.

Table 8

The normalized decision matrix

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	0.417	0.427	0.457	0.440	0.435	0.428	0.424	0.405	0.420	0.403	0.392	0.436
A2	0.469	0.481	0.457	0.475	0.435	0.464	0.440	0.405	0.454	0.455	0.460	0.436
A3	0.278	0.214	0.286	0.246	0.326	0.268	0.342	0.354	0.302	0.315	0.323	0.307
A4	0.260	0.285	0.247	0.281	0.326	0.339	0.310	0.354	0.302	0.298	0.323	0.307
A5	0.469	0.463	0.457	0.440	0.435	0.428	0.440	0.405	0.437	0.438	0.443	0.436
A6	0.417	0.427	0.400	0.422	0.381	0.411	0.391	0.405	0.403	0.438	0.426	0.420
A7	0.260	0.249	0.267	0.264	0.272	0.250	0.261	0.304	0.286	0.245	0.221	0.258

Table 9

The weighted ranking matrix

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4
A1	0.041	0.049	0.045	0.044	0.029	0.037	0.030	0.016	0.031	0.034	0.034	0.034
A2	0.046	0.055	0.045	0.048	0.029	0.040	0.031	0.016	0.033	0.038	0.040	0.034
A3	0.028	0.024	0.028	0.025	0.022	0.023	0.024	0.014	0.022	0.027	0.028	0.024
A4	0.026	0.032	0.025	0.028	0.022	0.029	0.022	0.014	0.022	0.025	0.028	0.024
A5	0.046	0.053	0.045	0.044	0.029	0.037	0.031	0.016	0.032	0.037	0.038	0.034
A6	0.041	0.049	0.040	0.042	0.025	0.035	0.028	0.016	0.030	0.037	0.037	0.033
A7	0.026	0.028	0.026	0.027	0.018	0.022	0.019	0.012	0.021	0.021	0.019	0.020

Table 10

Weighted proximity index, overall proximity index and ranking results

	E1	E2	E3	E4	S1	S2	S3	S4	G1	G2	G3	G4	μ_i	Rank
A1	0.015	0.024	0.021	0.019	0.011	0.015	0.012	0.004	0.010	0.013	0.015	0.014	0.174	5
A2	0.021	0.030	0.021	0.023	0.011	0.019	0.013	0.004	0.012	0.018	0.021	0.014	0.206	7
A3	0.002	0.000	0.004	0.000	0.004	0.002	0.006	0.002	0.001	0.006	0.009	0.004	0.038	2
A4	0.000	0.008	0.000	0.004	0.004	0.008	0.003	0.002	0.001	0.004	0.009	0.004	0.047	3
A5	0.021	0.028	0.021	0.019	0.011	0.015	0.013	0.004	0.011	0.016	0.019	0.014	0.193	6
A6	0.015	0.024	0.015	0.018	0.007	0.014	0.009	0.004	0.009	0.016	0.018	0.013	0.162	4
A7	0.000	0.004	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	1

Based on the calculated μ_i values, the overall ranking of the banks was obtained. The results indicate that A7 (Yapı Kredi) is ranked first with the lowest proximity value, reflecting the minimum deviation from the ideal solution. This is followed by A3 (Halkbank) and A4 (İş Bankası), which also demonstrate relatively strong performance. A6 (Vakıfbank) occupies the fourth position, while A1 (Akbank) and A5 (Şekerbank) are placed in the fifth and sixth ranks, respectively. Finally, A2 (Garanti BBVA) is ranked last, as it exhibits the highest deviation from the best option.

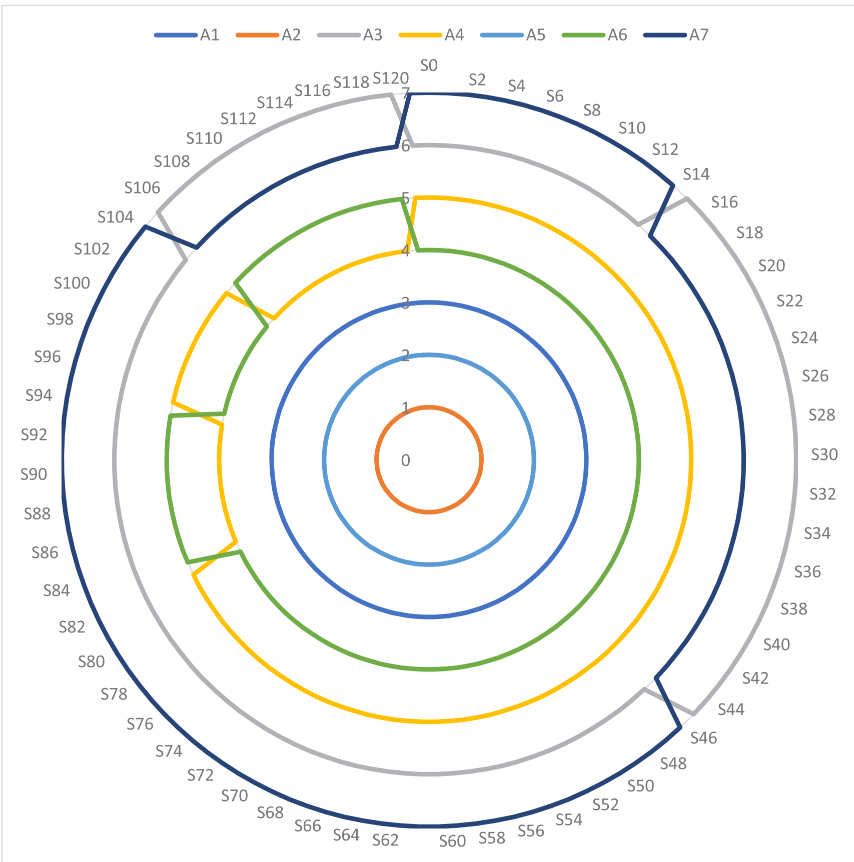
6. VALIDATION TESTS

The validation procedures employed in this study serve a dual purpose: first, to examine the sensitivity of the proposed model to variations in criterion weights, and second, to benchmark its performance against established multi-criteria decision-making techniques. The scenario analyses, encompassing 120 distinct weighting schemes, provide strong evidence that the model's outcomes are not unduly influenced by marginal changes in input parameters. This stability is particularly important in practical applications, where decision environments are often characterized by uncertainty and fluctuating stakeholder priorities. The comparative evaluation with MAUT and SAW further reinforces the credibility of the proposed hybrid framework. By demonstrating convergence in rankings across different methodological paradigms, the study confirms that the model is not only internally consistent but also externally validated against widely recognized approaches. Such methodological triangulation enhances confidence in the reliability of the results and underscores the model's potential applicability in diverse decision-making contexts.

6.1. Assessing the impacts of various weight values on rankings results

The robustness of the model was evaluated through 120 scenario analyses in which the weight values of all criteria were systematically varied (Görçün et al., 2022; Görçün et al., 2025). Specifically, in the first ten scenarios, the weight of the first criterion was gradually reduced from 10% to 100%, reaching 0%, while the weights of the remaining criteria were proportionally adjusted so that the sum of all fourteen criteria weights equaled one. The same procedure was subsequently applied to each of the other criteria, thereby generating ten scenarios per criterion and yielding a total of 120 distinct weighting schemes. As illustrated in Figure 2, alternative A7—identified as the optimal option under the proposed model—consistently retained its top ranking across all 120 scenarios. Likewise, alternatives A3 and A4 maintained their respective positions throughout the entire set of scenario analyses, confirming the stability of the ranking outcomes. While slight variations in the ranking occurred, these did not substantially affect the overall ordering of alternatives.

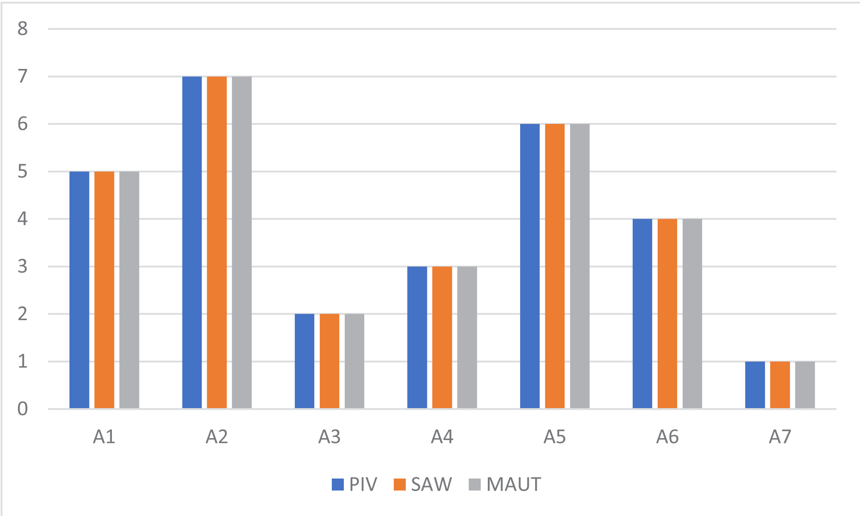
Figure 2
Impact of criteria weight changes on the ranking of bank alternatives



6.2. Comparison with other MCDM approaches

In the second phase of validating the proposed framework, a comparative analysis was undertaken using two established MCDM techniques, namely MAUT (Keeney and Raiffa, 1979) and SAW (MacCrimmon, 1968). The comparative results are presented in Figure 3. A review of the outcomes obtained from all three methods revealed that the ranking of alternatives remained unchanged. This consistency demonstrates the robustness of the suggested hybrid model and confirms its ability to deliver effective and reliable results, thereby reinforcing its suitability for application in diverse multi-criteria decision-making contexts.

Figure 3
Comparative ranking of alternatives obtained through alternative approaches



7. CONCLUSION

The growing importance of Environmental, Social, and Governance (ESG) risk management in the banking sector underscores the necessity of adopting rigorous analytical frameworks that can capture the multidimensional nature of sustainability challenges. By integrating the CRISUS weighting method with the PIV ranking procedure, this study provides a transparent and replicable approach to evaluating ESG risks among Turkish commercial banks listed in the BIST Sustainability Index. The primary objective was to identify the most critical ESG risk dimensions and to establish a comparative hierarchy of banks' resilience, thereby offering insights relevant to both academic research and practical policymaking.

The CRISUS analysis demonstrates that Carbon-Intensive Portfolio Risk (E2) holds the highest weight (w=0.114, rank=1), followed closely by Environmental Compliance Risk (E4) (w=0.100, rank=2), Carbon Emission Risk (E1) (w=0.099, rank=3), and Climate-Related Physical Damage Risk (E3) (w=0.099, rank=4). This outcome clearly indicates that environmental dimensions dominate the ESG risk landscape for Turkish banks. The predominance of E2 reflects the systemic vulnerability of banks' loan portfolios to transition risks associated with carbon-intensive industries. In parallel, the strong weight of E4 underscores the critical importance of regulatory alignment with environmental standards, suggesting that compliance failures could generate substantial financial and reputational costs. Within the governance dimension, Regulatory Compliance Risk (G3) (w=0.087, rank=5) and Corruption and Ethical Misconduct Risk (G2) (w=0.084, rank=7) emerge as highly influential. These findings highlight that governance failures, particularly in regulatory adherence and ethical conduct, remain material threats to institutional resilience. Transparency and ESG disclosure (G4) also occupies a mid-level position (w=0.079, rank=8), reflecting the growing importance of accurate reporting in sustaining investor confidence and access to sustainable finance. Social risks, by contrast, exhibit relatively lower weights. Financial Inclusion Risk (S2) (w=0.086, rank=6) is the only social criterion with moderate influence, suggesting that inclusive finance remains a relevant but secondary differentiator among Turkish banks. Customer Protection Risk (S1) (w=0.067, rank=11), Cybersecurity Risk (S3) (w=0.071, rank=10), and Human Capital Risk (S4) (w=0.040, rank=12) occupy the lowest ranks. This pattern implies that, while social risks are acknowledged, they do not significantly differentiate banks' ESG performance in the current dataset. Overall, the CRISUS results reveal a hierarchy in which environmental and governance risks dominate, while social risks play a comparatively limited role. This distribution reflects both the regulatory pressures shaping environmental compliance and the structural importance of governance integrity in the Turkish banking sector.

The comparative evaluation of the banks based on the given criteria reveals a distinct ranking pattern. Yapı Kredi emerges as the best-performing alternative with the lowest score (0.008), indicating the minimum deviation from the ideal solution. It is followed by Halkbank (0.038) and İş Bankası (0.047), both of which demonstrate strong proximity to the optimal outcome. Vakıfbank occupies the fourth position (0.162), while Akbank (0.174) and Şekerbank (0.193) are placed in the middle range, reflecting moderate performance. Garanti BBVA, with the highest score (0.206), ranks last, signifying the greatest deviation from the ideal solution.

Building on the empirical evidence, the study translates its results into concrete policy implications for strengthening ESG risk management across stakeholder groups. For bank management, the outcomes highlight the importance of giving precedence to criteria with higher relative weights in strategic decision-making. Institutions exposed to elevated carbon portfolio risks should accelerate the adoption of green lending practices, while those with shortcomings in ESG reporting need to strengthen disclosure mechanisms to comply with international standards. Enhancing cybersecurity and governance structures is equally essential to reduce operational vulnerabilities and reputational exposure. For regulators, the evidence indicates that policy measures should concentrate on domains where banks display notable divergence, particularly in environmental compliance and governance transparency. Stricter disclosure obligations, incentives for green financial instruments, and sanctions for non-compliance would mitigate systemic ESG risks and promote greater consistency across the sector. In areas of relative uniformity, such as financial inclusion, regulators may set more ambitious objectives to encourage progress beyond baseline compliance. For investors, the PIV-based rankings serve as a valuable instrument for embedding ESG risk considerations into portfolio allocation strategies. Banks demonstrating stronger ESG risk management are likely to benefit from lower risk premiums and improved access to sustainable finance, whereas weaker performers may encounter higher funding costs. This mechanism of market discipline can accelerate the convergence of Turkish banks with global sustainability benchmarks.

Despite its methodological rigor, this manuscript is subject to certain limitations. The findings are confined to the context of Turkish banks and therefore cannot be generalized to other banking sectors. Moreover, the evaluation relies on expert-based judgments; although the panel comprises professionals with substantial expertise in ESG and banking practices, the number of experts remains relatively limited. Future research could strengthen the proposed framework by engaging a larger and more diverse pool of experts or by triangulating expert opinions with large-scale ESG databases. Expanding the empirical scope to include banks across multiple jurisdictions would enhance the comparative validity of ESG risk assessments. From a methodological standpoint, integrating CRISUS–PIV with advanced fuzzy, grey-based, or hybrid multi-criteria decision-making extensions may better capture uncertainty, dynamic interactions, and interdependencies among criteria. Comparative analyses between emerging and developed economies could further illuminate how institutional maturity, regulatory environments, and market structures shape ESG risk prioritization. Additionally, incorporating qualitative dimensions—such as stakeholder perceptions, corporate culture, and strategic orientation—into quantitative models would enrich the explanatory power of ESG evaluations. Finally, coupling CRISUS–PIV with machine learning and explainable AI techniques offers promising avenues for predictive modeling, scenario analysis, and benchmarking, thereby equipping both academics and practitioners with a more comprehensive toolkit for advancing sustainable finance research.

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