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Evaluating ESG-Based Sustainability in Software Companies: A Performance Analysis Using MPSI-OPLO-POCOD Framework

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ABSTRACT

In today's world, companies are restructuring their operations focusing on Environmental, Social, and Governance (ESG) criteria to build a sustainable economy. In this context, efforts to meet sustainability requirements are increasingly on the rise. By establishing a sustainable financial performance structure, companies are enhancing their efforts to gain both short-term and long-term competitive advantages. This research explores ESG-based sustainable performance analysis, supported by practical applications. Additionally, a model based on *Multi-Criteria Decision-Making* (MCDM) is proposed, and an approach for sustainable performance analysis is implemented in this study. The *Modified Preference Selection Index-Opportunity Losses-Based Polar Coordinate Distance* (MPSI-OPLO-POCOD) method is used for performance analysis in this research. In this method, the MPSI approach applies objective criteria weighting to determine the importance of different factors, while the OPLO-POCOD method is used to derive the performance values and rankings of companies. The performance levels for 17 software companies listed in the S&P 500 index for 2021, 2020, 2019, and 2018 are determined using the MPSI-OPLO-POCOD method. Four applications are conducted within this scope. The decision model for the research includes ESG scores and financial ratios as the criteria. In the application results, the most important criteria for the years 2021, 2020, 2019, and 2018 are identified as *Return on Equity* (ROE), *ROE*, *Tobin Q Ratio*, and *Earnings Before Interest, Taxes, Depreciation, and Amortization* (EBITDA), respectively. In the performance rankings of software companies, the companies with the highest performance levels for the years 2021, 2020, 2019, and 2018 are identified as PTC Inc (PTC.OQ), Autodesk Inc (ADSK.OQ), Cadence Design Systems Inc (CDNS.OQ), and Autodesk Inc (ADSK.OQ), respectively. Furthermore, the research includes assessments of performance changes before and after the COVID-19 period. The application results are also validated through sensitivity analyses.

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1. Introduction

Environmental, Social, and Governance (ESG) considerations have become increasingly significant in the contemporary economic landscape. There is a growing acknowledgment that corporations must integrate sustainability and ethical responsibilities alongside financial performance. As global challenges such as climate change, resource depletion, poor labor conditions, and corporate misconduct intensify, businesses are expected to adopt more ethical and accountable practices. In response to these concerns, stakeholders and investors are closely monitoring corporate engagement in social and environmental responsibilities and evaluating investment strategies. Consequently, there is an increasing preference for companies that align with sustainability principles and demonstrate adherence to ESG standards [1].

ESG-focused investments have attracted significant investor interest, particularly due to their demonstrated resilience during market volatility and economic uncertainty. Companies that integrate ESG principles into their operations gain a strategic advantage by prioritizing long-term sustainability objectives over short-term financial gains. Empirical research indicates that ESG considerations have evolved into a widely adopted investment strategy, with firms aligning their practices to meet the increasing demands of investors and stakeholders. This alignment not only enhances corporate reputation, but also contributes to financial sustainability.

However, the existing literature presents mixed findings regarding the impact of ESG activities on corporate performance. While some studies highlight a positive correlation between ESG practices and financial performance, others report negative or statistically insignificant relationships. These inconsistencies can be attributed to several factors, including the lack of standardized ESG reporting frameworks, industry-specific differences, and variations in market maturity between developed and emerging economies [2].

The positive impact of ESG practices is often examined through the lens of Stakeholder Theory, which posits that firms have obligations not only to shareholders but also to employees, customers, and broader stakeholder groups. From this perspective, ESG initiatives strengthen stakeholder relations, ultimately enhancing long-term corporate performance [3]. Additionally, Resource Dependency Theory suggests that ESG can serve as a strategic asset, creating financial advantages for firms. ESG-oriented practices—such as reducing environmental emissions, promoting workplace safety and equal opportunity, and ensuring strong corporate governance—can lead to higher credit ratings, lower financing costs, and improved investment returns [4]. Moreover, ESG engagement plays a critical role in risk management by mitigating stock price volatility and reducing default risk.

Conversely, Agency Theory presents a more skeptical view, arguing that ESG investments may have an adverse effect on profitability. According to this perspective, managers might allocate resources to ESG initiatives for personal reputation gains rather than for the firm's financial benefit, potentially leading to economic inefficiencies due to excessive costs. Despite this critique, the prevailing consensus in the literature supports the notion that ESG activities positively contribute to corporate performance over the long term, aligning with sustainability principles and fostering value creation for firms [5].

In this study, a Multi-Criteria Decision-Making (MCDM) approach is adopted for performance analysis, aiming to utilize decision model-based analysis. The primary motivation of the research is to determine company performance based on the importance levels of criteria using MCDM methods. The main objective is to assess the performance of software companies listed in the S&P 500 over four years—pre-COVID-19, during COVID-19, and post-COVID-19—using the MPSI (Modified Preference Selection Index)-OPLO-POCOD (Opportunity Losses-Based Polar Coordinate Distance) method. The MPSI method [6] facilitates the determination of criterion weights through an objective weighting approach [7], while OPLO-POCOD is employed for performance ranking [8].

This paper consists of six sections. Section 2 presents the literature review, while Section 3 explains the MPSI-OPLO-POCOD method and outlines the research methodology. Section 4 applies performance analyses to 17 companies for 2021, 2020, 2019, and 2018. Section 5 discusses the research findings, key insights, and sensitivity analyses, whereas Section 6 concludes the study with final remarks.

2. Literature Review

This paper provides a comprehensive overview of the diverse applications of MCDM methods in performance evaluation across various industries. It highlights the growing significance of MCDM techniques in balancing returns, risk, and sustainability objectives, particularly in ESG assessments.

The studies referenced illustrate how hybrid MCDM approaches enhance decision-making precision in banking, energy, e-commerce, manufacturing, hospitality, tourism, and finance. These methodologies facilitate stakeholder-oriented evaluations, improve transparency, and accommodate sector-specific complexities. For example, Işık *et al.* [9] integrate F-LBWA, F-LMAW, and MARCOS to assess bank performance, while Molavi *et al.* [10] employ Entropy, TOPSIS, fuzzy DEMATEL, and ANP to analyze open service innovation in the banking sector of developing economies.

Similarly, Tan *et al.* [11] introduced a novel hybrid method SOCP with MCDM to evaluate UK hotel sector performance, offering actionable policy recommendations. Other scholars, including Wang *et al.* [12], Lam *et al.* [13], and Akdemir & Simsek [14], apply TODIM, Entropy, CRITIC, COPRAS, and ARAS to assess oil companies, financial institutions, and e-commerce giants like Amazon.

Further contributions from Makki & Alqahtani [15], Ersoy [16], and Baydaş et al. [17] emphasize hybrid MCDM models in evaluating the Saudi energy sector, Fortune 500 firms, and 140 manufacturing companies, respectively. Additionally, Peng *et al.* [18] and Sofiane *et al.* [19] leverage ANP, Fuzzy TOPSIS, and Delphi-based methods to analyze rural homestays in China and water supply services in Algeria.

The extensive application of MCDM techniques, such as PROMETHEE, FUCA, VIKOR, WASPAS, and MOORA, as seen in the works of Baydaş & Pamucar [20], Ghosh & Bhattacharya [21], and Kumaran *et al.* [22], underscores their role in sector-wide performance assessments. Ecer & Pamucar [23] further extend this research by applying LOPCOW and DOBI methods to analyze banking sector performance in developing countries.

Finally, Deng *et al.* [24] demonstrate the adaptability of MCDM and DEA methodologies in assessing power system sustainability, reflecting the broader applicability of MCDM approaches across corporate governance, finance, and sustainable development domains. These studies affirm the methodological robustness of MCDM approaches, reinforcing their efficacy in performance measurement, strategic decision-making, and ESG-driven corporate evaluations. Table 1 presents the literature review from the perspectives of methodology and sector.

Table 1
Literature review.

Studies	*Sector*	*MCMD Methods*
Wang *et al.* [12]	Oil company	TODIM
Lam *et al.* [13]	Financial Sector	Entropy, F-TOPSIS
Akdemir & Simsek [14]	E-commerce	Hybrid MCDM
Makki & Alqahtani [15]	Energy	Hybrid MCDM
Ersoy [16]	Retail & Trade	LOPCOW, RSMVC
Baydas *et al.* [17]	Manufacturing	SWARA, FUCA, CRADIS
Peng *et al.* [18]	Rural Homestays	CLFPR-Based ANP, F- TOPSIS
Sofiane *et al.* [19]	Water Supply Service	Hybrid MCDM
Demir [25]	Insurance	PSI-SD-MABAC
Demir [26]	Banking	LMAW-DNMA
Demir [27]	Banking	SWARA-RAFSI
Demir [28]	Banking	ROC-ITARA-CODAS
Demir [29]	Cement	F-SWARA-COPRAS-MAUT
Kara & Gezen [30]	Transportation and Storage	DEA
Ghosh & Bhattacharya [21]	Hospitality and Tourism	MEREC, CoCoSo
Kumaran *et al.* [22]	IPO Firms	VIKOR, CRITIC
Singh et al. [31]	Third-Party Logistics	CRITIC, MOORA, COPRA
Hsu *et al.* [32]	Electronics Manufacturing	Hybrid MCDM
Liang *et al.* [33]	Telecommunications	Hybrid MCDM
Lin *et al.* [34]	Global Shipping Industry	Hybrid MCDM
Liew *et al.* [35]	Financial	Entropy-DEMATEL, TOPSIS
Okudan *et al.* [36]	Construction	F-VIKOR
Trung et al. [37]	Banking	Hybrid MCDM
Ecer & Pamucar [23]	Banking	LOPCOW, DOBI
Deng *et al.* [24]	Power System	Hybrid MCDM
Kara *et al.* [38]	Sustainability Index	IVSF-RBNAR
Kara *et al.* [39]	Sustainability Index	MEREC-RBNAR
Kara *et al.* [40]	Technology	SVN-CIMAS-CRITIC-RBNAR

3. Methodology

The MPSI-OPLO-POCOD method is utilized in this research for performance analysis due to its ability to provide objective criteria weighting through the MPSI method, while the OPLO-POCOD method allows for performance ranking based on opportunity achievement levels in the alternative set. This approach enables the derivation of more robust and reliable results for performance analysis. For the implementation of the MPSI-OPLO-POCOD method, a decision model is required initially. As the study aims to assess Sustainability Performance Based on ESG, a set of criteria that includes ESG scores and financial ratios is defined, and companies are selected for the alternative set. After the initial decision matrices for the model are constructed, the MPSI-OPLO-POCOD method is applied in two stages. In Stage 1, five steps of the MPSI method are applied to derive the criteria weight matrix. In Stage 2, ten steps of the OPLO-POCOD method are implemented to determine the performance values of the companies. The results are then evaluated through the criteria weight matrix and the percentage of opportunity achievement matrix. Fig. 1 illustrates the methodological framework for the MPSI-OPLO-POCOD method. In the methodology section, the steps of the MPSI-OPLO-POCOD method are explained sequentially, and at the end of the section, these steps are presented in algorithmic form.

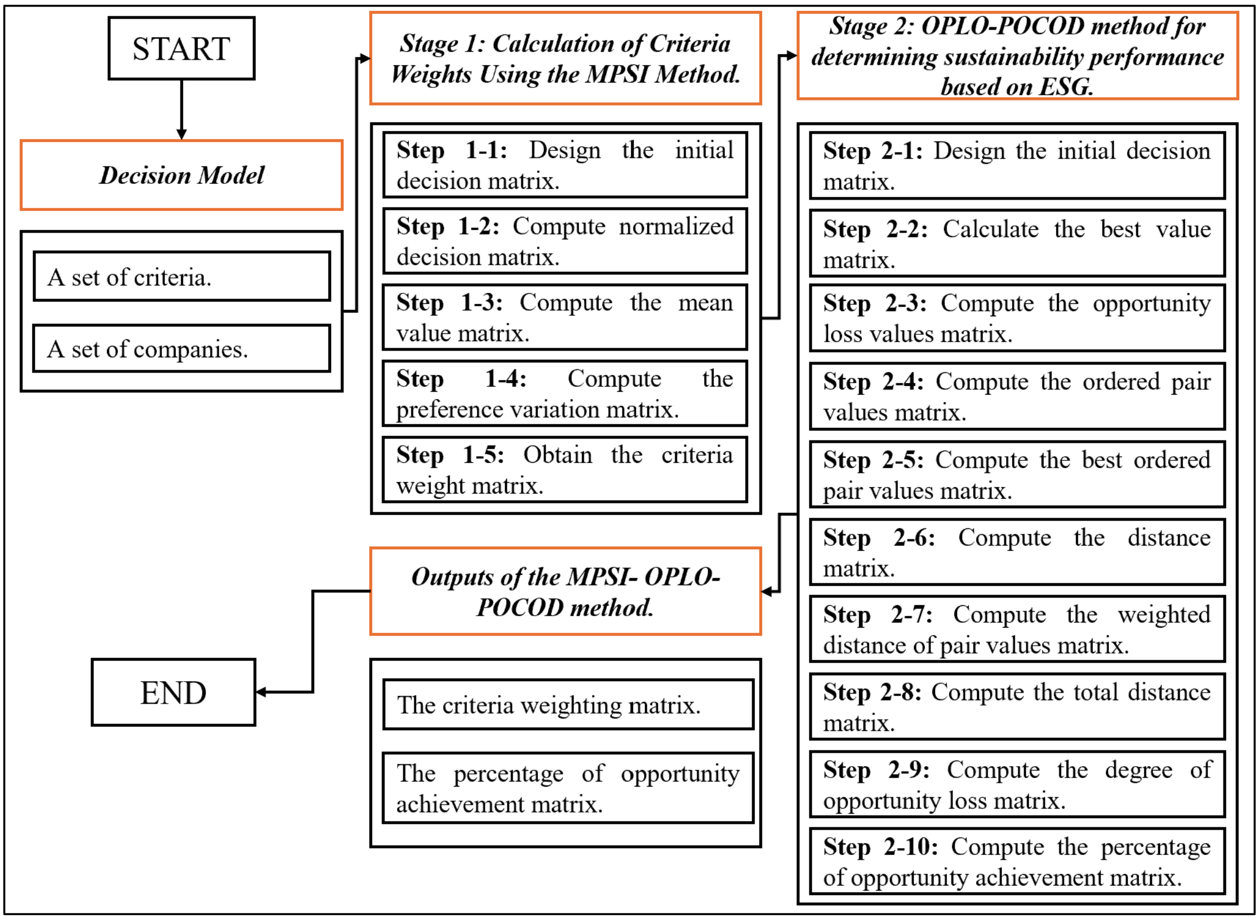

Fig. 1. The framework of methodology.

3.1 MPSI-OPLO-POCOD Method for ESG based Performance

In this research, the MPSI-OPLO-POCOD method is proposed for calculating sustainability performance based on ESG. This method utilizes company data to perform criteria weighting using the MPSI method, and similarly, to determine and rank companies' sustainable performances using the OPLO-POCOD method. The decision model in this method comprises criteria and alternatives, where criteria are defined as ESG scores and financial ratios. The criterion set is denoted as $\kappa = \{\kappa_1, \kappa_2, \dots, \kappa_{b}, \dots, \kappa_{\mathcal{B}}\}$ $(b = 1,2,\dots,\mathcal{B})$, while the alternative set is denoted as $\mathring{A} = \{\mathring{A}_1, \mathring{A}_2, \dots, \mathring{A}_{s}, \dots, \mathring{A}_{\mathcal{S}}\}$ $(s = 1,2,\dots,\mathcal{S})$. Definitions of the notations used in the MPSI-OPLO-POCOD method are presented in the Appendix. This method consists of two stages, each characterized by the following steps.

Stage 1: *Calculation of Criteria Weights Using the MPSI Method* [6]:

Step 1-1: To calculate the criteria weighing, the initial decision matrix must first be constructed. In the initial decision matrix, the values for each alternative are determined based on the criteria. Subsequently, the initial decision matrix $(\mathbb{X} = [\mathbb{X}_{sb}]_{\mathcal{S}\mathcal{B}})$ is formulated.

Step 1-2: To standardize the initial decision matrix, the MPSI method is applied for normalization. As a result, the normalized decision matrix ($\mathbb{Y} = [\mathbb{Y}_{sb}]_{\mathcal{SB}}$) is obtained. Eq. (1) is used to determine the normalized values.

$$\mathbb{Y}_{sb} = \begin{cases} \frac{\mathbb{X}_{sb}}{\max\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{X}_{sb})} \; for \; b \in \kappa^{+} \\ \frac{\min\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{X}_{sb})}{\mathbb{X}_{sb}} \; for \; b \in \kappa^{-} \end{cases} ; (s = 1,2,\ldots,\mathcal{S}; b = 1,2,\ldots,\mathcal{B}). \quad (1)$$

Step 1-3: Eq. (2) is applied to determine the mean value based on the normalized decision matrix. Consequently, the mean value matrix ($\mathbb{Z} = [\mathbb{Z}_{b}]_{\mathcal{B}}$) is obtained. This matrix is prepared for use in calculating preference variation values.

$$\mathbb{Z}_{b} = \frac{1}{\mathcal{S}}\sum_{s=1}^{\mathcal{S}} \mathbb{Y}_{sb} \; ; (s = 1,2,\ldots,\mathcal{S}; b = 1,2,\ldots,\mathcal{B}). \quad (2)$$

Step 1-4: The sum of the squared distances between the normalized values and the mean value is calculated using Eq. (3) to determine the preference variation value. Consequently, the preference variation matrix ($\mathbb{V} = [\mathbb{V}_{b}]_{\mathcal{B}}$) is obtained. This matrix is then used to compute the criteria weights.

$$\mathbb{V}_{b} = \sum_{s=1}^{\mathcal{S}}(\mathbb{Y}_{sb} - \mathbb{Z}_{b})^2 \; ; (s = 1,2,\ldots,\mathcal{S}; b = 1,2,\ldots,\mathcal{B}). \quad (3)$$

Step 1-5: To determine the final criteria weights, a linear normalization process is applied. Each preference variation value is divided by the total preference variation value using Eq. (4). Consequently, the criteria weight matrix ($\mathbb{W} = [\mathbb{W}_{b}]_{\mathcal{B}}$) is obtained.

$$\mathbb{W}_{b} = \frac{\mathbb{V}_{b}}{\sum_{b=1}^{\mathcal{B}} \mathbb{V}_{b}} \; ; (b = 1,2,\ldots,\mathcal{B}). \quad (4)$$

Stage 2: *OPLO-POCOD method for determining sustainability performance based on ESG* [8]:

Step 2-1: The initial decision matrix, which is created for the MPSI criteria weighting method and represents the criterion-based values of each alternative, is also used as the initial decision matrix ($\mathbb{X} = [\mathbb{X}_{sb}]_{\mathcal{SB}}$) for the OPLO-POCOD method, as presented in Step 1-1.

Step 2-2: In the OPLO-POCOD method, calculating opportunity loss values requires determining the best values. The best value for each criterion is computed using Eq. (5). Consequently, the best value matrix ($\mathbb{U} = [\mathbb{U}_{b}]_{\mathcal{B}}$) is obtained.

$$\mathbb{U}_{b} = \begin{cases} \max\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{X}_{sb}) \; for \; b \in \kappa^{+} \\ \min\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{X}_{sb}) \; for \; b \in \kappa^{-} \end{cases} ; (s = 1,2,\ldots,\mathcal{S}; b = 1,2,\ldots,\mathcal{B}). \quad (5)$$

Step 2-3: Calculating the ordered pair values requires the computation of opportunity loss values. Therefore, Eq. (6) is applied to determine the opportunity loss values. Consequently, the opportunity loss values matrix ($\mathbb{T} = [\mathbb{T}_{sb}]_{\mathcal{SB}}$) is obtained.

$$\mathbb{T}_{sb} = |\mathbb{X}_{sb} - \mathbb{U}_{b}| ; (s = 1,2,\ldots,\mathcal{S}; b = 1,2,\ldots,\mathcal{B}). \quad (6)$$

Step 2-4: In the OPLO-POCOD method, alternative rankings are determined based on the ordered pair values. Eq. (7) is applied to compute the ordered pair values, resulting in the ordered pair values matrix ($\mathbb{S} = [\mathbb{S}_{sb}]_{\mathcal{SB}}$).

$$\mathbb{S}_{sb} = (\mathbb{X}_{sb}, \mathbb{T}_{sb}) ; (s = 1,2,\ldots,\mathcal{S}; b = 1,2,\ldots,\mathcal{B}). \quad (7)$$

Step 2-5: The best ordered pair value within the ordered pair values matrix are determined by applying Eq. (8). Consequently, the best ordered pair values matrix ($\mathbb{R} = [\mathbb{R}_{b}]_{\mathcal{B}}$) is obtained.

$$\mathbb{R}_{b} = \begin{cases} \left(\left(\max\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{X}_{sb})\right), \left(\min\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{T}_{sb})\right)\right) \; for \; b \in \kappa^{+} \\ \left(\left(\min\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{X}_{sb})\right), \left(\min\limits_{1\leq\cdots<s<\cdots\leq\mathcal{S}}(\mathbb{T}_{sb})\right)\right) for \; b \in \kappa^{-} \end{cases} ; (s = 1,2,\ldots,\mathcal{S}; b = 1,2,\ldots,\mathcal{B}). \quad (8)$$

Step 2-6: Using the best ordered pair value, the distances are calculated by applying Eq. (9). Consequently, the distance matrix ($\mathbb{Q} = [\mathbb{Q}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) is obtained.

$$\mathbb{Q}_{\mathcal{s}\mathcal{b}} = \begin{cases} \sqrt{\left(\mathbb{X}_{\mathcal{s}\mathcal{b}} - \left(\max_{1\leq\cdots<\mathcal{s}<\cdots\leq\mathcal{S}}(\mathbb{X}_{\mathcal{s}\mathcal{b}})\right)\right)^2 + \left(\mathbb{T}_{\mathcal{s}\mathcal{b}} - \left(\min_{1\leq\cdots<\mathcal{s}<\cdots\leq\mathcal{S}}(\mathbb{T}_{\mathcal{s}\mathcal{b}})\right)\right)^2} & for\ \mathcal{b} \in \kappa^+ \\ \sqrt{\left(\mathbb{X}_{\mathcal{s}\mathcal{b}} - \left(\min_{1\leq\cdots<\mathcal{s}<\cdots\leq\mathcal{S}}(\mathbb{X}_{\mathcal{s}\mathcal{b}})\right)\right)^2 + \left(\mathbb{T}_{\mathcal{s}\mathcal{b}} - \min_{1\leq\cdots<\mathcal{s}<\cdots\leq\mathcal{S}}(\mathbb{T}_{\mathcal{s}\mathcal{b}})\right)^2} & for\ \mathcal{b} \in \kappa^- \end{cases}; (\mathcal{s} = 1,2,\dots,\mathcal{S}; \mathcal{b} = 1,2,\dots,\mathcal{B}). \quad (9)$$

Step 2-7: Using the weights of criteria calculated by the MPSI method, Eq. (10) is applied to obtain the weighted distance of pair values matrix ($\mathbb{P} = [\mathbb{P}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$).

$$\mathbb{S}_{\mathcal{s}\mathcal{b}} = \mathbb{W}_{\mathcal{b}}\mathbb{Q}_{\mathcal{s}\mathcal{b}}; (\mathcal{s} = 1,2,\dots,\mathcal{S}; \mathcal{b} = 1,2,\dots,\mathcal{B}). \quad (10)$$

Step 2-8: To calculate the degree of opportunity loss values, the total distances are computed using Eq. (11), resulting in the total distance matrix ($\mathbb{O} = [\mathbb{O}_{\mathcal{s}}]_{\mathcal{S}}$).

$$\mathbb{O}_{\mathcal{s}} = \sum_{\mathcal{b}=1}^{\mathcal{B}} \mathbb{S}_{\mathcal{s}\mathcal{b}}; (\mathcal{s} = 1,2,\dots,\mathcal{S}; \mathcal{b} = 1,2,\dots,\mathcal{B}). \quad (11)$$

Step 2-9: To determine the final alternative ranking, the degree of opportunity loss values is calculated using Eq. (12), resulting in the degree of opportunity loss matrix ($\mathbb{N} = [\mathbb{N}_{\mathcal{s}}]_{\mathcal{S}}$).

$$\mathbb{N}_{\mathcal{s}} = \frac{\mathbb{O}_{\mathcal{s}}}{\sum_{\mathcal{s}=1}^{\mathcal{S}} \mathbb{O}_{\mathcal{s}}}; (\mathcal{s} = 1,2,\dots,\mathcal{S}). \quad (12)$$

Step 2-10: In the OPLO-POCOD alternative ranking method, the final ranking of the alternatives is determined based on the percentage of opportunity achievement values. To calculate these values, Eq. (13) is applied, resulting in the percentage of opportunity achievement matrix ($\Omega = [\Omega_{\mathcal{s}}]_{\mathcal{S}}$).

$$\Omega_{\mathcal{s}} = 1 - \mathbb{N}_{\mathcal{s}}; (\mathcal{s} = 1,2,\dots,\mathcal{S}). \quad (13)$$

The implementation steps of the MPSI-OPLO-POCOD method are presented in Table 2.

Table 2
The implementation steps of the MPSI-OPLO-POCOD method.

Algorithm	***The implementation steps of the MPSI-OPLO-POCOD method for ESG-based sustainability performance calculation are presented.***
Input	A set of criteria $\kappa = \{\kappa_1, \kappa_2, \dots, \kappa_{\mathcal{b}}, \dots, \kappa_{\mathcal{B}}\}$ ($\mathcal{b} = 1,2,\dots,\mathcal{B}$). A set of companies $\text{Å} = \{\text{Å}_1, \text{Å}_2, \dots, \text{Å}_{\mathcal{s}}, \dots, \text{Å}_{\mathcal{S}}\}$ ($\mathcal{s} = 1,2,\dots,\mathcal{S}$).
Begin	
Stage 1	*Calculation of Criteria Weights Using the MPSI Method;*
Step 1-1	Design the initial decision matrix ($\mathbb{X} = [\mathbb{X}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$).
Step 1-2	Compute normalized decision matrix ($\mathbb{Y} = [\mathbb{Y}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) by employing Eq. (1).
Step 1-3	Compute the mean value matrix ($\mathbb{Z} = [\mathbb{Z}_{\mathcal{b}}]_{\mathcal{B}}$) by employing Eq. (2).
Step 1-4	Compute the preference variation matrix ($\mathbb{V} = [\mathbb{V}_{\mathcal{b}}]_{\mathcal{B}}$) by employing Eq. (3).
Step 1-5	Obtain the criteria weight matrix ($\mathbb{W} = [\mathbb{W}_{\mathcal{b}}]_{\mathcal{B}}$) by employing Eq. (4).
Stage 2	*OPLO-POCOD method for determining sustainability performance based on ESG;*
Step 2-1	Design the initial decision matrix ($\mathbb{X} = [\mathbb{X}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$).
Step 2-2	Calculate the best value matrix ($\mathbb{U} = [\mathbb{U}_{\mathcal{b}}]_{\mathcal{B}}$) by employing Eq. (5).
Step 2-3	Compute the opportunity loss values matrix ($\mathbb{T} = [\mathbb{T}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) by employing Eq. (6).
Step 2-4	Compute the ordered pair values matrix ($\mathbb{S} = [\mathbb{S}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) by employing Eq. (7).
Step 2-5	Compute the best ordered pair values matrix ($\mathbb{R} = [\mathbb{R}_{\mathcal{b}}]_{\mathcal{B}}$) by employing Eq. (8).
Step 2-6	Compute the distance matrix ($\mathbb{Q} = [\mathbb{Q}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) by employing Eq. (9).
Step 2-7	Compute the weighted distance of pair values matrix ($\mathbb{P} = [\mathbb{P}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) by employing Eq. (10).
Step 2-8	Compute the total distance matrix ($\mathbb{O} = [\mathbb{O}_{\mathcal{s}}]_{\mathcal{S}}$) by employing Eq. (11).
Step 2-9	Compute the degree of opportunity loss matrix ($\mathbb{N} = [\mathbb{N}_{\mathcal{s}}]_{\mathcal{S}}$) by employing Eq. (12).
Step 2-10	Compute the percentage of opportunity achievement matrix ($\Omega = [\Omega_{\mathcal{s}}]_{\mathcal{S}}$) by employing Eq. (13).
Output	The criteria weight matrix ($\mathbb{W} = [\mathbb{W}_{\mathcal{b}}]_{\mathcal{B}}$),

	The percentage of opportunity achievement matrix ($\Omega = [\Omega_{\delta}]_{\mathcal{S}}$).
End.	

4. Application

In this study, the performance analysis of 17 software companies listed in the S&P 500 is conducted. Within this scope, four applications are developed and implemented for the years 2021, 2020, 2019, and 2018. This section systematically explains the components of the decision model, followed by the execution of the four applications using the MPSI-OPLO-POCOD method, and presents the findings.

4.1 Sustainability Performance Based on ESG: Criteria and Companies

In the applications, seven financial ratios—*ESG score, Tobin's Q, Leverage, Net Income After Tax, ROE, ROA, and EBITDA*—are utilized to assess the financial performance of companies listed in the S&P Index. These financial ratios offer insights into the companies' profitability, efficiency, leverage, and market performance. The financial ratios, considered as criteria in the decision model, are defined as follows:

ESG score $(\boldsymbol{\kappa_1})$: Driven by the expectations of investors and other stakeholders, there has been a growing emphasis on integrating sustainability goals into business practices, thereby increasing the significance of ESG criteria (benefit-based). These criteria serve as a benchmark for monitoring and evaluating companies' ESG commitments [41]. The ESG score is a metric that assesses a company's performance across environmental (E), social (S), and corporate governance (G) dimensions, as determined by independent third-party rating agencies. This score provides insights into a company's sustainability practices and the non-financial risks it presents to investors. The ESG score is derived from a comprehensive evaluation, encompassing aspects such as environmental impact management, workers' rights, and societal contributions. Corporate governance factors include ethical values, managerial transparency, and shareholder rights [42].

Tobin Q Ratio $(\boldsymbol{\kappa_2})$: This financial indicator (benefit-based) plays a crucial role in macroeconomics and financial theories and is widely utilized to explain corporate investment decisions. The model serves as a key tool for understanding the relationship between the financial and real sectors and optimizing their interactions. Tobin's Q is defined as the ratio of a company's market value to the replacement cost of its fixed capital. In other words, the Q value is calculated by dividing the company's market value by the cost of reproducing its fixed assets (capital goods). A Q value greater than 1 indicates that it is profitable for the company to invest, as new investments can be made at a lower cost relative to the market value, thereby encouraging further investment. Conversely, a Q value below 1 suggests that the company's investments are yielding lower returns, which may discourage new investments. Originally, Tobin's Q model assumed that companies did not base their investment decisions solely on interactions with financial markets. However, modern applications acknowledge the complexity of these interactions. The investment Q model recognizes that firms actively participate in multiple financial markets, and these interactions directly influence investment decisions. As a result, financial market signals and prices play a crucial role in shaping investment choices [43]. Tobin's Q model provides a valuable framework for analyzing corporate investment decisions. By examining financial market signals and the interaction of firms' investment strategies, this model enhances the understanding of investment dynamics at the macroeconomic level. It is frequently employed in the literature to evaluate firm performance, offering insights into how market conditions influence corporate investment behavior [40, 44-45].

Leverage Ratio $(\boldsymbol{\kappa_3})$: The leverage ratio (benefit-based) is a financial metric that reflects the extent to which a company relies on debt financing by measuring the proportion of debt relative to equity. A high leverage ratio indicates that the company is more dependent on debt financing, which may increase its financial risk and debt burden. Conversely, a low leverage ratio suggests that the company relies more on equity to fund its operations, reducing its exposure to financial risk associated with excessive debt [46-48].

Net income after tax $(\boldsymbol{\kappa_4})$: This criterion (benefit-based) represents the profit remaining after deducting all expenses, costs, and tax obligations from a company's total revenue. It serves as a key indicator for assessing a company's financial performance. After-tax net income directly reflects the company's operational efficiency and overall profitability. This metric indicates the total profit generated by the company and the portion of that profit remained as net income after taxes [49].

Return on Equity (ROE) $(\boldsymbol{\kappa_5})$: This ratio (benefit-based) is a performance indicator that measures how much profit a company generates relative to its equity. As a crucial metric for investors, ROE assesses how effectively a company utilizes its equity to generate returns. A high ROE indicates that the company is efficiently using its equity to produce greater profits and deliver value to shareholders, whereas a low ROE suggests that the company is not utilizing its equity efficiently. This ratio is a performance indicator that measures how much profit a company generates relative to its equity. As a crucial metric for investors, Return on Equity (ROE) assesses how effectively a company utilizes its equity to generate returns. A high ROE indicates that the company is efficiently using its equity to produce greater profits and deliver value to shareholders, whereas a low ROE suggests that the company is not utilizing its equity efficiently [50-51].

Return on Assets (ROA) $(\boldsymbol{\kappa_6})$: This ratio (benefit-based) measures how much profit a company generates by utilizing its total assets, reflecting the efficiency with which the company uses its assets. It is a critical indicator for evaluating whether the company is effectively managing its assets. A high ROA indicates that the company is efficiently utilizing its assets to generate substantial profits, while a low ROA suggests that the assets are not being used effectively. ROA is commonly used in performance analysis to assess firms' asset management and operational efficiency [52-53]

EBITDA $(\boldsymbol{\kappa_7})$: This criterion (cost-based), *Earnings Before Interest, Taxes, Depreciation, and Amortization* (EBITDA), is a financial metric used to assess a company’s operational profitability by excluding the effects of interest, taxes, depreciation, and amortization. This cost-based indicator provides insight into how much profit a company generates from its core operations, independent of factors such as debt, tax strategies, or non-cash expenses. EBITDA is particularly valuable when comparing the operational profitability of different companies, as it offers a clearer picture of a company's true operational performance [54-55].

This research aims to calculate the Sustainability Performance Based on ESG for 17 software companies listed in the S&P 500. Additionally, to observe the performance across periods before and after the COVID-19 pandemic, four different years (2021, 2020, 2019, and 2018) are presented as distinct applications. The 17 companies included in the decision model are as follows: Adobe Inc (ADBE.OQ) (Å_1), Autodesk Inc (ADSK.OQ) (Å_2), Cadence Design Systems Inc (CDNS.OQ) (Å_3), Fair Isaac Corp (FICO.N) (Å_4), Intuit Inc (INTU.OQ) (Å_5), Microsoft Corp (MSFT.OQ) (Å_6), Oracle Corp (ORCL.N) (Å_7), PTC Inc (PTC.OQ) (Å_8), Roper Technologies Inc (ROP.OQ) (Å_9), Gen Digital Inc (GEN.OQ) (Å_{10}), Synopsys Inc (SNPS.OQ) (Å_{11}), Tyler Technologies Inc (TYL.N) (Å_{12}), ANSYS Inc (ANSS.OQ) (Å_{13}), Salesforce Inc (CRM.N) (Å_{14}), Fortinet Inc (FTNT.OQ) (Å_{15}), ServiceNow Inc

(NOW.N) $(Å_{16})$, and Palo Alto Networks Inc (PANW.OQ) $(Å_{17})$. The values for the criteria in the decision model, i.e., the initial decision matrices for the years 2021, 2020, 2019, and 2018, are presented in Table 3, Table 4, Table 5, and Table 6, respectively. All values for the criteria have been obtained from ESG reports and the financial documents of the companies.

Table 3
Initial decision matrix for 2021.

Codes		κ_1	κ_2	κ_3	κ_4	κ_5	κ_6	κ_7
ADBE.OQ	$Å_1$	76.63	9.90	0.98	4822.00	42.79	17.70	6709.00
ADSK.OQ	$Å_2$	82.16	8.50	1.43	497.00	124.05	5.77	854.30
CDNS.OQ	$Å_3$	77.60	13.07	0.49	695.96	35.10	15.87	830.94
FICO.N	$Å_4$	44.60	8.15	2.31	373.54	-99.42	25.90	480.00
INTU.OQ	$Å_5$	77.08	6.43	0.85	2062.00	35.49	13.29	2922.00
MSFT.OQ	$Å_6$	93.18	5.04	0.69	61271.00	47.10	18.36	83729.00
ORCL.N	$Å_7$	56.56	1.45	1.48	13926.00	151.32	10.62	18770.00
PTC.OQ	$Å_8$	53.86	3.10	1.27	476.92	27.05	10.58	498.84
ROP.OQ	$Å_9$	58.97	2.19	4.01	805.30	13.70	3.40	2178.90
GEN.OQ	$Å_{10}$	79.89	2.18	4.57	836.00	14.90	12.04	1200.00
SNPS.OQ	$Å_{11}$	67.55	6.45	0.71	756.36	21.11	8.64	1097.01
TYL.N	$Å_{12}$	62.65	4.66	1.86	161.46	13.76	3.41	327.45
ANSS.OQ	$Å_{13}$	63.39	5.53	0.86	454.63	15.13	7.19	648.50
CRM.N	$Å_{14}$	66.25	2.63	1.69	1444.00	9.35	1.52	2430.00
FTNT.OQ	$Å_{15}$	62.83	9.93	0.89	614.30	81.33	10.38	761.30
NOW.N	$Å_{16}$	59.05	11.96	0.73	230.00	33.23	2.13	829.00
PANW.OQ	$Å_{17}$	52.91	4.48	9.63	-267.00	156.25	-2.18	2100.00

Table 4
Initial decision matrix for 2020.

Codes		κ_1	κ_2	κ_3	κ_4	κ_5	κ_6	κ_7
ADBE.OQ	$Å_1$	75.29	9.88	0.90	5260.00	41.21	21.66	5113.00
ADSK.OQ	$Å_2$	81.37	10.87	1.42	1208.20	217.76	16.60	557.10
CDNS.OQ	$Å_3$	85.39	11.34	0.50	590.64	34.02	14.95	649.29
FICO.N	$Å_4$	36.86	9.48	3.05	392.08	347.53	25.01	510.00
INTU.OQ	$Å_5$	78.43	6.24	0.65	1826.00	46.87	16.70	2441.00
MSFT.OQ	$Å_6$	93.40	3.99	0.73	44281.00	40.14	14.70	67798.00
ORCL.N	$Å_7$	54.59	1.47	1.51	10299.00	72.30	8.92	17447.00
PTC.OQ	$Å_8$	41.30	2.56	1.28	130.70	22.61	3.86	326.10
ROP.OQ	$Å_9$	61.84	1.88	4.69	673.80	13.48	2.80	1844.40
GEN.OQ	$Å_{10}$	74.32	1.93	4.90	696.00	-353.47	10.94	1000.00
SNPS.OQ	$Å_{11}$	74.91	4.94	0.71	663.45	19.23	8.26	984.95
TYL.N	$Å_{12}$	56.85	6.75	0.43	194.82	12.73	7.47	261.11
ANSS.OQ	$Å_{13}$	62.05	5.26	0.83	433.89	15.48	7.30	606.45
CRM.N	$Å_{14}$	65.19	3.08	1.73	4095.00	12.15	6.18	4800.00
FTNT.OQ	$Å_{15}$	61.30	5.96	0.81	488.50	51.66	12.08	619.10
NOW.N	$Å_{16}$	52.54	12.32	0.71	118.50	37.30	1.36	618.24
PANW.OQ	$Å_{17}$	40.86	3.30	8.01	-498.90	70.69	-4.87	1900.00

Table 5
Initial decision matrix for 2019.

Codes		κ_1	κ_2	κ_3	κ_4	κ_5	κ_6	κ_7
ADBE.OQ	$Å_1$	65.74	7.69	1.23	2954.41	38.89	14.23	4004.79
ADSK.OQ	$Å_2$	82.19	8.54	2.24	224.10	158.00	3.63	70.20
CDNS.OQ	$Å_3$	72.42	7.88	0.75	988.98	36.43	29.46	514.93
FICO.N	$Å_4$	44.51	6.76	2.28	236.41	94.13	14.72	420.00
INTU.OQ	$Å_5$	80.04	8.13	0.55	1557.00	58.40	24.78	2079.00
MSFT.OQ	$Å_6$	92.93	2.72	0.78	39397.00	39.81	13.75	56348.00
ORCL.N	$Å_7$	52.17	1.49	1.45	10846.00	38.92	9.98	16454.00
PTC.OQ	$Å_8$	37.51	3.69	1.16	-27.46	19.94	-1.03	140.87
ROP.OQ	$Å_9$	65.11	2.04	3.28	1640.00	15.91	9.06	1980.30
GEN.OQ	$Å_{10}$	71.08	2.06	4.32	578.00	20.04	7.47	970.00
SNPS.OQ	$Å_{11}$	70.30	3.27	0.78	532.37	18.58	8.31	875.96
TYL.N	$Å_{12}$	50.83	5.34	0.59	146.53	14.45	6.69	239.42
ANSS.OQ	$Å_{13}$	58.77	4.48	0.71	449.50	18.52	9.29	598.06
CRM.N	$Å_{14}$	61.05	2.62	1.39	132.00	10.28	0.24	1920.00
FTNT.OQ	$Å_{15}$	51.51	4.71	0.67	329.60	37.02	8.50	427.90
NOW.N	$Å_{16}$	35.84	8.84	0.68	626.70	39.90	10.41	358.44
PANW.OQ	$Å_{17}$	26.32	2.50	7.96	-267.00	36.06	-2.95	1590.00

Table 6
Initial decision matrix for 2018.

Codes		κ_1	κ_2	κ_3	κ_4	κ_5	κ_6	κ_7
ADBE.OQ	$Å_1$	78.54	5.88	1.54	2776.77	30.86	14.79	3186.86
ADSK.OQ	$Å_2$	80.38	6.85	1.75	-96.80	-95.65	-2.05	-400.70
CDNS.OQ	$Å_3$	46.05	5.07	0.97	344.37	46.15	13.95	439.48
FICO.N	$Å_4$	40.22	3.78	2.54	192.12	78.87	13.40	430.00
INTU.OQ	$Å_5$	86.88	7.86	0.67	1300.00	79.02	25.32	1813.00
MSFT.OQ	$Å_6$	93.20	2.55	0.82	30271.00	39.03	11.69	46904.00
ORCL.N	$Å_7$	52.51	1.42	1.04	10592.00	26.60	7.68	16049.00
PTC.OQ	$Å_8$	47.77	3.03	1.54	39.59	19.45	1.70	160.02
ROP.OQ	$Å_9$	57.28	1.81	3.65	930.30	16.89	6.10	1763.40
GEN.OQ	$Å_{10}$	73.62	0.76	3.19	-112.00	19.46	-0.70	680.00
SNPS.OQ	$Å_{11}$	61.92	2.05	1.01	546.52	17.76	8.89	569.43
TYL.N	$Å_{12}$	37.84	4.03	0.61	145.66	13.00	8.13	214.25
ANSS.OQ	$Å_{13}$	45.68	3.66	0.42	420.28	20.99	12.87	535.83
CRM.N	$Å_{14}$	72.88	3.41	1.97	1153.00	17.07	3.75	2978.00
FTNT.OQ	$Å_{15}$	47.12	3.90	0.69	364.80	39.97	11.85	286.70
NOW.N	$Å_{16}$	31.33	8.23	0.76	-26.70	49.78	-0.69	107.18
PANW.OQ	$Å_{17}$	29.40	2.71	6.26	-81.90	42.26	-1.24	750.00

4.2 Application 1: Sustainability Performance Based on ESG for the Year 2021

The MPSI-OPLO-POCOD method is used in this study to evaluate the performance of 17 software companies listed in the S&P 500. Within the scope of Application 1, the MPSI-OPLO-POCOD method is systematically applied to analyze the performance for the year 2021. The implementation steps are as follows:

Stage 1: *Calculation of Criteria Weights Using the MPSI Method:*

Step 1-1: The initial decision matrix ($\mathbb{X} = [\mathbb{X}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) for the MPSI criteria weighting method is presented in Table 3. This table displays the values for each software company $(\mathring{A}_{\mathcal{s}})$ across all criteria $(\kappa_{\mathcal{b}})$.

Step 1-2: For the criteria weight calculation, the values were normalized using Eq. (1), resulting in the normalized decision matrix ($\mathbb{Y} = [\mathbb{Y}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$), which is presented in Table 7.

Step 1-3: The mean value matrix ($\mathbb{Z} = [\mathbb{Z}_{\mathcal{b}}]_{\mathcal{B}}$) was calculated using Eq. (2) and is also presented in Table 7.

Step 1-4: The preference variation matrix ($\mathbb{V} = [\mathbb{V}_{\mathcal{b}}]_{\mathcal{B}}$) was calculated using Eq. (3) and is also shown in Table 7.

Step 1-5: The criteria weight matrix ($\mathbb{W} = [\mathbb{W}_{\mathcal{b}}]_{\mathcal{B}}$) was calculated using Eq. (4) and is also shown in Table 7.

Table 7
The normalized decision matrix and the matrix mean value matrix and the preference variation matrix and the criteria weighing matrix for Application-1.

	κ_1	κ_2	κ_3	κ_4	κ_5	κ_6	κ_7
$\mathring{A}_1$	0.8223	0.7577	0.1013	0.0787	0.2738	0.6833	0.0488
$\mathring{A}_2$	0.8817	0.6500	0.1488	0.0081	0.7939	0.2229	0.3833
$\mathring{A}_3$	0.8328	1.0000	0.0511	0.0114	0.2246	0.6125	0.3941
$\mathring{A}_4$	0.4787	0.6234	0.2401	0.0061	-0.6363	1.0000	0.6822
$\mathring{A}_5$	0.8272	0.4921	0.0881	0.0337	0.2271	0.5130	0.1121
$\mathring{A}_6$	1.0000	0.3854	0.0721	1.0000	0.3014	0.7087	0.0039
$\mathring{A}_7$	0.6070	0.1111	0.1533	0.2273	0.9684	0.4101	0.0174
$\mathring{A}_8$	0.5780	0.2368	0.1323	0.0078	0.1731	0.4085	0.6564
$\mathring{A}_9$	0.6329	0.1674	0.4161	0.0131	0.0877	0.1311	0.1503
$\mathring{A}_{10}$	0.8573	0.1666	0.4748	0.0136	0.0954	0.4648	0.2729
$\mathring{A}_{11}$	0.7250	0.4936	0.0732	0.0123	0.1351	0.3336	0.2985
$\mathring{A}_{12}$	0.6723	0.3563	0.1935	0.0026	0.0881	0.1317	1.0000
$\mathring{A}_{13}$	0.6803	0.4233	0.0888	0.0074	0.0968	0.2775	0.5049
$\mathring{A}_{14}$	0.7110	0.2011	0.1758	0.0236	0.0598	0.0585	0.1348
$\mathring{A}_{15}$	0.6743	0.7594	0.0927	0.0100	0.5205	0.4006	0.4301
$\mathring{A}_{16}$	0.6337	0.9151	0.0757	0.0038	0.2127	0.0822	0.3950
$\mathring{A}_{17}$	0.5678	0.3429	1.0000	-0.0044	1.0000	-0.0841	0.1559
$\mathbb{Z}_{\mathcal{b}}$	0.7166	0.4754	0.2105	0.0856	0.2719	0.3738	0.3318
$\mathbb{V}_{\mathcal{b}}$	0.2933	1.1796	0.8882	0.9360	2.3860	1.2332	1.1668
$\mathbb{W}_{\mathcal{b}}$	0.0363	0.1459	0.1099	0.1158	0.2952	0.1526	0.1444

Stage 2: *OPLO-POCOD method for determining sustainability performance based on ESG:*

Step 2-1: The initial decision matrix ($\mathbb{X} = [\mathbb{X}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) for the OPLO-POCOD alternative ranking method is presented in Table 3. This table displays the values for each software company $(Å_{\mathcal{s}})$ across all criteria $(\kappa_{\mathcal{b}})$.

Step 2-2: The best value matrix ($\mathbb{U} = [\mathbb{U}_{\mathcal{b}}]_{\mathcal{B}}$) was calculated using Eq. (5) and is shown in Table 8.

Step 2-3: The opportunity loss values matrix ($\mathbb{T} = [\mathbb{T}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) was calculated using Eq. (6) and is also shown in Table 8.

Table 8
The best value matrix and the opportunity loss values matrix for Application-1.

	κ_1	κ_2	κ_3	κ_4	κ_5	κ_6	κ_7
$\mathbb{U}_{\mathcal{b}}$	93.1816	13.0721	9.6349	61271.0000	156.2500	25.9038	327.4540
$Å_1$	16.5541	3.1677	8.6591	56449.0000	113.4610	8.2025	6381.5460
$Å_2$	11.0214	4.5754	8.2010	60774.0000	32.2010	20.1293	526.8460
$Å_3$	15.5834	0.0000	9.1421	60575.0450	121.1500	10.0372	503.4820
$Å_4$	48.5772	4.9223	7.3215	60897.4590	255.6700	0.0000	152.5460
$Å_5$	16.0996	6.6398	8.7858	59209.0000	120.7600	12.6143	2594.5460
$Å_6$	0.0000	8.0341	8.9407	0.0000	109.1500	7.5470	83401.5460
$Å_7$	36.6247	11.6195	8.1580	47345.0000	4.9300	15.2819	18442.5460
$Å_8$	39.3189	9.9764	8.3600	60794.0770	129.2000	15.3232	171.3900
$Å_9$	34.2106	10.8842	5.6261	60465.7000	142.5500	22.5079	1851.4460
$Å_{10}$	13.2962	10.8949	5.0601	60435.0000	141.3500	13.8629	872.5460
$Å_{11}$	25.6282	6.6195	8.9297	60514.6410	135.1410	17.2619	769.5580
$Å_{12}$	30.5349	8.4140	7.7703	61109.5420	142.4910	22.4918	0.0000
$Å_{13}$	29.7932	7.5381	8.7797	60816.3730	141.1200	18.7152	321.0410
$Å_{14}$	26.9311	10.4430	7.9410	59827.0000	146.9000	24.3871	2102.5460
$Å_{15}$	30.3488	3.1446	8.7413	60656.7000	74.9200	15.5255	433.8460
$Å_{16}$	34.1313	1.1095	8.9052	61041.0000	123.0230	23.7737	501.5460
$Å_{17}$	40.2734	8.5891	0.0000	61538.0000	0.0000	28.0827	1772.5460

Step 2-4: The ordered pair values matrix ($\mathbb{S} = [\mathbb{S}_{\mathcal{s}\mathcal{b}}]_{\mathcal{S}\mathcal{B}}$) was calculated using Eq. (7) and is shown in Table 9.

Step 2-5: The best ordered pair values matrix ($\mathbb{R} = [\mathbb{R}_{\mathcal{b}}]_{\mathcal{B}}$) was calculated using Eq. (8) and is also shown in Table 9.

Table 9
The ordered pair values matrix for Application-1.

	κ_1		κ_2		κ_3		κ_4		κ_5		κ_6		κ_7	
$Å_1$	76.63	16.55	9.90	3.17	0.98	8.66	4822.00	56449.00	42.79	113.46	17.70	8.20	6709.00	6381.55
$Å_2$	82.16	11.02	8.50	4.58	1.43	8.20	497.00	60774.00	124.05	32.20	5.77	20.13	854.30	526.85
$Å_3$	77.60	15.58	13.07	0.00	0.49	9.14	695.96	60575.05	35.10	121.15	15.87	10.04	830.94	503.48
$Å_4$	44.60	48.58	8.15	4.92	2.31	7.32	373.54	60897.46	-99.42	255.67	25.90	0.00	480.00	152.55
$Å_5$	77.08	16.10	6.43	6.64	0.85	8.79	2062.00	59209.00	35.49	120.76	13.29	12.61	2922.00	2594.55
$Å_6$	93.18	0.00	5.04	8.03	0.69	8.94	61271.00	0.00	47.10	109.15	18.36	7.55	83729.00	83401.55
$Å_7$	56.56	36.62	1.45	11.62	1.48	8.16	13926.00	47345.00	151.32	4.93	10.62	15.28	18770.00	18442.55
$Å_8$	53.86	39.32	3.10	9.98	1.27	8.36	476.92	60794.08	27.05	129.20	10.58	15.32	498.84	171.39
$Å_9$	58.97	34.21	2.19	10.88	4.01	5.63	805.30	60465.70	13.70	142.55	3.40	22.51	2178.90	1851.45
$Å_{10}$	79.89	13.30	2.18	10.89	4.57	5.06	836.00	60435.00	14.90	141.35	12.04	13.86	1200.00	872.55

$Å_{11}$	67.55	25.63	6.45	6.62	0.71	8.93	756.36	60514.64	21.11	135.14	8.64	17.26	1097.01	769.56
$Å_{12}$	62.65	30.53	4.66	8.41	1.86	7.77	161.46	61109.54	13.76	142.49	3.41	22.49	327.45	0.00
$Å_{13}$	63.39	29.79	5.53	7.54	0.86	8.78	454.63	60816.37	15.13	141.12	7.19	18.72	648.50	321.04
$Å_{14}$	66.25	26.93	2.63	10.44	1.69	7.94	1444.00	59827.00	9.35	146.90	1.52	24.39	2430.00	2102.55
$Å_{15}$	62.83	30.35	9.93	3.14	0.89	8.74	614.30	60656.70	81.33	74.92	10.38	15.53	761.30	433.85
$Å_{16}$	59.05	34.13	11.96	1.11	0.73	8.91	230.00	61041.00	33.23	123.02	2.13	23.77	829.00	501.55
$Å_{17}$	52.91	40.27	4.48	8.59	9.63	0.00	-267.00	61538.00	156.25	0.00	-2.18	28.08	2100.00	1772.55
$\mathbb{R}_{\mathscr{b}}$	93.18	0.00	13.07	0.00	9.63	0.00	61271.00	0.00	156.25	0.00	25.90	0.00	327.45	0.00

Step 2-6: The distance matrix ($\mathbb{Q} = [\mathbb{Q}_{\mathscr{s}\mathscr{b}}]_{\mathcal{S}\mathcal{B}}$) was calculated using Eq. (9) and is shown in Table 10.

Table 10
The distance matrix for Application-1.

	$\boldsymbol{\kappa_1}$	$\boldsymbol{\kappa_2}$	$\boldsymbol{\kappa_3}$	$\boldsymbol{\kappa_4}$	$\boldsymbol{\kappa_5}$	$\boldsymbol{\kappa_6}$	$\boldsymbol{\kappa_7}$
$Å_1$	23.4110	4.4798	12.2458	79830.9414	160.4581	11.6001	9024.8689
$Å_2$	15.5866	6.4706	11.5979	85947.4150	45.5391	28.4671	745.0728
$Å_3$	22.0382	0.0000	12.9288	85666.0502	171.3320	14.1947	712.0311
$Å_4$	68.6986	6.9612	10.3542	86122.0124	361.5720	0.0000	215.7326
$Å_5$	22.7683	9.3901	12.4250	83734.1708	170.7804	17.8392	3669.2421
$Å_6$	0.0000	11.3619	12.6440	0.0000	154.3614	10.6731	117947.5975
$Å_7$	51.7952	16.4325	11.5371	66955.9411	6.9721	21.6119	26081.6987
$Å_8$	55.6054	14.1088	11.8228	85975.8082	182.7164	21.6703	242.3821
$Å_9$	48.3812	15.3926	7.9566	85511.4130	201.5961	31.8309	2618.3400
$Å_{10}$	18.8037	15.4077	7.1561	85467.9966	199.8991	19.6050	1233.9664
$Å_{11}$	36.2438	9.3614	12.6286	85580.6260	191.1182	24.4120	1088.3194
$Å_{12}$	43.1828	11.8992	10.9888	86421.9431	201.5127	31.8082	0.0000
$Å_{13}$	42.1339	10.6605	12.4164	86007.3395	199.5738	26.4673	454.0205
$Å_{14}$	38.0864	14.7686	11.2302	84608.1548	207.7480	34.4886	2973.4491
$Å_{15}$	42.9196	4.4472	12.3620	85781.5278	105.9529	21.9564	613.5509
$Å_{16}$	48.2689	1.5690	12.5938	86325.0101	173.9808	33.6211	709.2932
$Å_{17}$	56.9552	12.1468	0.0000	87027.8742	0.0000	39.7149	2506.7586

Step 2-7: The weighted distance of pair values matrix ($\mathbb{P} = [\mathbb{P}_{\mathscr{s}\mathscr{b}}]_{\mathcal{S}\mathcal{B}}$) was calculated using Eq. (10) and is shown in Table 11.

Table 11
The weighted distance of pair values matrix for Application-1.

	$\boldsymbol{\kappa_1}$	$\boldsymbol{\kappa_2}$	$\boldsymbol{\kappa_3}$	$\boldsymbol{\kappa_4}$	$\boldsymbol{\kappa_5}$	$\boldsymbol{\kappa_6}$	$\boldsymbol{\kappa_7}$
$Å_1$	0.8495	0.6537	1.3456	9244.0275	47.3655	1.7698	1302.7548
$Å_2$	0.5656	0.9443	1.2744	9952.2848	13.4426	4.3431	107.5525
$Å_3$	0.7997	0.0000	1.4206	9919.7042	50.5753	2.1657	102.7829
$Å_4$	2.4929	1.0159	1.1377	9972.5024	106.7321	0.0000	31.1414
$Å_5$	0.8262	1.3703	1.3652	9696.0021	50.4125	2.7217	529.6612
$Å_6$	0.0000	1.6580	1.3893	0.0000	45.5658	1.6284	17025.9311
$Å_7$	1.8795	2.3980	1.2677	7753.1663	2.0581	3.2973	3764.9364
$Å_8$	2.0178	2.0589	1.2991	9955.5726	53.9359	3.3062	34.9883
$Å_9$	1.7556	2.2463	0.8743	9901.7980	59.5090	4.8564	377.9617
$Å_{10}$	0.6823	2.2485	0.7863	9896.7706	59.0080	2.9911	178.1251
$Å_{11}$	1.3152	1.3661	1.3876	9909.8125	56.4160	3.7245	157.1007
$Å_{12}$	1.5670	1.7365	1.2074	10007.2328	59.4843	4.8529	0.0000

$Å_{13}$	1.5289	1.5557	1.3643	9959.2238	58.9120	4.0380	65.5386
$Å_{14}$	1.3821	2.1552	1.2340	9797.2051	61.3249	5.2618	429.2223
$Å_{15}$	1.5575	0.6490	1.3583	9933.0759	31.2761	3.3498	88.5671
$Å_{16}$	1.7516	0.2290	1.3838	9996.0085	51.3572	5.1295	102.3876
$Å_{17}$	2.0668	1.7726	0.0000	10077.3967	0.0000	6.0592	361.8548

Step 2-8: The total distance matrix ($\mathbb{O} = [\mathbb{O}_{\mathcal{s}}]_S$) was calculated using Eq. (11) and is shown in Table 12.

Step 2-9: The degree of opportunity loss matrix ($\mathbb{N} = [\mathbb{N}_{\mathcal{s}}]_S$) was calculated using Eq. (12) and is also shown in Table 12.

Step 2-10: The percentage of opportunity achievement matrix ($\Omega = [\Omega_{\mathcal{s}}]_S$) was calculated using Eq. (12) and is also shown in Table 12 with performance ranking.

Table 12
The total distance matrix and the degree of opportunity loss matrix and the percentage of opportunity achievement matrix for Application-1.

Codes		$\mathbb{O}_{\mathcal{s}}$	$\mathbb{N}_{\mathcal{s}}$	$\boldsymbol{\Omega_{\mathcal{s}}}$	***Rank***
ADBE.OQ	$Å_1$	10598.7664	0.0584	0.9416	15th
ADSK.OQ	$Å_2$	10080.4073	0.0555	0.9445	5th
CDNS.OQ	$Å_3$	10077.4483	0.0555	0.9445	4th
FICO.N	$Å_4$	10115.0223	0.0557	0.9443	7th
INTU.OQ	$Å_5$	10282.3593	0.0566	0.9434	11th
MSFT.OQ	$Å_6$	17076.1726	0.0940	0.9060	17th
ORCL.N	$Å_7$	11529.0032	0.0635	0.9365	16th
PTC.OQ	$Å_8$	10053.1787	0.0554	0.9446	1st
ROP.OQ	$Å_9$	10349.0012	0.0570	0.9430	13th
GEN.OQ	$Å_{10}$	10140.6119	0.0559	0.9441	9th
SNPS.OQ	$Å_{11}$	10131.1226	0.0558	0.9442	8th
TYL.N	$Å_{12}$	10076.0810	0.0555	0.9445	3rd
ANSS.OQ	$Å_{13}$	10092.1614	0.0556	0.9444	6th
CRM.N	$Å_{14}$	10297.7854	0.0567	0.9433	12th
FTNT.OQ	$Å_{15}$	10059.8337	0.0554	0.9446	2nd
NOW.N	$Å_{16}$	10158.2472	0.0559	0.9441	10th
PANW.OQ	$Å_{17}$	10449.1500	0.0576	0.9424	14th

4.3 Application 2: Sustainability Performance Based on ESG for the Year 2020

In Application-2, the MPSI-OPLO-POCOD method was applied following the same procedural steps as demonstrated in Application-1. The initial decision matrix for Application-2 is presented in Table 4. As a result of the application, two key outputs were obtained: the first output is the criteria weight matrix, and the second output is the performance ranking represented by the percentage of opportunity achievement matrix. The criteria weights are presented in Table 11, while the performance values and rankings are provided in Table 12.

4.4 Application 3: Sustainability Performance Based on ESG for the Year 2019

Application-3 was conducted by applying the MPSI-OPLO-POCOD method steps. The initial decision matrix for this application, as shown in Table 5, was utilized. As a result, the criteria weight matrix was obtained and is presented in Table 11. Additionally, the performance values and rankings of the 17 software companies listed in the S&P 500 were calculated and are displayed in Table 12.

4.5 Application 4: Sustainability Performance Based on ESG for the Year 2018

For Application-4, the MPSI-OPLO-POCOD steps were re-applied. The initial decision matrix for this application is presented in Table 6. As a result, the criteria weight matrix is provided in Table 13, while the performance rankings and values of the companies are displayed in Table 14. Additionally, to present all application results in the same tables, the results from Application-1 have also been included in the tables.

Table 13
Criteria weights based on the results of Application-1, Application-2, Application-3, and Application-4.

Applications		$\boldsymbol{\kappa_1}$	$\boldsymbol{\kappa_2}$	$\boldsymbol{\kappa_3}$	$\boldsymbol{\kappa_4}$	$\boldsymbol{\kappa_5}$	$\boldsymbol{\kappa_6}$	$\boldsymbol{\kappa_7}$
Application-1 (2021)	$\mathbb{W}_{b}$	0.0363	0.1459	0.1099	0.1158	0.2952	0.1526	0.1444
	Rank	7th	3rd	6th	5th	1st	2nd	4th
Application-2 (2020)	$\mathbb{W}_{b}$	0.0545	0.1525	0.1209	0.1039	0.2652	0.1640	0.1391
	Rank	7th	3rd	5th	6th	1st	2nd	4th
Application-3 (2019)	$\mathbb{W}_{b}$	0.0854	0.1986	0.1318	0.1370	0.1219	0.1831	0.1421
	Rank	7th	1st	5th	4th	6th	2nd	3rd
Application-4 (2018)	$\mathbb{W}_{b}$	0.0259	0.0405	0.0326	0.0352	0.1291	0.0482	0.6885
	Rank	7th	4th	6th	5th	2nd	3rd	1st

Table 14
Performances based on the results of Application-1, Application-2, Application-3, and Application-4.

Companies		***Application-1 (2021)***		***Application-2 (2020)***		***Application-3 (2019)***		***Application-4 (2018)***	
		$\boldsymbol{\Omega_s}$	***Rank***	$\boldsymbol{\Omega_s}$	***Rank***	$\boldsymbol{\Omega_s}$	***Rank***	$\boldsymbol{\Omega_s}$	***Rank***
ADBE.OQ	$Å_1$	0.9416	15th	0.9445	11th	0.9422	13th	0.9534	15th
ADSK.OQ	$Å_2$	0.9445	5th	0.9475	1st	0.9442	2nd	0.9852	1st
CDNS.OQ	$Å_3$	0.9445	4th	0.9460	4th	0.9445	1st	0.9778	7th
FICO.N	$Å_4$	0.9443	7th	0.9469	2nd	0.9436	6th	0.9779	6th
INTU.OQ	$Å_5$	0.9434	11th	0.9446	10th	0.9431	12th	0.9656	13th
MSFT.OQ	$Å_6$	0.9060	17th	0.8906	17th	0.9168	17th	0.5591	17th
ORCL.N	$Å_7$	0.9365	16th	0.9307	16th	0.9350	16th	0.8372	16th
PTC.OQ	$Å_8$	0.9446	1st	0.9459	6th	0.9435	8th	0.9802	3rd
ROP.OQ	$Å_9$	0.9430	13th	0.9441	13th	0.9432	10th	0.9657	12th
GEN.OQ	$Å_{10}$	0.9441	9th	0.9444	12th	0.9432	11th	0.9753	10th
SNPS.OQ	$Å_{11}$	0.9442	8th	0.9455	8th	0.9433	9th	0.9767	9th
TYL.N	$Å_{12}$	0.9445	3rd	0.9460	3rd	0.9437	5th	0.9798	4th
ANSS.OQ	$Å_{13}$	0.9444	6th	0.9458	7th	0.9436	7th	0.9769	8th
CRM.N	$Å_{14}$	0.9433	12th	0.9434	14th	0.9411	14th	0.9545	14th
FTNT.OQ	$Å_{15}$	0.9446	2nd	0.9460	5th	0.9437	4th	0.9792	5th

NOW.N	$Å_{16}$	0.9441	10th	0.9454	9th	0.9442	3rd	0.9807	2nd
PANW.OQ	$Å_{17}$	0.9424	14th	0.9427	15th	0.9411	15th	0.9747	11th

5. Results and Implications

In this study, the MPSI-OPLO-POCOD method is proposed for calculating Sustainability Performance Based on ESG. The MPSI is used to calculate the criteria weights, while the OPLO-POCOD method is applied to obtain performance rankings. Four applications were conducted to implement the steps presented in the methodology section. The purpose of these applications is to calculate the performance of 17 software companies listed in the S&P 500 during the pre-COVID-19 period (2018), the COVID-19 period (2019 and 2020), and the post-COVID-19 period (2021). The results of the applications yield two key outputs. The first is the importance of levels of the performance criteria in the decision-making process. The second is the final performance rankings of the companies. Based on these two outputs, the results are as follows:

Output-1*: Criteria Weights*: The MPSI method was applied for 2021, 2020, 2019, and 2018. As a result of the application, the importance levels of the criteria are as follows:

- For Application-1 (2021), the criteria weights are: " *ROE* (κ_5) *> ROA* (κ_6) *> Tobin Q Ratio* (κ_2) *> EBITDA* (κ_7) *> Net income after tax* (κ_4) *> Leverage Ratio* (κ_3) *> ESG score* (κ_1)."
- For Application-2 (2020), the criteria weights are: " *ROE* (κ_5) *> ROA* (κ_6) *> Tobin Q Ratio* (κ_2) *> EBITDA* (κ_7) *> Leverage Ratio* (κ_3) *> Net income after tax* (κ_4) *> ESG score* (κ_1)."
- For Application-3 (2019), the criteria weights are: " *Tobin Q Ratio* (κ_2) *> ROA* (κ_6) *> EBITDA* (κ_7) *> Net income after tax* (κ_4) *> Leverage Ratio* (κ_3) *> ROE* (κ_5) *> ESG score* (κ_1) ."
- For Application-4 (2018), the criteria weights are: " *EBITDA* (κ_7) *> ROE* (κ_5) *> ROA* (κ_6) *> Tobin Q Ratio* (κ_2) *> Net income after tax* (κ_4) *> Leverage Ratio* (κ_3) *> ESG score* (κ_1) ."

When the rankings of the criteria presented above are examined, the following results emerge:

- In all years, the ESG score criterion has the lowest level of importance.
- In the pre-COVID-19 period, the EBITDA criterion was the most important, but its importance level gradually decreased. Additionally, this criterion had a higher importance level for the year 2018 compared to the other criteria.
- In the post-COVID-19 period, the ROE criterion became the most important.
- In the first year of the COVID-19 period, the importance of ROE was low, but by the second year, ROE became the most important criterion.

The criteria weights for the applications are shown in Fig. 2, and the rankings based on the criteria weights are presented in Fig. 3.

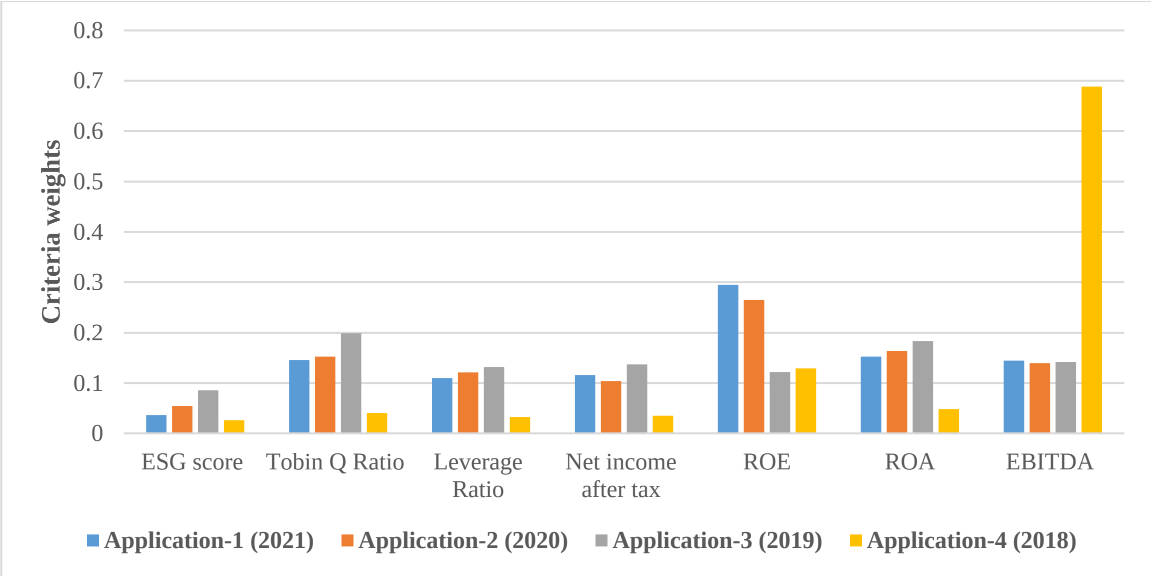

Fig. 2. Results of the criteria weights.

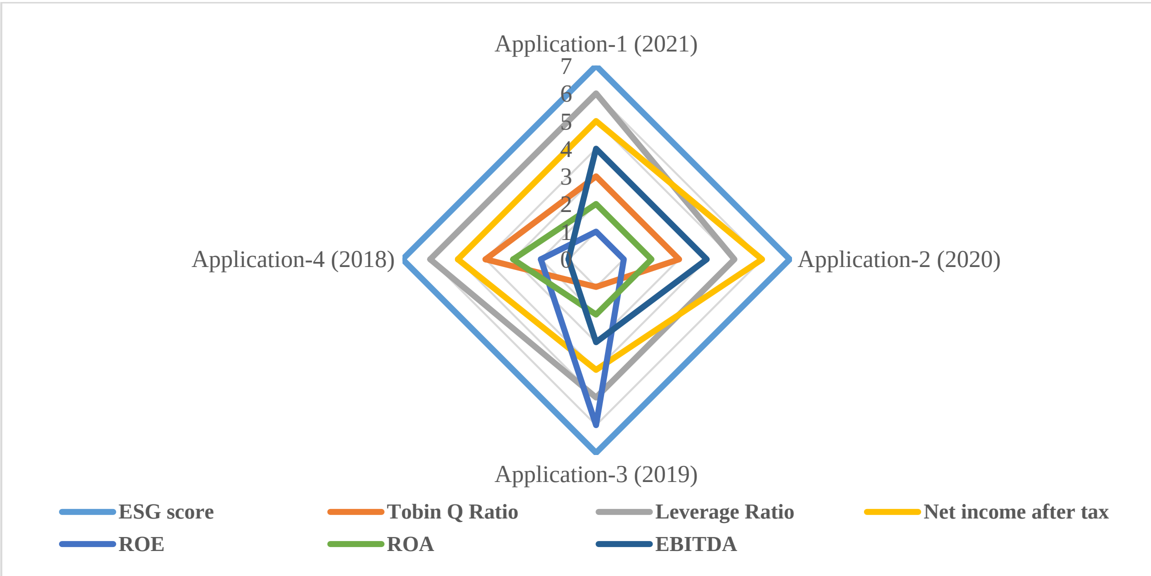

Fig. 3. Results of the criteria ranks.

Output-2: *Performance Rankings*: By applying the OPLO-POCOD method, performance rankings for software companies for the years 2021, 2020, 2019, and 2018 were obtained. The top three companies in terms of performance for each period are as follows:

- For Application-1 (2021), the top three companies with the highest performance are: " *PTC.OQ* $\left(\text{Å}_8\right)$ > *FTNT.OQ* $\left(\text{Å}_{15}\right)$ > *TYL.N* $\left(\text{Å}_{12}\right)$ "
- For Application-1 (2020), the top three companies with the highest performance are: " *ADSK.OQ* $\left(\text{Å}_2\right)$ > *FICO.N* $\left(\text{Å}_4\right)$ > *TYL.N* $\left(\text{Å}_{12}\right)$ "
- For Application-1 (2019), the top three companies with the highest performance are: " *CDNS.OQ* $\left(\text{Å}_3\right)$ > *ADSK.OQ* $\left(\text{Å}_2\right)$ > *NOW.N* $\left(\text{Å}_{16}\right)$ "

- For Application-1 (2018), the top three companies with the highest performance are: " *ADSK.OQ* (Å_2) > *NOW.N* (Å_{16}) > *PTC.OQ* (Å_8) "

The general performance levels of the companies are shown in Fig. 4, and the performance rankings are presented in Fig. 5. Based on the changes in these rankings, the key findings are as follows:

- ADSK.OQ and NOW.N had the best performance in the pre-COVID-19 period, but their performance levels declined in the post-COVID-19 period.
- ORCL.N and ORCL.N were the lowest-ranked companies in the pre-COVID-19 period, and this situation remained unchanged during and after the COVID-19 period. Among the companies included in the decision model, these companies consistently had the lowest performance across all periods.
- PTC.OQ, FTNT.OQ, and TYL.N showed improved performance after the COVID-19 period compared to previous periods.
- NOW.N was identified as the company with the greatest decline in performance compared to the pre-COVID-19 period.

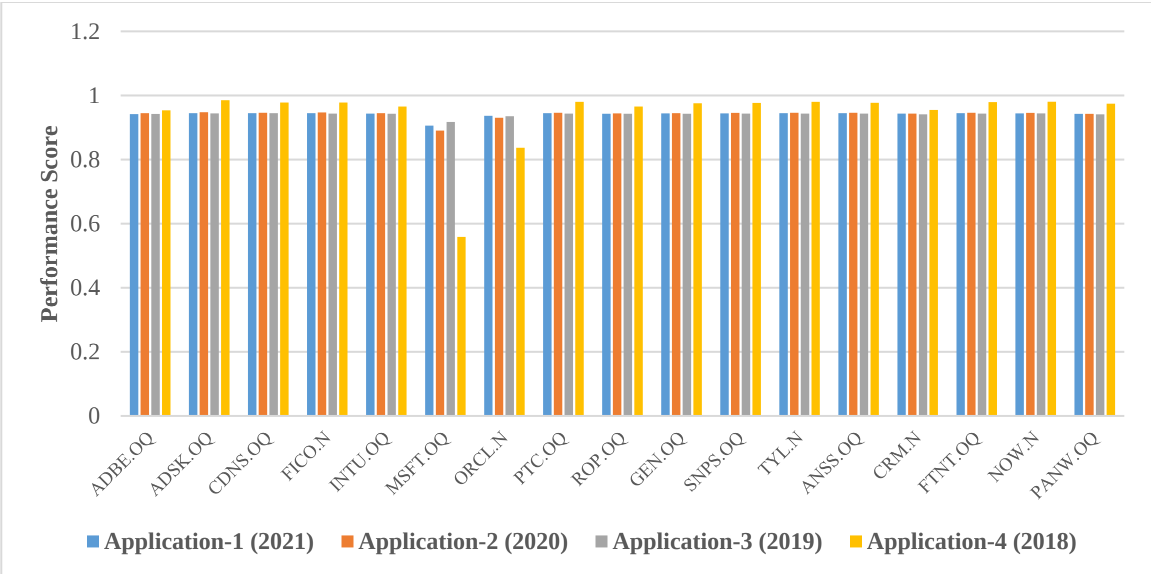

Fig. 4. Results of the performance.

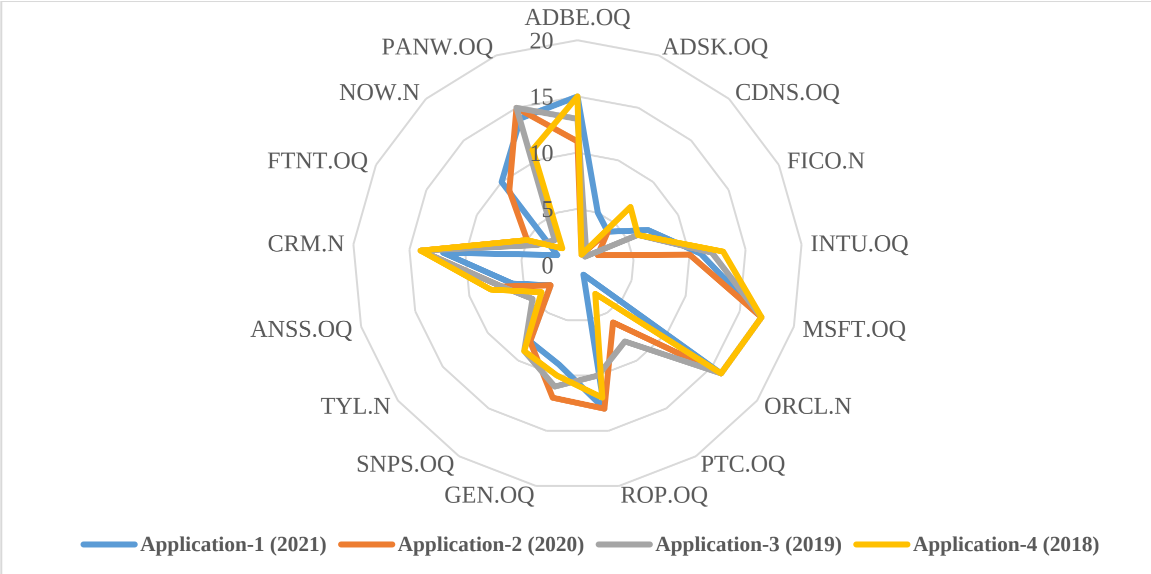

Fig. 5. Results of the performance ranking.

5.1 Sensitivity analysis for the MPSI-OPLO-POCOD Method

The MPSI-OPLO-POCOD method was employed in this study to evaluate the performance of companies across four applications. These applications assessed the performance of 17 software companies for the years 2021, 2020, 2019, and 2018. To validate the robustness of the application results, sensitivity analyses were conducted. Separate sensitivity analysis scenarios (SAS) were developed for each year, and the MPSI-OPLO-POCOD method was applied accordingly.

- SAS-1: In 2021, the best-performing company was identified as PTC.OQ. To confirm this result, each company was systematically removed from the decision model one by one until the top-performing company was identified. The results of SAS-1 confirmed that the best-performing company remained PTC.OQ. The outcomes of SAS-1 are presented in Fig. 6.
- SAS-2: For 2020, the best-performing company was ADSK.OQ. In SAS-2, other companies were systematically removed from the decision model to examine whether ADSK.OQ retained its top ranking. The analysis confirmed that ADSK.OQ remained the best performing company. The results of SAS-2 are shown in Fig. 7.
- SAS-3: The reliability of the 2019 performance rankings was examined in SAS-3. The sensitivity analysis verified that CDNS.OQ, which was determined to be the top-performing company in Application-3, was indeed the best-performing company for 2019. The findings of SAS-3 are presented in Fig. 8.
- SAS-4: For 2018, a sensitivity analysis was conducted by systematically removing the lowest-performing companies. The results demonstrated that ADSK.OQ remained the best-performing company across all stages of the analysis. The outcomes of SAS-4 are displayed in Fig. 9.

The sensitivity analyses confirmed the robustness of the MPSI-OPLO-POCOD method's application results. The findings support the reliability of the performance rankings and validate the effectiveness of the proposed methodology.

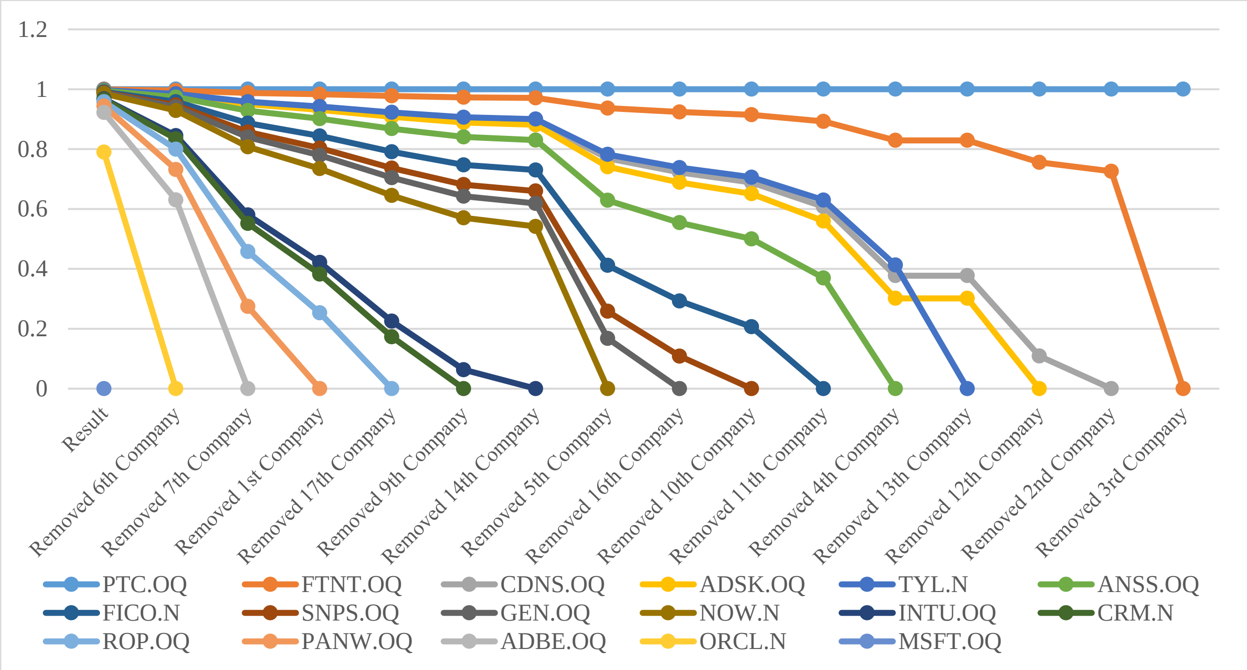

Fig. 6. Results of SAS-1 (2021).

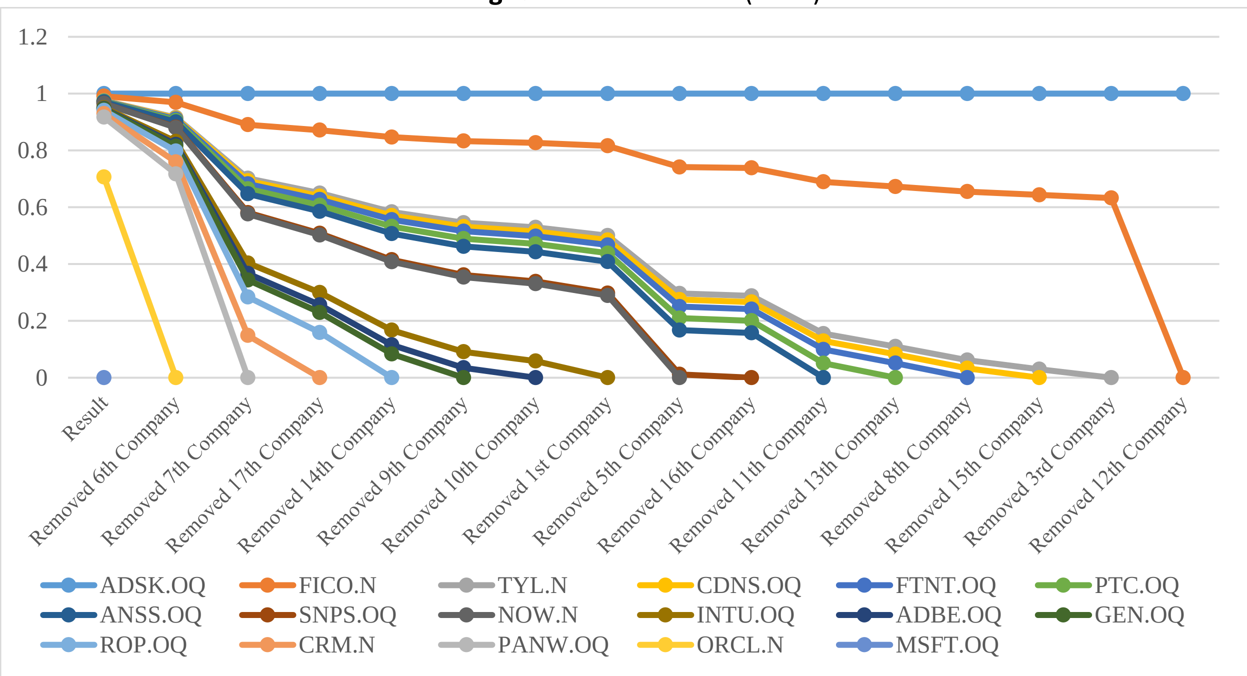

Fig. 7. Results of SAS-2 (2020).

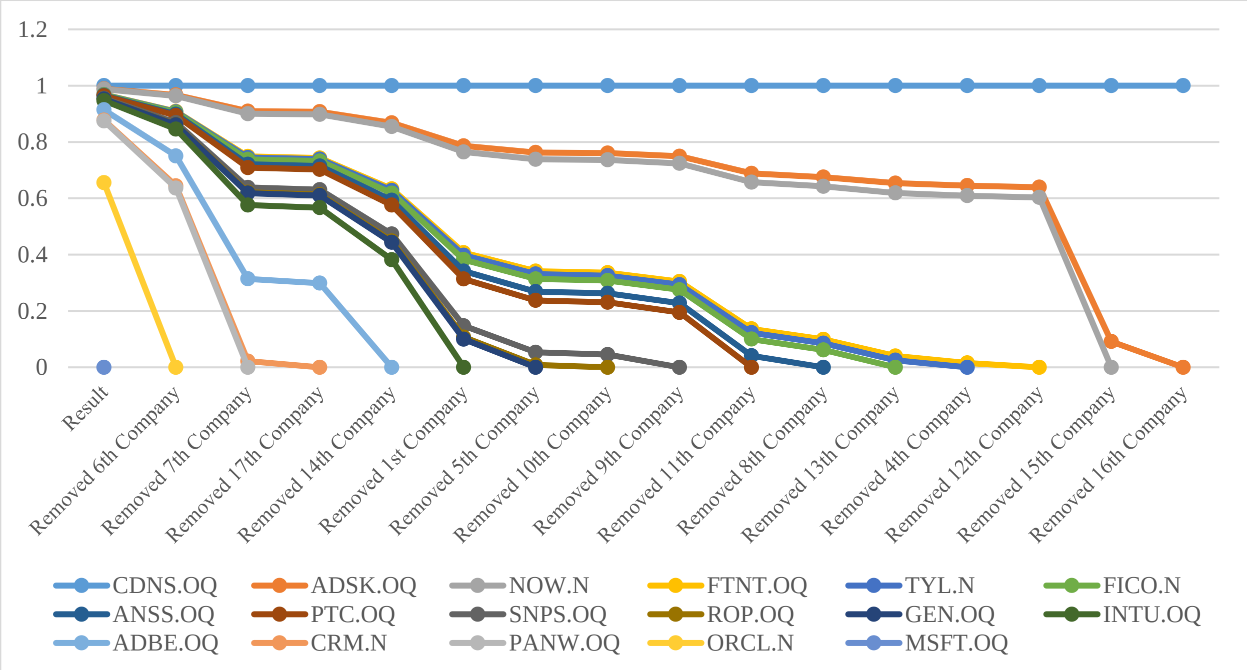

Fig. 8. Results of SAS-3 (2019).

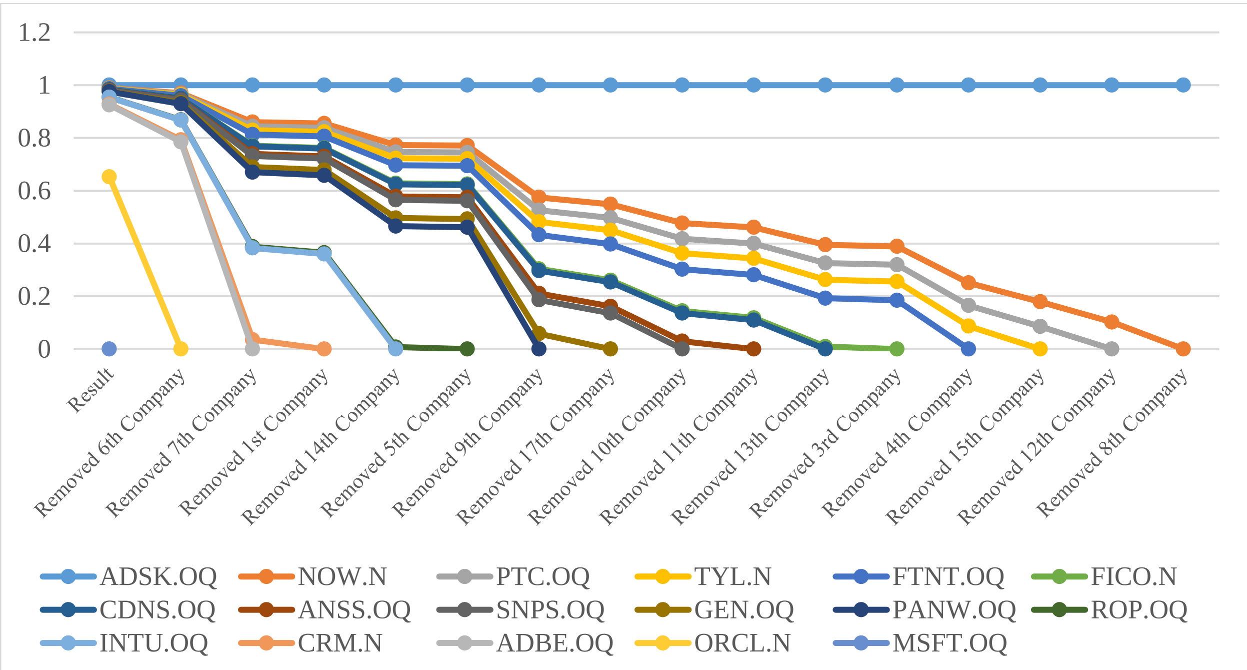

Fig. 9. Results of SAS-4 (2018).

5.2 Implication of the research

This research has several significant implications for academia, industry, and policymaking, providing valuable insights into ESG-based performance analysis within the software sector. The key research implications are as follows:

- *Contribution to ESG Performance Literature*: This study contributes to the growing body of literature on ESG performance by providing a systematic, MCDM approach to evaluating the sustainability and financial performance of companies in the software industry. By integrating both financial and ESG criteria, the research extends current knowledge on how these factors influence corporate success.

- *Advancement of MCDM Methodology*: The use of the MPSI-OPLO-POCOD methodology offers a novel approach for performance evaluation, combining objective criteria weighting and alternative ranking methods. This research demonstrates how these methods can be effectively applied in the context of ESG-based corporate performance analysis, offering a valuable tool for future studies in various sectors.
- *Implications for Investors*: For investors, this research highlights the importance of considering ESG performance when making investment decisions. The findings suggest that companies with strong ESG practices tend to perform better during uncertain economic periods, such as the COVID-19 pandemic, thereby offering greater resilience. This underscores the growing significance of sustainable investment strategies that align financial performance with social and environmental responsibility.
- *Strategic Insights for Software Companies*: For software companies, the study provides actionable insights into which ESG, and financial performance criteria are most important for competitive advantage. The ranking of companies based on their performance across different periods helps firms assess their positioning in the market and provides guidance for improving sustainability practices, which can, in turn, enhance both reputation and financial outcomes.
- *Sector-Specific ESG Insight*s: This study also demonstrates how sector-specific variations in ESG performance exist, particularly in response to external shocks like the COVID-19 pandemic. Future research could build on this by investigating sector-specific ESG impacts more comprehensively, offering tailored frameworks for different industries.
- *Potential for Broader Application*: Although this study focuses on software companies, the methodology and findings have broader applicability. Researchers can apply the MPSI-OPLO-POCOD method to other sectors, thereby expanding the understanding of ESG-based performance evaluations across different industries and market conditions.

In conclusion, this research not only enhances the academic understanding of ESG-driven performance in the software sector but also provides practical insights for investors, companies, and policymakers aiming to promote sustainability in business practices. Further studies could refine the methodology and explore additional sectors to strengthen the generalizability and impact of ESG performance analysis.

5. Conclusions

This research successfully applies an ESG-based performance analysis to software companies listed on the S&P 500, utilizing the MCDM approach for a comprehensive evaluation. By employing the MPSI-OPLO-POCOD methodology, the study effectively calculates and ranks the performance of 17 software companies across the years 2018, 2019, 2020, and 2021, providing valuable insights into how these companies have fared before, during, and after the COVID-19 pandemic. The findings highlight the impact of ESG criteria, including ROE, Tobin Q Ratio, and EBITDA, in determining corporate performance, with the research showing that companies with strong ESG practices tend to perform better, particularly during the uncertainties caused by the pandemic.

The results of this study emphasize the importance of incorporating both financial and ESG factors when assessing corporate performance. Notably, the findings suggest that companies with superior ESG scores, along with key financial indicators like ROE and Tobin Q Ratio, demonstrate resilience and adaptability in periods of economic disruption, such as the COVID-19 crisis. The methodology used—combining objective criterion weighting with performance ranking—proves effective for performance analysis, offering a robust framework for evaluating not only financial outcomes but also sustainability and corporate responsibility, which have become increasingly critical in today's business environment.

In conclusion, this research contributes to the growing body of knowledge on ESG performance assessment by providing a clear and actionable methodology for evaluating companies in the software sector. It also offers valuable insights for investors, corporate managers, and policymakers, encouraging a more holistic approach to performance evaluation that integrates both financial metrics and sustainability factors. Moving forward, future studies can expand on this framework by incorporating additional sectors and refining the decision-making processes to further enhance the understanding of how ESG practices affect long-term corporate performance and sustainability.

Despite the valuable insights provided by this study, there are certain limitations that must be acknowledged. One primary limitation is the focus on only 17 software companies from the S&P 500, which may not fully represent the broader software industry or other sectors within the market. The sample size, although significant for the purpose of this research, limits the generalizability of the findings to companies outside the S&P 500 or those in different market conditions. Expanding the study to include a more diverse range of companies, including those from various industries and market sizes, could offer a more comprehensive view of ESG performance across sectors.

Another limitation of the research is the reliance on available financial and ESG data, which may be subject to discrepancies or inconsistencies due to variations in reporting standards across companies. While the use of the MPSI-OPLO-POCOD methodology helps in objectively analyzing performance, the accuracy of the results is contingent on the quality and completeness of the data. Additionally, the study does not account for the potential influence of external factors, such as regulatory changes or geopolitical events, that might affect the performance of these companies during the specified periods. Future research could consider these external influences and incorporate more dynamic and up-to-date data to strengthen the robustness of the findings.

Future research could build upon the findings of this study by expanding the scope to include a larger and more diverse sample of companies across different industries. This would provide a more comprehensive understanding of ESG-based performance and its implications on a global scale. Additionally, incorporating more advanced techniques, such as machine learning models, to analyze and predict ESG performance trends could further enhance the robustness of the analysis. Researchers could also consider exploring the impact of additional variables, such as corporate governance or environmental initiatives, on financial performance to develop a more holistic view of sustainability. Lastly, investigating the long-term effects of the COVID-19 pandemic on ESG performance beyond the initial years examined in this study could offer valuable insights into the lasting impacts of global crises on corporate sustainability strategies.

Appendix

The list of references should only include works that are cited in the text and that have been published or accepted for publication. Personal communications and unpublished works should only be mentioned in the text. Reference style should be in **APA style.** Please use this link for the **DOI number**.

Indices and sets:	
$\mathcal{s} = 1,2,\ldots,\mathcal{S}$	index of companies,
$\mathcal{b} = 1,2,\ldots,\mathcal{B}$	index of criteria,
$\text{Å} = \{\text{Å}_1, \text{Å}_2, \ldots, \text{Å}_{\mathcal{s}}, \ldots, \text{Å}_{\mathcal{S}}\}$	set of companies,
$\kappa = \{\kappa_1, \kappa_2, \ldots, \kappa_{\mathcal{b}}, \ldots, \kappa_{\mathcal{B}}\}$	set of criteria,
$\kappa^- \subseteq \kappa$	set of the cost-based criteria,
$\kappa^+ \subseteq \kappa$	set of the benefit-based criteria,
Parameters:	
$\mathcal{S} \geq 2$	number of companies,
$\mathcal{B} \geq 2$	number of criteria,
Variables:	
$\mathbb{X}_{\mathcal{s}\mathcal{b}}(\mathcal{s} \in \text{Å}, \mathcal{b} \in \kappa)$	value of the company $\text{Å}_{\mathcal{s}}$ depending on the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{Y}_{\mathcal{s}\mathcal{b}}(\mathcal{s} \in \text{Å}, \mathcal{b} \in \kappa)$	normalized value of the company $\text{Å}_{\mathcal{s}}$ depending on the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{Z}_{\mathcal{b}}(\mathcal{b} \in \kappa)$	mean value of the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{V}_{\mathcal{b}}(\mathcal{b} \in \kappa)$	preference variation value of the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{W}_{\mathcal{b}}(\mathcal{b} \in \kappa)$	weighed of the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{U}_{\mathcal{b}}(\mathcal{b} \in \kappa)$	best value of the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{T}_{\mathcal{s}\mathcal{b}}(\mathcal{s} \in \text{Å}, \mathcal{b} \in \kappa)$	opportunity loss value of the company $\text{Å}_{\mathcal{s}}$ depending on the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{S}_{\mathcal{s}\mathcal{b}}(\mathcal{s} \in \text{Å}, \mathcal{b} \in \kappa)$	ordered pair value of the company $\text{Å}_{\mathcal{s}}$ depending on the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{R}_{\mathcal{b}}(\mathcal{b} \in \kappa)$	best ordered pair value of the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{P}_{\mathcal{s}\mathcal{b}}(\mathcal{s} \in \text{Å}, \mathcal{b} \in \kappa)$	weighted distance of pair value of the company $\text{Å}_{\mathcal{s}}$ depending on the criterion $\kappa_{\mathcal{b}}$,
$\mathbb{O}_{\mathcal{s}}(\mathcal{s} \in \text{Å})$	total distance value of the company $\text{Å}_{\mathcal{s}}$,
$\mathbb{N}_{\mathcal{s}}(\mathcal{s} \in \text{Å})$	degree of opportunity loss value of the company $\text{Å}_{\mathcal{s}}$,
$\Omega_{\mathcal{s}}(\mathcal{s} \in \text{Å})$	percentage of opportunity achievement value of the company $\text{Å}_{\mathcal{s}}$.

Author Contributions

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “Conceptualization, K.K., H.Ö. and G.C.Y; methodology, K.K., H.Ö. and G.C.Y.; K.K., H.Ö. and G.C.Y.; validation, K.K., H.Ö. and G.C.Y.; formal analysis, K.K., H.Ö. and G.C.Y.; investigation, K.K., H.Ö. and G.C.Y.; resources, K.K., H.Ö. and G.C.Y.; data curation, K.K., H.Ö. and G.C.Y.; writing—original draft preparation, K.K., H.Ö. and G.C.Y.; writing—review and editing, K.K., H.Ö. and G.C.Y.; visualization, K.K., H.Ö. and G.C.Y.; supervision, K.K., H.Ö. and G.C.Y.; project administration, K.K., H.Ö. and G.C.Y. All authors have read and agreed to the published version of the manuscript.” Authorship must be limited to those who have contributed substantially to the work reported.

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Data Availability Statement

In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. You might choose to exclude this statement if the study did not report any data.

Conflicts of Interest

Declare conflicts of interest or state "The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper." Authors must identify and declare any personal circumstances or interest that may be perceived as inappropriately influencing the representation or interpretation of reported research results. Any role of the funders in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript, or in the decision to publish the results must be declared in this section. If there is no role, please state "The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results".

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