

ORIGINAL ARTICLE

A HYBRID FRAMEWORK FOR ASSESSING MULTI-DIMENSIONAL BANK SUSTAINABILITY WITH MULTI-CRITERIA DECISION MAKING

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Abstract

This paper proposes a hybrid multi-criteria decision-making (MCDM) framework to comprehensively assess the multi-dimensional sustainability performance in the banking industry. The suggested framework integrates the Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) and the Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN) to ensure objective, consistent, and robust evaluation. The proposed hybrid framework is empirically applied to a real-world case study of Bank of America-recognized as the most valuable banking brand in the United States-to assess its performance across Environmental, Social, Governance, and Profitability (ESG-P) dimensions over the 2008–2021 period. Fourteen performance indicators were selected to reflect the bank’s multi-dimensional sustainability profile. Indicator weights were determined objectively employing the LOPCOW technique, while the bank’s annual performance rankings were obtained via the AROMAN method. The weighting analysis revealed that innovation, community, and corporate social responsibility (CSR) strategies had the most substantial influence on the bank’s performance. In contrast, indicators related to human rights and certain profitability metrics exhibited relatively lower weight. Ranking outputs indicated notable fluctuations in Bank of America’s ESG-P performance over the years, with 2019 emerging as the most successful year and 2008 as the least. Furthermore, sensitivity analyses validated the stability and reliability of the proposed hybrid decision-making framework.

Keywords

Banking sector, Sustainability performance, MCDM, LOPCOW, AROMAN

JEL Classification

C54, G17, G21, G32, G53.

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1. INTRODUCTION

Financial intermediaries play a central role in modern economies by facilitating the flow of funds between savers and borrowers and supporting the efficient functioning of financial systems. Among these intermediaries, banks remain the most influential actors due to their dominant position in credit creation, deposit mobilization, and payment services (Işık et al., 2025a). In recent years, however, the evaluation of banking performance has expanded beyond traditional financial indicators, as banks are increasingly expected to balance profitability with environmental responsibility, social accountability, and sound governance practices. This shift has driven the need for multidimensional performance assessment frameworks that can capture the sustainability-oriented transformation of banking activities.

The banking industry continues to play a crucial role in promoting economic growth, efficient capital allocation, and financial stability (Shabir et al., 2021). Through its core functions—such as fund allocation, credit intermediation, payment system management, and risk mitigation—banking directly affects both the real economy and the public sector (Işık et al., 2025b). However, globalization, digital transformation, and sustainability-oriented regulatory and policy frameworks have significantly reshaped the operational priorities of modern banks. Beyond their traditional intermediation role, banks are now expected to contribute to social development, environmental accountability, and effective corporate governance structures (Ayyagari et al., 2007; Işık, 2023). Consequently, assessing bank performance through a multidimensional sustainability perspective provides deeper insights not only into institutional success but also into the broader economic and societal impact of banking activities (McDonald and Lai, 2011). This growing complexity exposes the limitations of one-dimensional or purely financial evaluation approaches.

Within this evolving context, large and systemically important banks constitute an appropriate setting for examining multidimensional sustainability performance, as they simultaneously face intense market competition, regulatory scrutiny, and increasing stakeholder expectations. Institutions operating at this scale are required to align environmental, social, governance, and profitability objectives in a consistent and measurable manner. Moreover, sustainability-oriented strategic decisions—such as innovation investments, responsible financing, and governance reforms—play a critical role in enhancing long-term resilience and financial stability (Kim and Li, 2021; Cohen, 2023). Therefore, the longitudinal assessment of ESG-based performance in a major banking institution can offer valuable insights into how sustainability and profitability dimensions interact over time, particularly in response to economic shocks and structural transformations (Shen, 2024; Juthi et al., 2024).

Therefore, this study aims to propose a hybrid multi-criteria decision-making (MCDM) framework for investigating environmental, social, governance, and profitability (ESG-P) performance in the banking sector. The proposed framework integrates the Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) method and the Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN) to ensure an objective, consistent, and robust evaluation. To demonstrate the applicability and validity of the proposed framework, an empirical case study is conducted using the ESG-P indicators of Bank of America over the 2008–2021 period. Within this framework, LOPCOW is employed to derive the objective importance of ESG-P criteria, while AROMAN is utilized to obtain a time-sensitive ranking of performance across years. Based on this integrated approach, the study seeks to address the following research questions:

What is the analytical value of evaluating banks' environmental, social, governance, and profitability (ESG-P) performance within an integrated and multidimensional decision-making framework?

Which ESG-P dimensions and indicators exert the greatest and least influence on overall sustainability performance when objectively weighted using the LOPCOW method?

How does the ESG-P performance of a large banking institution evolve over time when assessed through the integrated LOPCOW–AROMAN framework?

How robust and stable are the resulting ESG-P performance rankings when subjected to alternative multi-criteria decision-making approaches and sensitivity scenarios?

The remainder of this paper is organized as follows: Section 2 presents a comprehensive review of the national and international literature on performance measurement in the banking sector. Section 3 presents the methodological framework of the study, while Section 4 presents the dataset and sampling procedure used in the analysis. Section 5 reports the empirical results obtained by implementing the proposed model. Section 6 presents a series of sensitivity analyses to demonstrate the robustness of the integrated decision model. Section 7 presents the discussion of the results obtained by applying the proposed model to a real-time case study. Finally, Section 8 offers overall conclusions, outlines the limitations of the study, and provides recommendations for future research.

2. LITERATURE REVIEW

This section reviews national and international empirical research that has assessed environmental, social, governance, and profitability (ESG-P) performance in the banking sector. The methodologies applied, sample characteristics, and key findings of the reviewed literature are presented comparatively in Table 1.

Table 1*Literature Review*

| Author(s) | Method(s) | Country | Sample |
|------------------------------------|----------------------------------|------------------------|---|
| Ozcelik and Ozturk (2014) | GIA | Turkey | The sustainability performance of three banks was assessed. |
| Raut et al., (2017) | Fuzzy AHP and Fuzzy TOPSIS | India | A comparative analysis was carried out on the sustainability performance of six large commercial banks |
| Omurbek et al., (2017) | Entropy, ARAS, MOOSRA and COPRAS | Turkey | The sustainability performance of the seven largest Turkish deposit-taking banks in terms of total assets was analysed. |
| Siew et al., (2017) | Equal Weight and TOPSIS | Malaysia | The performance of eight shares traded on the stock exchange was comparatively investigated. |
| Korzeb and Samaniego-Medina (2019) | TOPSIS | Poland | The performance of eight shares traded on the stock exchange was comparatively investigated. |
| Laha and Biswas (2019) | Entropy and CODAS | India | An assessment of the financial performance of ten banks was performed. |
| Yesmine et al., (2022) | VZA | Bangladesh | The performance and effectiveness of 20 banks with different ownership patterns were analysed. |
| Chaudhuri et al., (2023) | VZA | India | The contribution of ten private banks to environmental sustainability was examined. |
| Quynh (2023) | AHP and TOPSIS | Vietnam | The performance of four state-owned banks in terms of multidimensional sustainability has been assessed. |
| Sharma and Kumar (2024) | Entropy, TOPSIS and VIKOR | India | The banking industry has been subjected to a comprehensive multidimensional performance evaluation. |
| Akbulut (2024) | Grey LOPCOW and Grey PIV | Turkey | The environmental sustainability performance of six deposit-taking banks traded on the BIST was analysed. |
| Ali et al. (2024) | CRITIC ve RAFSI | Iraq | The financial sustainability performance of 19 banks was examined for the period 2007-2020. |
| Mastilo et al., (2024) | MEREC and MARCOS | Bosnia and Herzegovina | A study was carried out to comparatively analyze the financial performance of 21 banks. |
| Goel et al., (2024) | Equal Weight and GIA | India | The study used data from 10 banks to compare their performance. |
| Işık et al. (2025b) | F-LBWA, F-LMAW and MARCOS | Pakistan | An overall performance evaluation was conducted for 13 commercial banks. |
| Peci et al. (2025) | F-AHP and F-TOPSIS | Albania | A sample covering 8 financial indicators for 11 banks in 2020, 2021 and 2022 was employed. |

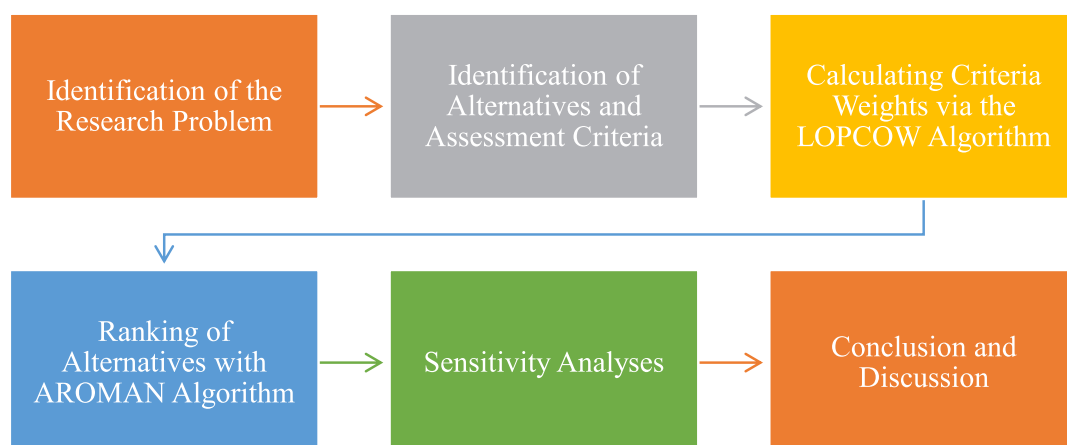
Although the existing literature demonstrates a growing reliance on MCDM approaches for evaluating banking performance, important methodological shortcomings remain unresolved. In particular, many prior studies predominantly employ subjective or semi-subjective weighting techniques (e.g., AHP, fuzzy AHP, expert-based methods), which may introduce evaluator bias into sustainability assessments. Even when objective weighting schemes are adopted, they are frequently combined with conventional ranking methods based on single-stage normalization, potentially limiting the stability and robustness of the resulting rankings. Moreover, the majority of existing frameworks rely on static, cross-sectional analyses and thus fail to capture the dynamic evolution of bank performance over time. Notably, fully integrated environmental, social, governance, and profitability (ESG-P) performance assessments that simultaneously employ objective weighting schemes and time-sensitive ranking structures remain scarce in the existing banking literature. To address these gaps, the present study integrates LOPCOW method with the AROMAN. LOPCOW enables the objective determination of criterion importance based on information dispersion and logarithmic variation, while AROMAN provides a robust and time-sensitive ranking mechanism through its two-step normalization structure. By combining these complementary methods within a longitudinal ESG-P performance evaluation framework, this study offers a more objective, stable, and comprehensive decision-support model compared to existing approaches in the banking sustainability literature.

3. METHODOLOGICAL FRAMEWORK

This work assesses the ESG-P-based performance of Bank of America, one of the leading banks in the United States, by employing a hybrid multi-criteria decision-making framework. The proposed assessment process integrates LOPCOW and AROMAN. The selection of LOPCOW and AROMAN is motivated not only by their technical properties but also by their practical relevance for sustainability assessment in the banking sector. LOPCOW enables the derivation of fully objective criterion weights by capturing logarithmic percentage changes and information dispersion, thereby minimizing subjective bias in the evaluation of ESG-P indicators. AROMAN, on the other hand, incorporates a two-step normalization structure that ensures stable and time-sensitive rankings, making it particularly suitable for longitudinal performance analysis. Compared to commonly used MCDM techniques, the integrated LOPCOW-AROMAN framework offers a more robust, transparent, and analytically consistent decision-support tool for practitioners and policymakers seeking to assess bank sustainability performance under dynamic conditions. The overall structure of the proposed decision framework is illustrated in Figure 1, and the subsequent sections present the implementation steps of the adopted decision algorithms in detail.

Figure 1

Research Framework of the Proposed ESG-P Performance Model



3.1. LOPCOW Objective Criteria Weighting Algorithm

The LOPCOW algorithm was introduced to the literature by Ecer and Pamucar (2022). This innovative decision algorithm is often used by decision makers to objectively weight assessment criteria. The LOPCOW methodology calculates the criterion weights based on the standard deviation values of the assessment criteria, thereby taking into account the discriminative power of each criterion (Demir, 2025). The key contribution of this algorithm lies in its ability to integrate the information richness and significance of each criterion from a statistical perspective. In doing so, it allows for a systematic assessment of both the variability between criteria and the divergence between alternatives, resulting in more objective weight values (Biswas et al., 2022; Işık et al., 2024). The computational procedure of the LOPCOW approach consists of the following four steps (Ecer and Pamucar, 2022; Işık et al., 2023).

Step 1. The decision matrix is constructed in accordance with Eq. (1).

$$X = [x_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2. The values in the decision matrix are normalised by taking into account the beneficial and non-beneficial characteristics of the criteria. Accordingly, Eq. (2) is applied for the beneficial criteria, while Eq. (3) is employed for the non-beneficial criteria.

$$r_{ij} = \frac{x_{ij} - \min_{ij}}{\max_{ij} - \min_{ij}} \quad (2)$$

$$r_{ij} = \frac{\max_{ij} - x_{ij}}{\max_{ij} - \min_{ij}} \quad (3)$$

Step 3. The percentage values and standard deviation values of the assessment criteria are calculated by means of Eq. (4) and Eq. (5), respectively.

$$PV_{ij} = \left| \ln \left| \frac{\sqrt{\frac{\sum_{i=1}^n r_{ij}^2}{n}}}{\sigma} \right| \right| \times 100 \quad (4)$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (r_{ij} - \bar{r}_j)^2}{m}} \quad (5)$$

Step 4. In the final phase of the LOPCOW algorithm, the objective weight values for each criterion are calculated based on Eq. (6).

$$w_j = \frac{PV_{ij}}{\sum_{j=1}^m PV_{ij}}; \sum_{j=1}^m w_j = 1 \quad (6)$$

Where, the highest weighted criterion is taken into account, it is considered to have the greatest impact on performance.

3.2. AROMAN Ranking Algorithm

AROMAN procedure, developed and introduced to the literature by Bošković et al., (2023), is applied to the ranking of decision alternatives. The main difference of the AROMAN procedure from other existing methodologies in the literature is that the normalization process is performed in two steps. In this way, it provides the decision maker with an average matrix for solving the decision problem. The application of the AROMAN procedure consists of the following 5 steps (Bošković et al., 2023; Bošković et al., 2024).

Step 1. The initial matrix introduced in Eq. (1) is prepared.

Step 2. The values in the decision matrix are normalized regardless of their characteristics. Eq. (7) is applied for the linear normalization of the decision matrix. Meanwhile, Eq. (8) is applied for the vectorial normalization of the decision matrix.

Step 2.1. Linear Normalization

$$t_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (7)$$

Step 2.2. Vectorial Normalization

$$t_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m (x_{ij})^2}} \quad (8)$$

Step 2.3. After the two-stage normalization process, the total average normalized matrix values are obtained from Eq. (9).

$$t_{ij}^{\text{norm}} = \frac{\beta t_{ij} + (1-\beta)t_{ij}^*}{2} \quad (9)$$

The coefficient β in the equation is a weighting coefficient that can take values between 0-1. This coefficient is generally accepted in the literature as 0.5.

Step 3. Weighted normalized matrix is created through Eq. (10).

$$t_{ij}^{\wedge} = w_{ij} \times t_{ij}^{\text{norm}} \quad (10)$$

Step 4. The sums of the weighted values are obtained according to the type of criteria (beneficial-non-beneficial). Accordingly, Eq. (11) is employed for the beneficial criteria and Eq. (12) for the non-beneficial criteria.

$$A_i = \sum_{j=1}^n t_{ij}^{\wedge(\max)} \quad (11)$$

$$L_i = \sum_{j=1}^n t_{ij}^{\wedge(\min)} \quad (12)$$

Step 5. At the end of the AROMAN procedure, Eq. (13) is used to derive the success scores of the alternatives and the success rankings based on these scores.

$$R_i = L_i^\lambda + A_i^{(1-\lambda)} \quad (13)$$

The parameter λ in the equation expresses the coefficient degree of the criterion type. As there are two types of criteria in the study, this parameter is taken as 0.5 in the calculations. In addition, the alternative with the highest success score is taken as the most successful.

4. DATA AND SAMPLE

The objective of this paper is to develop and apply a novel hybrid decision-making framework integrating LOPCOW and AROMAN to assess the ESG-P performance of Bank of America, which holds the highest brand value among banking institutions in the United States. The empirical analysis covers the period from 2008 to 2021 and is based on an annual data set comprising 14 consecutive years, allowing for a longitudinal evaluation of multidimensional sustainability performance. Bank of America represents a large, systemically important financial institution operating at the core of the U.S. and global financial system. Founded in 1904, the bank has evolved into the second-largest banking institution in the United States in terms of asset size, customer base, and market capitalization, while also maintaining a strong presence in sustainable finance initiatives. As a leading financial intermediary, the bank faces the dual challenge of sustaining financial performance while complying with increasingly stringent environmental, social, and governance requirements. In response, Bank of America has embedded ESG considerations into its corporate strategy, with particular emphasis on environmental accountability, community engagement, diversity, inclusive governance, and innovation-driven sustainability practices. Its proactive involvement in digital transformation, carbon emission reduction, and sustainable investment financing further supports its suitability as a representative case for ESG-P performance assessment. To capture the bank's multidimensional sustainability profile, a total of 14 performance indicators were selected based on their relevance in the sustainability performance literature and data availability. Annual data for all indicators were obtained from the Refinitiv Eikon database, ensuring consistency and reliability of the empirical inputs. Detailed definitions and descriptive information regarding the selected indicators are provided in Table 2.

Table 2
ESG-P Measures

| Rank | Type | Indicators | Code | Optimization |
|------|--------------------------|-----------------------------------|------|--------------|
| 1 | Environmental Indicators | Resource Use | E1 | Max. |
| 2 | | Emissions | E2 | Max. |
| 3 | | Innovation | E3 | Max. |
| 4 | Social Indicators | Workforce | S1 | Max. |
| 5 | | Human Rights | S2 | Max. |
| 6 | | Community | S3 | Max. |
| 7 | | Product Responsibility | S4 | Max. |
| 8 | Governance Indicators | Management | G1 | Max. |
| 9 | | Shareholders | G2 | Max. |
| 10 | | Corporate Social Responsibility | G3 | Max. |
| 11 | Profitability Indicators | NIM (Net Interest Margin) | P1 | Max. |
| 12 | | ROA (Return on Assets) | P2 | Max. |
| 13 | | ROE (Return on Equity) | P3 | Max. |
| 14 | | ROIC (Return on Invested Capital) | P4 | Max. |

5. FINDINGS OF THE RESEARCH

This section presents the results of the integrated decision model that combines the LOPCOW and AROMAN algorithms. First, the LOPCOW algorithm was utilized to obtain the relative importance of the assessment criteria, and the objective weight coefficients for each indicator were computed. The AROMAN approach was then employed to rank Bank of America's ESG-P performance for the period 2008-2021, based on the calculated weight coefficients.

5.1. Findings of the LOPCOW Algorithm

To identify the importance weights of the ESG-P performance indicators, the LOPCOW methodology was first used in the analysis process. In this context, the decision matrix was first constructed based on Eq. (1) and is displayed in Table 3.

Table 3
Decision Matrix

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|------|-------|------|
| 2008 | 75.00 | 55.76 | 42.50 | 70.05 | 20.46 | 77.48 | 87.13 | 87.80 | 49.65 | 58.94 | 2.98 | 0.59 | 1.82 | 1.34 |
| 2009 | 74.35 | 60.76 | 94.57 | 65.70 | 14.69 | 97.87 | 88.40 | 75.77 | 65.32 | 68.97 | 2.65 | 0.81 | -1.33 | 1.80 |
| 2010 | 78.68 | 62.13 | 90.63 | 69.73 | 18.55 | 98.15 | 60.31 | 88.09 | 73.23 | 82.31 | 2.78 | 0.30 | -1.77 | 0.67 |
| 2011 | 93.75 | 71.93 | 87.17 | 82.63 | 17.24 | 97.88 | 55.83 | 70.01 | 29.28 | 87.90 | 2.48 | 0.42 | 0.04 | 0.99 |
| 2012 | 94.55 | 73.62 | 85.93 | 80.81 | 15.83 | 96.60 | 57.44 | 71.07 | 25.15 | 85.14 | 2.35 | 0.48 | 1.29 | 1.22 |
| 2013 | 94.34 | 75.00 | 87.21 | 70.38 | 20.42 | 97.62 | 58.93 | 72.31 | 57.47 | 84.75 | 2.46 | 0.84 | 4.61 | 2.27 |
| 2014 | 94.49 | 82.68 | 89.20 | 68.64 | 31.15 | 99.54 | 63.57 | 16.33 | 57.16 | 85.92 | 2.25 | 0.49 | 1.71 | 1.41 |
| 2015 | 94.11 | 82.13 | 89.01 | 71.11 | 34.47 | 98.94 | 71.13 | 48.56 | 67.19 | 84.85 | 2.20 | 1.02 | 6.29 | 3.01 |
| 2016 | 96.44 | 81.84 | 87.56 | 84.81 | 29.93 | 99.02 | 76.76 | 42.13 | 65.81 | 95.61 | 2.25 | 0.81 | 6.82 | 3.36 |
| 2017 | 99.83 | 83.17 | 85.81 | 92.27 | 91.80 | 97.62 | 78.14 | 29.05 | 70.44 | 84.49 | 2.37 | 1.11 | 6.84 | 3.56 |
| 2018 | 99.86 | 84.69 | 83.84 | 84.43 | 87.40 | 97.66 | 77.74 | 39.97 | 78.87 | 95.30 | 2.42 | 1.68 | 10.94 | 5.52 |
| 2019 | 99.65 | 84.74 | 83.44 | 90.65 | 87.14 | 98.11 | 76.18 | 59.23 | 75.86 | 95.43 | 2.43 | 1.61 | 10.73 | 5.50 |
| 2020 | 96.26 | 85.42 | 79.40 | 97.87 | 87.37 | 98.45 | 74.27 | 57.58 | 77.34 | 97.29 | 1.90 | 0.84 | 6.73 | 3.11 |
| 2021 | 99.09 | 91.14 | 81.76 | 95.08 | 89.56 | 82.16 | 75.00 | 35.09 | 76.39 | 97.67 | 1.66 | 1.15 | 12.38 | 4.61 |

The chosen performance measures were normalized on the basis of their beneficial and non-beneficial characteristics, respectively, using Eq. (2). The results of the normalisation process are presented in Table 4.

Table 4
Normalized Decision Matrix

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 2008 | 0.03 | 0.00 | 0.00 | 0.14 | 0.07 | 0.00 | 0.96 | 1.00 | 0.46 | 0.00 | 1.00 | 0.21 | 0.25 | 0.14 |
| 2009 | 0.00 | 0.14 | 1.00 | 0.00 | 0.00 | 0.92 | 1.00 | 0.83 | 0.75 | 0.26 | 0.75 | 0.37 | 0.03 | 0.23 |
| 2010 | 0.17 | 0.18 | 0.92 | 0.13 | 0.05 | 0.94 | 0.14 | 1.00 | 0.90 | 0.60 | 0.85 | 0.00 | 0.00 | 0.00 |
| 2011 | 0.76 | 0.46 | 0.86 | 0.53 | 0.03 | 0.92 | 0.00 | 0.75 | 0.08 | 0.75 | 0.62 | 0.09 | 0.13 | 0.07 |
| 2012 | 0.79 | 0.50 | 0.83 | 0.47 | 0.01 | 0.87 | 0.05 | 0.76 | 0.00 | 0.68 | 0.52 | 0.13 | 0.22 | 0.11 |
| 2013 | 0.78 | 0.54 | 0.86 | 0.15 | 0.07 | 0.91 | 0.10 | 0.78 | 0.60 | 0.67 | 0.61 | 0.39 | 0.45 | 0.33 |
| 2014 | 0.79 | 0.76 | 0.90 | 0.09 | 0.21 | 1.00 | 0.24 | 0.00 | 0.60 | 0.70 | 0.45 | 0.14 | 0.25 | 0.15 |
| 2015 | 0.77 | 0.75 | 0.89 | 0.17 | 0.26 | 0.97 | 0.47 | 0.45 | 0.78 | 0.67 | 0.41 | 0.52 | 0.57 | 0.48 |
| 2016 | 0.87 | 0.74 | 0.87 | 0.59 | 0.20 | 0.98 | 0.64 | 0.36 | 0.76 | 0.95 | 0.45 | 0.37 | 0.61 | 0.55 |
| 2017 | 1.00 | 0.77 | 0.83 | 0.83 | 1.00 | 0.91 | 0.68 | 0.18 | 0.84 | 0.66 | 0.54 | 0.59 | 0.61 | 0.60 |
| 2018 | 1.00 | 0.82 | 0.79 | 0.58 | 0.94 | 0.91 | 0.67 | 0.33 | 1.00 | 0.94 | 0.58 | 1.00 | 0.90 | 1.00 |
| 2019 | 0.99 | 0.82 | 0.79 | 0.78 | 0.94 | 0.94 | 0.62 | 0.60 | 0.94 | 0.94 | 0.58 | 0.95 | 0.88 | 1.00 |
| 2020 | 0.86 | 0.84 | 0.71 | 1.00 | 0.94 | 0.95 | 0.57 | 0.57 | 0.97 | 0.99 | 0.18 | 0.39 | 0.60 | 0.50 |
| 2021 | 0.97 | 1.00 | 0.75 | 0.91 | 0.97 | 0.21 | 0.59 | 0.26 | 0.95 | 1.00 | 0.00 | 0.62 | 1.00 | 0.81 |

The percentages for each assessment criterion were calculated with the help of Eq. (4) and Eq. (5). The results of these calculations are given in Table 5.

Table 5
Matrix of Percentage Values

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 2008 | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 | 0.00 | 0.92 | 0.99 | 0.21 | 0.00 | 1.00 | 0.04 | 0.06 | 0.02 |
| 2009 | 0.00 | 0.02 | 1.00 | 0.00 | 0.00 | 0.85 | 1.00 | 0.69 | 0.56 | 0.07 | 0.56 | 0.14 | 0.00 | 0.05 |
| 2010 | 0.03 | 0.03 | 0.85 | 0.02 | 0.00 | 0.88 | 0.02 | 1.00 | 0.80 | 0.36 | 0.72 | 0.00 | 0.00 | 0.00 |
| 2011 | 0.58 | 0.21 | 0.74 | 0.28 | 0.00 | 0.86 | 0.00 | 0.56 | 0.01 | 0.56 | 0.39 | 0.01 | 0.02 | 0.00 |
| 2012 | 0.63 | 0.25 | 0.70 | 0.22 | 0.00 | 0.75 | 0.00 | 0.58 | 0.00 | 0.46 | 0.27 | 0.02 | 0.05 | 0.01 |
| 2013 | 0.61 | 0.30 | 0.74 | 0.02 | 0.01 | 0.83 | 0.01 | 0.61 | 0.36 | 0.44 | 0.37 | 0.15 | 0.20 | 0.11 |
| 2014 | 0.62 | 0.58 | 0.80 | 0.01 | 0.05 | 1.00 | 0.06 | 0.00 | 0.36 | 0.49 | 0.20 | 0.02 | 0.06 | 0.02 |
| 2015 | 0.60 | 0.56 | 0.80 | 0.03 | 0.07 | 0.95 | 0.22 | 0.20 | 0.61 | 0.45 | 0.17 | 0.27 | 0.32 | 0.23 |
| 2016 | 0.75 | 0.54 | 0.75 | 0.35 | 0.04 | 0.95 | 0.41 | 0.13 | 0.57 | 0.90 | 0.20 | 0.14 | 0.37 | 0.31 |
| 2017 | 1.00 | 0.60 | 0.69 | 0.68 | 1.00 | 0.83 | 0.47 | 0.03 | 0.71 | 0.44 | 0.29 | 0.34 | 0.37 | 0.36 |
| 2018 | 1.00 | 0.67 | 0.63 | 0.34 | 0.89 | 0.84 | 0.45 | 0.11 | 1.00 | 0.88 | 0.33 | 1.00 | 0.81 | 1.00 |
| 2019 | 0.98 | 0.67 | 0.62 | 0.60 | 0.88 | 0.87 | 0.39 | 0.36 | 0.89 | 0.89 | 0.34 | 0.90 | 0.78 | 0.99 |
| 2020 | 0.74 | 0.70 | 0.50 | 1.00 | 0.89 | 0.90 | 0.32 | 0.33 | 0.94 | 0.98 | 0.03 | 0.15 | 0.36 | 0.25 |
| 2021 | 0.94 | 1.00 | 0.57 | 0.83 | 0.94 | 0.05 | 0.35 | 0.07 | 0.91 | 1.00 | 0.00 | 0.38 | 1.00 | 0.66 |

In the final step of the LOPCOW methodology, the importance weights for each ESG-P indicator were determined applying Eq. (6). The weighting scores for the performance criteria are reported in Table 6.

Table 6
LOPCOW Results

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------------|-------|-------|--------|-------|-------|--------|-------|-------|-------|-------|-------|-------|-------|-------|
| Σ | 8.48 | 6.13 | 9.39 | 4.40 | 4.77 | 10.57 | 4.62 | 5.66 | 7.93 | 7.91 | 4.87 | 3.56 | 4.40 | 4.02 |
| Σ/m | 0.61 | 0.44 | 0.67 | 0.31 | 0.34 | 0.75 | 0.33 | 0.40 | 0.57 | 0.56 | 0.35 | 0.25 | 0.31 | 0.29 |
| σ_j | 0.36 | 0.30 | 0.24 | 0.34 | 0.43 | 0.31 | 0.33 | 0.31 | 0.32 | 0.28 | 0.25 | 0.30 | 0.33 | 0.34 |
| PV_{ij} | 78.19 | 78.38 | 123.66 | 49.54 | 29.82 | 104.38 | 56.47 | 72.29 | 86.16 | 97.18 | 85.40 | 50.99 | 53.88 | 46.60 |
| w_j | 0.08 | 0.08 | 0.12 | 0.05 | 0.03 | 0.10 | 0.06 | 0.07 | 0.09 | 0.10 | 0.08 | 0.05 | 0.05 | 0.05 |
| Sıra | 7 | 6 | 1 | 12 | 14 | 2 | 9 | 8 | 4 | 3 | 5 | 11 | 10 | 13 |

According to the weighting results obtained using the LOPCOW methodology, E3 (innovation) emerged as the most critical indicator in determining Bank of America's ESG-P performance over the 2008-2021 period. This outcome indicates that innovation-related activities constitute the most influential component within the bank's multidimensional sustainability structure. The innovation indicator was followed by S3 (community) and G3 (corporate social responsibility strategy), which ranked second and third, respectively. The relative prominence of these indicators suggests that dimensions associated with strategic adaptation, social embeddedness, and sustainability-oriented governance exert a stronger influence on ESG-P performance differentiation across years. In contrast, indicators such as S2 (human rights), P4 (return on invested capital), and S1 (workforce) received comparatively lower weights. This finding implies that, within the examined period, these criteria contributed less to distinguishing annual ESG-P performance outcomes under the objective weighting structure. Overall, the LOPCOW results reveal a weighting pattern in which innovation-led and community-oriented dimensions dominate the ESG-P evaluation framework, while certain social compliance and profitability-related indicators exhibit more limited discriminative importance.

5.2. Findings of the AROMAN Algorithm

In this stage of the present research, the weights obtained from the LOPCOW model were incorpo-

rated into the AROMAN model in order to compare the multidimensional performance of Bank of America across years. In the first step of the AROMAN procedure, the decision matrix was created based on Eq. (1) and is displayed in Table 1. The values in the decision matrix were then normalised without distinguishing between beneficial and npn-beneficial criteria. In this context, the criteria were linearly normalised by means of Eq. (7). The findings of the linear normalization are reported in Table 7.

Table 7
Linear Normalization

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 2008 | 0.03 | 0.00 | 0.00 | 0.14 | 0.07 | 0.00 | 0.96 | 1.00 | 0.46 | 0.00 | 1.00 | 0.21 | 0.14 | 0.14 |
| 2009 | 0.00 | 0.14 | 1.00 | 0.00 | 0.00 | 0.92 | 1.00 | 0.83 | 0.75 | 0.26 | 0.75 | 0.37 | 0.10 | 0.23 |
| 2010 | 0.17 | 0.18 | 0.92 | 0.13 | 0.05 | 0.94 | 0.14 | 1.00 | 0.90 | 0.60 | 0.85 | 0.00 | 0.14 | 0.00 |
| 2011 | 0.76 | 0.46 | 0.86 | 0.53 | 0.03 | 0.92 | 0.00 | 0.75 | 0.08 | 0.75 | 0.62 | 0.09 | 0.00 | 0.07 |
| 2012 | 0.79 | 0.50 | 0.83 | 0.47 | 0.01 | 0.87 | 0.05 | 0.76 | 0.00 | 0.68 | 0.52 | 0.13 | 0.10 | 0.11 |
| 2013 | 0.78 | 0.54 | 0.86 | 0.15 | 0.07 | 0.91 | 0.10 | 0.78 | 0.60 | 0.67 | 0.61 | 0.39 | 0.37 | 0.33 |
| 2014 | 0.79 | 0.76 | 0.90 | 0.09 | 0.21 | 1.00 | 0.24 | 0.00 | 0.60 | 0.70 | 0.45 | 0.14 | 0.14 | 0.15 |
| 2015 | 0.77 | 0.75 | 0.89 | 0.17 | 0.26 | 0.97 | 0.47 | 0.45 | 0.78 | 0.67 | 0.41 | 0.52 | 0.51 | 0.48 |
| 2016 | 0.87 | 0.74 | 0.87 | 0.59 | 0.20 | 0.98 | 0.64 | 0.36 | 0.76 | 0.95 | 0.45 | 0.37 | 0.55 | 0.55 |
| 2017 | 1.00 | 0.77 | 0.83 | 0.83 | 1.00 | 0.91 | 0.68 | 0.18 | 0.84 | 0.66 | 0.54 | 0.59 | 0.55 | 0.60 |
| 2018 | 1.00 | 0.82 | 0.79 | 0.58 | 0.94 | 0.91 | 0.67 | 0.33 | 1.00 | 0.94 | 0.58 | 1.00 | 0.88 | 1.00 |
| 2019 | 0.99 | 0.82 | 0.79 | 0.78 | 0.94 | 0.94 | 0.62 | 0.60 | 0.94 | 0.94 | 0.58 | 0.95 | 0.87 | 1.00 |
| 2020 | 0.86 | 0.84 | 0.71 | 1.00 | 0.94 | 0.95 | 0.57 | 0.57 | 0.97 | 0.99 | 0.18 | 0.39 | 0.54 | 0.50 |
| 2021 | 0.97 | 1.00 | 0.75 | 0.91 | 0.97 | 0.21 | 0.59 | 0.26 | 0.95 | 1.00 | 0.00 | 0.62 | 1.00 | 0.81 |

In the second stage, vector normalization was carried out by means of Eq. (8). The results of the vector normalisation calculations are presented in Table 8.

Table 8
Vector Normalization

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 2008 | 0.22 | 0.19 | 0.13 | 0.23 | 0.10 | 0.22 | 0.32 | 0.39 | 0.21 | 0.18 | 0.33 | 0.16 | 0.07 | 0.11 |
| 2009 | 0.21 | 0.21 | 0.30 | 0.22 | 0.07 | 0.27 | 0.33 | 0.33 | 0.27 | 0.21 | 0.30 | 0.23 | 0.05 | 0.15 |
| 2010 | 0.23 | 0.21 | 0.29 | 0.23 | 0.09 | 0.27 | 0.22 | 0.39 | 0.30 | 0.25 | 0.31 | 0.08 | 0.07 | 0.06 |
| 2011 | 0.27 | 0.25 | 0.28 | 0.27 | 0.08 | 0.27 | 0.21 | 0.31 | 0.12 | 0.27 | 0.28 | 0.12 | 0.00 | 0.08 |
| 2012 | 0.27 | 0.25 | 0.27 | 0.27 | 0.08 | 0.27 | 0.21 | 0.31 | 0.10 | 0.26 | 0.26 | 0.13 | 0.05 | 0.10 |
| 2013 | 0.27 | 0.26 | 0.28 | 0.23 | 0.10 | 0.27 | 0.22 | 0.32 | 0.24 | 0.26 | 0.27 | 0.23 | 0.19 | 0.19 |
| 2014 | 0.27 | 0.29 | 0.28 | 0.23 | 0.15 | 0.28 | 0.24 | 0.07 | 0.24 | 0.26 | 0.25 | 0.14 | 0.07 | 0.12 |
| 2015 | 0.27 | 0.28 | 0.28 | 0.23 | 0.16 | 0.28 | 0.26 | 0.21 | 0.28 | 0.26 | 0.25 | 0.28 | 0.26 | 0.25 |
| 2016 | 0.28 | 0.28 | 0.28 | 0.28 | 0.14 | 0.28 | 0.28 | 0.19 | 0.27 | 0.29 | 0.25 | 0.23 | 0.28 | 0.28 |
| 2017 | 0.29 | 0.29 | 0.27 | 0.30 | 0.44 | 0.27 | 0.29 | 0.13 | 0.29 | 0.26 | 0.26 | 0.31 | 0.28 | 0.30 |
| 2018 | 0.29 | 0.29 | 0.27 | 0.28 | 0.42 | 0.27 | 0.29 | 0.18 | 0.33 | 0.29 | 0.27 | 0.47 | 0.45 | 0.47 |
| 2019 | 0.29 | 0.29 | 0.26 | 0.30 | 0.41 | 0.27 | 0.28 | 0.26 | 0.32 | 0.29 | 0.27 | 0.45 | 0.44 | 0.47 |
| 2020 | 0.28 | 0.29 | 0.25 | 0.32 | 0.42 | 0.27 | 0.27 | 0.25 | 0.32 | 0.30 | 0.21 | 0.23 | 0.27 | 0.26 |
| 2021 | 0.29 | 0.31 | 0.26 | 0.31 | 0.43 | 0.23 | 0.28 | 0.15 | 0.32 | 0.30 | 0.19 | 0.32 | 0.51 | 0.39 |

Following the two-step normalisation process, the aggregated mean normalized matrix values were obtained via Eq. (9). As emphasised earlier, the β coefficient in Eq. (9) is a weighting factor that ranges between 0 and 1. A review of previous empirical research in the literature reveals that researchers generally take a value of 0.5 for this coefficient in their calculations. Accordingly, in line with the literature, β was also set at 0.5 in this paper. The findings of these calculations are presented in Table 9.

Table 9*Total Mean Normalized Matrix*

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 2008 | 0.12 | 0.10 | 0.07 | 0.18 | 0.09 | 0.11 | 0.64 | 0.69 | 0.33 | 0.09 | 0.67 | 0.19 | 0.11 | 0.13 |
| 2009 | 0.11 | 0.18 | 0.65 | 0.11 | 0.03 | 0.60 | 0.66 | 0.58 | 0.51 | 0.24 | 0.52 | 0.30 | 0.08 | 0.19 |
| 2010 | 0.20 | 0.20 | 0.61 | 0.18 | 0.07 | 0.61 | 0.18 | 0.69 | 0.60 | 0.43 | 0.58 | 0.04 | 0.11 | 0.03 |
| 2011 | 0.52 | 0.35 | 0.57 | 0.40 | 0.06 | 0.60 | 0.10 | 0.53 | 0.10 | 0.51 | 0.45 | 0.10 | 0.00 | 0.07 |
| 2012 | 0.53 | 0.38 | 0.55 | 0.37 | 0.04 | 0.57 | 0.13 | 0.54 | 0.05 | 0.47 | 0.39 | 0.13 | 0.08 | 0.11 |
| 2013 | 0.53 | 0.40 | 0.57 | 0.19 | 0.09 | 0.59 | 0.16 | 0.55 | 0.42 | 0.46 | 0.44 | 0.31 | 0.28 | 0.26 |
| 2014 | 0.53 | 0.52 | 0.59 | 0.16 | 0.18 | 0.64 | 0.24 | 0.04 | 0.42 | 0.48 | 0.35 | 0.14 | 0.10 | 0.14 |
| 2015 | 0.52 | 0.51 | 0.59 | 0.20 | 0.21 | 0.62 | 0.37 | 0.33 | 0.53 | 0.47 | 0.33 | 0.40 | 0.38 | 0.37 |
| 2016 | 0.57 | 0.51 | 0.57 | 0.44 | 0.17 | 0.63 | 0.46 | 0.27 | 0.52 | 0.62 | 0.35 | 0.30 | 0.41 | 0.42 |
| 2017 | 0.64 | 0.53 | 0.55 | 0.57 | 0.72 | 0.59 | 0.49 | 0.15 | 0.57 | 0.46 | 0.40 | 0.45 | 0.42 | 0.45 |
| 2018 | 0.64 | 0.55 | 0.53 | 0.43 | 0.68 | 0.59 | 0.48 | 0.25 | 0.66 | 0.62 | 0.42 | 0.73 | 0.66 | 0.73 |
| 2019 | 0.64 | 0.56 | 0.53 | 0.54 | 0.68 | 0.60 | 0.45 | 0.43 | 0.63 | 0.62 | 0.43 | 0.70 | 0.65 | 0.73 |
| 2020 | 0.57 | 0.57 | 0.48 | 0.66 | 0.68 | 0.61 | 0.42 | 0.41 | 0.65 | 0.65 | 0.20 | 0.31 | 0.41 | 0.38 |
| 2021 | 0.63 | 0.66 | 0.51 | 0.61 | 0.70 | 0.22 | 0.43 | 0.21 | 0.64 | 0.65 | 0.09 | 0.47 | 0.75 | 0.60 |

Based on Eq. (10), the weighted normalized matrix was established and is shown in Table 10.

Table 10*Weighted Normalized Matrix*

| | E1 | E2 | E3 | S1 | S2 | S3 | S4 | G1 | G2 | G3 | P1 | P2 | P3 | P4 |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 2008 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.04 | 0.05 | 0.03 | 0.01 | 0.06 | 0.01 | 0.01 | 0.01 |
| 2009 | 0.01 | 0.01 | 0.08 | 0.01 | 0.00 | 0.06 | 0.04 | 0.04 | 0.04 | 0.02 | 0.04 | 0.01 | 0.00 | 0.01 |
| 2010 | 0.02 | 0.02 | 0.07 | 0.01 | 0.00 | 0.06 | 0.01 | 0.05 | 0.05 | 0.04 | 0.05 | 0.00 | 0.01 | 0.00 |
| 2011 | 0.04 | 0.03 | 0.07 | 0.02 | 0.00 | 0.06 | 0.01 | 0.04 | 0.01 | 0.05 | 0.04 | 0.01 | 0.00 | 0.00 |
| 2012 | 0.04 | 0.03 | 0.07 | 0.02 | 0.00 | 0.06 | 0.01 | 0.04 | 0.00 | 0.05 | 0.03 | 0.01 | 0.00 | 0.00 |
| 2013 | 0.04 | 0.03 | 0.07 | 0.01 | 0.00 | 0.06 | 0.01 | 0.04 | 0.04 | 0.04 | 0.04 | 0.02 | 0.01 | 0.01 |
| 2014 | 0.04 | 0.04 | 0.07 | 0.01 | 0.01 | 0.07 | 0.01 | 0.00 | 0.04 | 0.05 | 0.03 | 0.01 | 0.01 | 0.01 |
| 2015 | 0.04 | 0.04 | 0.07 | 0.01 | 0.01 | 0.06 | 0.02 | 0.02 | 0.05 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 |
| 2016 | 0.04 | 0.04 | 0.07 | 0.02 | 0.01 | 0.06 | 0.03 | 0.02 | 0.04 | 0.06 | 0.03 | 0.01 | 0.02 | 0.02 |
| 2017 | 0.05 | 0.04 | 0.07 | 0.03 | 0.02 | 0.06 | 0.03 | 0.01 | 0.05 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 |
| 2018 | 0.05 | 0.04 | 0.06 | 0.02 | 0.02 | 0.06 | 0.03 | 0.02 | 0.06 | 0.06 | 0.04 | 0.04 | 0.04 | 0.03 |
| 2019 | 0.05 | 0.04 | 0.06 | 0.03 | 0.02 | 0.06 | 0.03 | 0.03 | 0.05 | 0.06 | 0.04 | 0.04 | 0.03 | 0.03 |
| 2020 | 0.04 | 0.04 | 0.06 | 0.03 | 0.02 | 0.06 | 0.02 | 0.03 | 0.06 | 0.06 | 0.02 | 0.02 | 0.02 | 0.02 |
| 2021 | 0.05 | 0.05 | 0.06 | 0.03 | 0.02 | 0.02 | 0.02 | 0.01 | 0.05 | 0.06 | 0.01 | 0.02 | 0.04 | 0.03 |

In the final step of the AROMAN algorithm, the sums of the values in the weighted normalized matrix were computed by taking into account the beneficial and non-beneficial features of the assessment criteria. Accordingly, Eq. (11) was applied to calculate the L_i values for the beneficial type indicators, while Eq. (12) was employed to obtain the A_i values for the non-beneficial type indicators. Finally, the performance score (R_i) for each alternative was calculated based on Eq. (13). The outputs of all these calculations are reported in Table 11.

Table 11
AROMAN Results

| | L_i | A_i | R_i | Rank |
|------|--------|--------|--------|------|
| 2008 | 0.0000 | 0.2469 | 0.4969 | 14 |
| 2009 | 0.0000 | 0.3859 | 0.6212 | 10 |
| 2010 | 0.0000 | 0.3873 | 0.6224 | 9 |
| 2011 | 0.0000 | 0.3666 | 0.6055 | 12 |
| 2012 | 0.0000 | 0.3599 | 0.5999 | 13 |
| 2013 | 0.0000 | 0.4219 | 0.6495 | 8 |
| 2014 | 0.0000 | 0.3778 | 0.6147 | 11 |
| 2015 | 0.0000 | 0.4514 | 0.6719 | 7 |
| 2016 | 0.0000 | 0.4787 | 0.6919 | 6 |
| 2017 | 0.0000 | 0.4976 | 0.7054 | 4 |
| 2018 | 0.0000 | 0.5618 | 0.7495 | 2 |
| 2019 | 0.0000 | 0.5734 | 0.7572 | 1 |
| 2020 | 0.0000 | 0.5034 | 0.7095 | 3 |
| 2021 | 0.0000 | 0.4891 | 0.6993 | 5 |

According to the ranking scores obtained using the AROMAN methodology, Bank of America's ESG-P performance exhibits notable fluctuations over the 2008–2021 period, reflecting the dynamic nature of multidimensional sustainability performance across time. The highest performance score is observed in 2019, followed by 2018, 2020, and 2017, indicating that the bank achieved a more balanced and effective alignment of environmental, social, governance, and profitability dimensions during these years. In contrast, the relatively lower rankings recorded in 2008 and the subsequent early years correspond to the peak of the global financial crisis, a period characterized by heightened financial instability and limited integration of sustainability-oriented strategies within banking operations. These results suggest that during crisis conditions, multidimensional ESG-P performance may deteriorate as financial pressures constrain strategic flexibility and sustainability investments.

6. SENSITIVITY AND COMPARATIVE ANALYSES

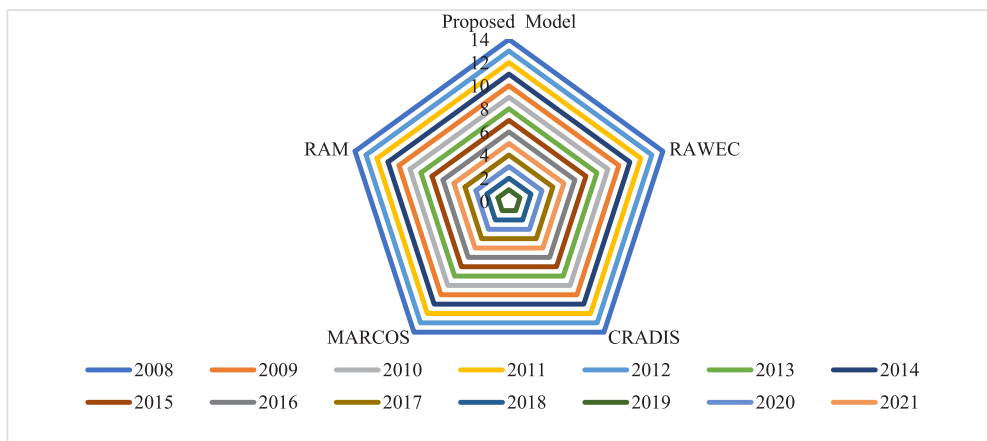
In MCDM-based analyses, sensitivity and comparative analyses are essential tools for ensuring methodological rigor and decision reliability. Sensitivity analysis involves systematically varying criteria weights or model parameters to assess the robustness and stability of the initial outcomes. On the other hand, comparative analysis involves evaluating the consistency of the initial results by comparing the suggested MCDM approach with other MCDM techniques. This not only validates the performance and reliability of the adopted methodology but also highlights its relative advantages or limitations. Together, these analyses contribute significantly to verifying the credibility, robustness, and practical applicability of the decision-making model, particularly in complex sustainability assessments (Işık and Adalar, 2025)

Assessing the robustness and reliability of the developed decision algorithm is crucial for the evaluation of ESG-P performance. In this case study, a comprehensive set of sensitivity analyses was performed to validate the conceptual framework proposed in this work. First, in order to show the consistency of the proposed integrated model, the ranking results obtained by the AROMAN procedure were compared with those obtained by other established decision-making methods. Secondly, the impact of changes in the λ parameter embedded in the AROMAN procedure on the ranking performance of decision alternatives was investigated.

6.1. Comparison of the Developed Model with Alternative Decision Frameworks

In this case study, the ranking results obtained by the proposed decision algorithm were compared with those generated by alternative multi-criteria decision methods commonly used by researchers in the literature, including RAWEC (Puška et al., 2024), CRADIS (Puška et al., 2022), MARCOS (Stević et al., 2020) and RAM (Sotoudeh-Anvari, 2023). The results of the comparative ranking are shown in Figure 2. Accordingly, the proposed conceptual model provides highly robust and reliable results, demonstrating its validity across different methodological frameworks.

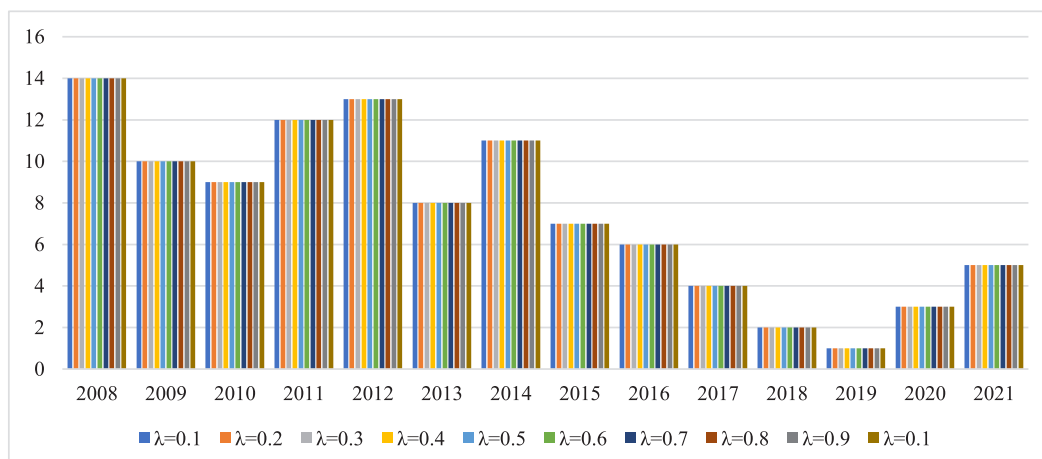
Figure 2
Rankings Based on Different MCDM Approaches



6.2. Analysis of the Effects of Variation of the λ Parameter on the Rankings in the AROMAN Approach

In the final part of the AROMAN procedure, the λ parameter was included in the ranking calculations with a value of 0.5, based on previous literature. However, this parameter can take different values in the range from 0 to 1. Therefore, in the final stage of the sensitivity analysis, the effect of variations in the λ parameter on the ranking of the decision alternatives was assessed. The results of this analysis are displayed in Figure 3. As indicated in Figure 3, variations in the λ parameter did not result in any change in the ranking of the alternative years. This result indicates that the proposed decision algorithm is consistent and reliable.

Figure 3
Re-Ranking of Alternatives Based on the λ Parameter



7. DISCUSSION

This study employed a hybrid multi-criteria decision-making (MCDM) framework, integrating the LOPCOW and AROMAN methods, to objectively evaluate the sustainability and profitability performance of Bank of America (BoA) over the 2008–2021 period. A total of 14 performance indicators were selected to assess Bank of America's sustainability and financial performance across four primary dimensions: Environmental, Social, Governance, and Profitability. Each indicator is treated as a maximization criterion, meaning higher values represent better performance. The findings from the weighting and ranking analyses offer critical insights into the evolving priorities in corporate sustainability and performance assessment.

The LOPCOW-based weightings reveal the relative importance of the 14 selected indicators under the ESG-P framework. Among all criteria, Environmental Innovation (E3) received the highest weight (0.12), signaling its pivotal role in shaping the bank's long-term sustainability profile. This reflects growing investor and regulatory pressure on financial institutions to foster environmentally innovative practices, such as green finance, carbon-conscious lending, and eco-friendly operational strategies. Other high-weight indicators include Community (S3) and CSR (G3), with weights of 0.10 each. These results emphasize the increasing relevance of social outreach and governance transparency, both of which contribute significantly to stakeholder trust and reputational capital. Conversely, traditional financial indicators like ROIC (P4) and Employee Welfare (S2) had comparatively lower weights (0.05 and 0.03 respectively), suggesting that their variability and impact across the years were less pronounced, or that they played a more stable, background role in overall performance.

The application of the AROMAN method to rank annual ESG-P performance produced nuanced results, reflecting BoA's varying success in integrating sustainability and profitability goals over time. The best-performing year was 2019, followed closely by 2018 and 2020. These years coincide with the bank's increased disclosure practices, robust CSR initiatives, and enhanced environmental funding commitments, aligning with its public sustainability pledges and improvements in stakeholder engagement. On the other hand, 2008, the year of the global financial crisis, recorded the lowest performance score, underscoring the vulnerability of ESG-P performance in periods of systemic financial distress. The years 2012 and 2011 also ranked among the lowest, suggesting that the bank's post-crisis restructuring period was marked by inconsistencies in sustainability efforts and profitability recovery. Notably, the middle-ranking years (2013–2017) represent a transitional phase, with steady yet moderate performance improvements as BoA worked to rebuild its ESG profile and align its operations with evolving sustainability standards.

The integration of the LOPCOW and AROMAN methods not only ensured objectivity and robustness in the analysis but also highlighted critical strategic areas for improvement. The results suggest that enhancing governance practices, fostering environmental innovation, and deepening community relations should remain central to BoA's long-term sustainability agenda. Additionally, the sharp contrast between the highest and lowest performing years demonstrates the importance of resilience and consistency in ESG-P efforts. The findings validate the usefulness of MCDM techniques in tracking longitudinal performance and identifying weak points in a firm's sustainability strategy.

8. CONCLUSION AND RECOMMENDATIONS

In today's context, the integrated assessment of environmental, social and governance (ESG) factors alongside financial performance is of strategic significance not only for corporate sustainability, but also for long-term value creation and stakeholder trust. For large institutions in the financial sector in particular, ESG performance has a direct impact on both market perception and corporate reputation. In this context, assessing ESG performance in conjunction with profitability indicators has become a paramount necessity, enabling companies to more effectively manage the relationship between their environmental and social impacts and financial success. This paper aims to assess the environmental,

social, governance and profitability (ESG-P) performance of Bank of America, one of the largest financial institutions in the United States, over the period 2008-2021. In this regard, the multidimensional performance of the bank was measured on an annual basis using 14 performance indicators chosen from the relevant literature. The LOPCOW procedure was applied to identify the weights of the criteria, while the AROMAN procedure was utilized to rank the alternative years. Both ESG-based corporate sustainability performance and financial performance indicators were analyzed in an integrated manner, and a decision support model sensitive to temporal changes was proposed.

The LOPCOW weighting process reveals pronounced differences in the relative importance of the ESG-P indicators considered in the analysis, underscoring the heterogeneous contribution of sustainability dimensions to overall bank performance. The results indicate that innovation emerges as the most influential indicator shaping the multidimensional sustainability performance of Bank of America over the 2008-2021 period. This finding suggests that innovation-oriented practices—particularly those related to environmental sustainability and strategic transformation—play a central role in enhancing the bank's ESG-P profile. Following innovation, community engagement and corporate social responsibility strategy also receive relatively high weights, implying that social embeddedness and strategically aligned CSR initiatives constitute key drivers of performance differentiation across years. In contrast, indicators such as human rights, return on invested capital, and workforce exhibit comparatively lower weights within the LOPCOW framework. This outcome indicates that these criteria contribute less to distinguishing ESG-P performance over time, reflecting lower informational content and discriminative power under an objective weighting structure. Overall, the weighting results demonstrate that ESG-P components do not contribute uniformly to sustainability assessment, with innovation-led and socially oriented indicators exerting a more decisive influence on multidimensional performance outcomes.

From a broader sectoral perspective, the prominence of innovation- and CSR-related indicators is consistent with prevailing trends in sustainable finance and contemporary banking practice. In recent years, banks have increasingly relied on innovation capacity, community-oriented initiatives, and strategically embedded CSR policies to strengthen reputational capital, address stakeholder expectations, and respond to evolving regulatory and societal pressures. Conversely, the relatively lower importance assigned to human rights and certain profitability indicators can be attributed to a high degree of regulatory standardization and compliance-driven convergence among large, well-regulated banking institutions, which constrains cross-temporal variability. Likewise, profitability measures such as return on invested capital may convey diminished informational value during periods characterized by macroeconomic volatility or heightened regulatory intervention. Taken together, these findings indicate that ESG-P performance differentiation in major banks is increasingly driven by innovation-centered and socially embedded strategies rather than by traditionally standardized financial or compliance-oriented indicators.

The ranking, based on the AROMAN approach, revealed that Bank of America's ESG-P performance showed significant fluctuations during the time period from 2008 to 2021. The year 2019 stood out with the highest performance score, followed by 2018, 2020 and 2017, implying that the bank demonstrated a more balanced and impactful performance across environmental, social, governance and profitability dimensions during these years. In comparison, the years after 2008, which coincided with the aftermath of the global financial crisis, were characterized by relatively low performance scores. In this regard, the AROMAN methodology not only provided a ranking of alternatives, but also allowed for a time-sensitive analysis of the bank's performance, allowing for the identification of both improvements and deteriorations over time. Building upon these temporal ranking outcomes, the observed performance patterns provide broader insights into the evolving role of sustainability-oriented strategies in large banking institutions. The superior ESG-P performance achieved in later years reflects the gradual institutionalization of environmental, social, and governance considerations within corporate decision-making, as well as the increasing alignment between sustainability initiatives and financial objectives. From a managerial perspective, these findings suggest that sustained

investments in innovation, community engagement, and strategically embedded CSR practices can enhance a bank's ability to achieve balanced performance across ESG and profitability dimensions. Moreover, from a methodological standpoint, the ability of the AROMAN approach to capture such temporal dynamics reinforces its suitability as a decision-support tool for evaluating sustainability performance under changing economic and regulatory conditions. Consequently, the proposed hybrid LOPCOW-AROMAN framework offers not only a robust ranking mechanism but also a valuable analytical lens for understanding the long-term evolution of bank sustainability performance.

The sensitivity analyses carried out in the final phase of the research provided important insights into the robustness of the proposed decision-making framework. Firstly, the ranking scores obtained by the AROMAN algorithm were compared with those created by other decision-making methodologies widely available in the literature, and a high degree of consistency was identified. This finding reinforces the methodological reliability of the model. Secondly, the effect of changes in the λ parameter embedded in the AROMAN procedure was investigated in relation to the ranking results. It was observed that changes in the value of λ , within the range of 0 to 1, did not cause any changes in the ranking of the alternative years. This result indicates that the proposed decision strategy is highly stable with respect to parameter sensitivity, and provides reliable results for decision makers.

Despite the methodological robustness of the proposed hybrid LOPCOW-AROMAN framework, several limitations of this study should be acknowledged. First, the empirical analysis is confined to a single large banking institution, Bank of America, which may limit the generalizability of the findings to other banks with different ownership structures, regulatory environments, or business models. While the selected case represents a systemically important and highly visible financial institution, extending the analysis to a multi-bank or cross-country sample would allow for more comprehensive benchmarking and comparative assessment across heterogeneous banking systems. Second, the selection of ESG and profitability indicators was guided by data availability and established practices in the sustainability performance literature. Although this approach ensures consistency and replicability, alternative indicator sets or the inclusion of additional qualitative ESG dimensions could potentially lead to different weighting structures and ranking outcomes. Future studies may therefore explore the sensitivity of ESG-P performance assessments to alternative indicator specifications and data sources. Third, from a methodological perspective, this study employs the LOPCOW method for objective weighting and the AROMAN approach for performance ranking. While this combination offers notable advantages in terms of objectivity, robustness, and temporal sensitivity, the integration of alternative weighting and ranking techniques—such as entropy-based, distance-based, or outranking methods—could further enrich comparative methodological insights. Conducting large-scale robustness and consensus analyses across multiple MCDM frameworks would provide deeper evidence regarding the stability of sustainability performance rankings. Finally, future research could benefit from integrating advanced analytical tools, including modern time-series techniques and artificial intelligence-driven decision support systems, to capture non-linear dynamics and long-term structural changes in ESG performance. Such extensions would not only enhance the predictive and explanatory power of sustainability assessments but also contribute to the development of more adaptive and forward-looking decision-support models in the banking and finance literature.

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