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ORIGINAL RESEARCH

A new ESG scoring methodology for small and medium-sized enterprises

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Abstract

Small and medium-sized enterprises (SMEs) are vital to economic growth and sustainability, yet most existing Environmental, Social, and Governance (ESG) scoring systems focus on large, publicly listed firms, leaving SMEs largely overlooked. This research introduces a new ESG scoring methodology specifically designed for SMEs, which addresses the challenges of limited disclosure, sector-specific materiality, and data quantifiability. Using publicly available information and expert input, we construct a questionnaire-based ESG index aligned with the Sustainability Accounting Standards Board (SASB) framework to ensure sector-specific materiality. The methodology applies advanced optimization techniques to determine indicator weights and uses multiple mapping functions to generate robust, interpretable ESG scores. The findings contribute to advancing methodologies for ESG scoring in SMEs and inform policy discussions on enhancing sustainability disclosures tailored to SMEs' operational contexts.

Keywords Sustainability · Environmental, social, governance scores · Small and medium-sized enterprises · Optimization · Regulation

JEL classification G32 · G38 · M14 · Q56 · C61 · C81 · C83

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1 Introduction and background

SMEs are pivotal to the European Union (EU) economy, comprising over 99% of all businesses within the region, with approximately 24 million SMEs operating across various sectors (World Economic Forum, 2024). These enterprises are fundamental to job creation, employing over 94 million people and providing two-thirds of private sector employment (European Economic & Social Committee, 2021). Their contribution to the EU's gross domestic product (GDP) is substantial, accounting for more than half of the economic output, which underscores their role in fostering economic growth and innovation (European Commission, 2024a). Unlike larger corporations, SMEs often remain deeply rooted in their local communities, enhancing regional stability and social cohesion by providing local jobs and contributing to the local economy (European Economic & Social Committee, 2021). This resilience makes them less likely to relocate operations abroad, thus sustaining local economies even in the face of global economic shifts (European Economic & Social Committee, 2021). The academic literature further corroborates these points, with studies highlighting the innovation and growth SMEs drive within high-tech sectors (Coad & Rao, 2008) and their essential role in the entrepreneurial economy (Audretsch & Thurik, 2001). Given these contributions, SMEs are rightly considered the backbone of Europe's economy, crucial for achieving a sustainable, innovative, and resilient economic future (European Commission, 2020).

The massively increasing demand for company sustainability-related information underscores the relevance of disclosing sustainability data and the need for its assessment. Regulatory policies, benchmarking of company sustainability performance against peers, and the growth in sustainable, green investing are key trends that drive the disclosure of sustainability information and the development of multiple scoring approaches, with ESG scores becoming mainstream. In this regard, the European Commission's strategy to enhance corporate sustainability among SMEs centers on the Directive on corporate sustainability due diligence, adopted on February 23, 2022 (European Commission, 2024b). This Directive aims to foster sustainable and responsible corporate behavior by mandating companies to identify and mitigate adverse human rights and environmental impacts across their global operations and supply chains (European Commission, 2024b).[1] Simultaneously, the Corporate Sustainability Reporting Directive (CSRD), effective from January 5, 2023, requires large public-interest companies to report on sustainability aspects, with plans to extend this mandate to listed SMEs in the future (European Commission Environment, 2024). To facilitate compliance, the European Financial Reporting Advisory Group (EFRAG) is developing proportionate reporting standards tailored for both listed SMEs and non-listed SMEs (European Commission Environment, 2024).[2] The OECD's insights further highlight the challenges SMEs face in securing financing for sustainable transitions (Organization for Economic

[1] Although the Directive primarily targets large EU and non-EU companies, it includes provisions to support SMEs indirectly involved as business partners in value chains. The Directive offers a harmonized legal framework that creates legal certainty and a level playing field across the EU. It helps companies manage risks, improve resilience, and increase competitiveness. SMEs, despite not being directly covered by the new rules, benefit from protective measures that facilitate compliance without imposing an undue burden (European Commission, 2024).

[2] The European Financial Reporting Advisory Group (EFRAG) has published two Exposure Drafts on sustainability reporting standards for SMEs under the Corporate Sustainability Reporting Directive (CSRD) (European Commission Environment, 2024). These drafts aim to provide proportionate reporting standards for listed SMEs (LSMEs) and voluntary standards for non-listed SMEs (VSMEs) (European Commission Environment, 2024). The CSRD, effective from January 5, 2023, enhances transparency by mandating sustainability reporting for large public-interest companies and extending this requirement to listed SMEs in

Co-operation and Development, 2024), which underscores the multifaceted nature of ESG considerations and the pivotal role SMEs play in advancing broader sustainability goals.

A wide array of broad sustainability assessment scores and indices have been developed by competing providers such as MSCI KLD, Bloomberg ESG, Sustainalytics, Moody's ESG, S&P Global, and Refinitiv. In addition, many indices have been developed with a specific focus on sustainability, including Sustainability Performance Index, Ecological Footprint, Composite Sustainable Development Index, Composite Sustainability Performance Index, and Dow Jones Sustainability Group Indices. The diversity of these indices and scores along with their varying approaches, objectives, structures, and applications, presents challenges for investors, managers, institutions, and policymakers when evaluating company sustainability performance, which sparks fast-growing research in this area.

Previous empirical studies on ESG ratings, indices, and other metrics for assessing sustainability performance (Margolis et al., 2007; Singh et al., 2012; Lu et al., 2014; Berg et al., 2022;) examine their divergence and different conceptual backgrounds—value-driven, financial value-driven, and different institutional frameworks (Rowley et al., 2012; Amel-Zadeh, 2018; Eccles et al., 2020; Sipiczki, 2022). Edmans (2023) noted that "*An ESG rating isn't fact; it's opinion*". Although SMEs are pivotal drivers of economic growth and play an increasingly crucial role in promoting sustainable practices, assessing their sustainability performance remains challenging due to their varying degrees of voluntary disclosure and sector-specific operational contexts. Moreover, the lack of a universally accepted definition of sustainability and its metrics suggests that the field remains underexplored, which highlights the need for further development of methodologies for assessing sustainability performance with a comprehensive set of metrics.

A growing body of studies on sustainability and ESG ratings indicates a bias towards large-size companies (Giese et al., 2019). As suggested by Drempetic et al. (2020), this bias results from larger companies' better availability of resources for reporting and more advanced implementation of sustainable management tools. However, the debate about whether concepts and frameworks developed for large firms are also applicable to SMEs remains open. Hammann et al. (2009) highlight the specifics of SMEs, such as their value-based, socially responsible orientation towards doing business, driven by their entrepreneurial nature. According to Mezzio et al. (2022), stakeholders have unique engagement opportunities at SMEs, since they have better access to SME management, allowing them to convey their own sustainability-linked expectations more effectively than with large companies. Previous studies have also indicated limitations in sustainability-oriented research on SMEs due to a lack of proper sustainability disclosure, diversity of performance drivers, unstructured communication practices, and challenges in sustainability measurement in SMEs (Scagnelli, et al., 2013; Giacomelli, 2022; Cardoni et al., 2023). Most sustainability-linked studies on SMEs are qualitative (cases, interviews), with limited quantitative research. A review of previous studies suggests that the SME context is under-investigated.

Footnote 2 continued
subsequent years (European Commission Environment, 2024). The European Sustainability Reporting Standards (ESRS) for large companies were adopted in July 2023, covering diverse environmental, social, and governance aspects (European Commission Environment, 2024). The new drafts published in January 2024 seek to ease SMEs into sustainable economic practices, with significant consideration for the Eco-Management and Audit Scheme (EMAS), which many SMEs already follow (European Commission Environment, 2024). These standards incorporate EMAS data and processes to prevent double reporting burdens (European Commission Environment, 2024). Stakeholders, especially EMAS-registered SMEs, are encouraged to provide feedback to ensure the new standards align well with existing EMAS requirements. Public consultations, webinars, and field tests are organized to facilitate this feedback process, aiming to refine and implement these standards effectively by 2026 (European Commission Environment, 2024).

2 The contribution and the structure of the paper

Current methodologies often fall short in capturing these nuances, which highlights the need for tailored sustainability assessment frameworks. This paper addresses this gap by proposing a structured ESG rating and scoring methodology designed specifically for SMEs. Drawing on the Sustainability Accounting Standards Board (SASB) framework (SASB, 2025a), the methodology systematically selects, weighs, and aggregates ESG indicators from publicly available sources. The SASB framework helps to maintain industry standards when disclosing sustainability information. SASB standards define how organizations manage and communicate sustainability-related disclosure practices within financial reporting frameworks (SASB, 2025a). The presented methodology integrates optimization techniques to refine sustainability scores and employs mapping functions (logistic, hyperbolic tangent, and cumulative distribution function) and diverse scoring methods for comprehensive evaluation.

Focusing on sectors like meat, dairy, and agriculture across Europe, this research identifies key challenges and insights crucial for developing effective ESG scoring systems designed for SMEs. Our approach not only advances methodologies for assessing SME sustainability but also provides critical insights for policymakers and regulators aiming to enhance sustainability disclosures within SMEs.

The main contribution of this research is methodological. The paper contributes in three important ways. Firstly, it addresses the scarcity of relevant data on SMEs' sustainability performance by leveraging publicly accessible sources. Secondly, it pioneers sector-specific sustainability assessments tailored to individual companies. Thirdly, it constructs a data sample sourced from companies' websites, media posts, registry sources, and third-party providers. This methodological approach is tested on SMEs within specific sectors to pinpoint key aspects and challenges in devising an ESG scoring and rating system customized for SMEs.

While initially validated within the dairy and meat sectors, and agricultural companies, our ESG rating methodology is adaptable for application across SMEs in diverse industries. This adaptability enables us to discern critical aspects and challenges necessary for developing bespoke ESG scoring and rating systems tailored specifically for SMEs. Our selection of European companies relies on their voluntary sustainability disclosures, highlighting the increasing importance of sustainability despite the current limitations of mandatory reporting, which restricts automated data collection.

The paper is structured as follows. In Sect. 3, a literature review is presented on the diversity of ESG scores and indices, followed by a discussion of various sustainability assessment methodologies. In Sect. 4, the paper introduces the research design for assessing sustainability in SMEs based on the ESG index and ranking, which is applied to a data sample from selected industry SMEs. Section 5 concludes and provides a summary discussion on the advantages and limitations of the suggested ESG index and ranking approach.

3 Literature review

Sustainability assessment methodologies and practices are grounded in multiple definitions of sustainability which have emerged and evolved alongside advances in the sustainability political agenda. In addition to efforts to mitigate the negative effects of climate change, political agreements among global players, such as the UN 2030 agenda and the Sustainable Development Goals (SDGs), as well as the European Green Deal 2019, have underscored the need to address complex challenges and risks. These transformations have triggered regulatory developments towards standardizing the assessment of sustainable business economic activities (via the EU taxonomy), as well as increasing transparency and sustainability reporting through EU Directives on non-financial reporting, and more recently, Corporate Sustainability Reporting.

These transformations also influence the development in sustainability scores, indices, and ratings. The commonly accepted ESG scores and ratings are based on the need to focus on three major dimensions—Environmental, Social, and Governance—when assessing sustainability risks, performance, and impacts. Prominent providers include MSCI KLD, Bloomberg ESG, Sustainalytics, Moody's ESG, S&P Global, and Refinitiv. The number of diverse ESG metrics, scores, indices, ratings, and rankings has grown significantly, reaching over 600 suggested ESG ratings and rankings (Wong et al., 2019). The diversity of these approaches stems from the complexity of the issues they address, and the varied objectives of the scores and ratings, leading to different methodologies for their development. MSCI provides firm-level ratings based on their exposure to ESG risks and opportunities, assessing a company's resilience to long-term, industry-material ESG risks. Refinitiv's rating evaluates company ESG performance and disclosure of controversial activities, considering industry materiality and company size biases, and company size biases. Sustainalytics measures a company's exposure to industry-specific and financially material ESG risks and their management. These indices and ratings are predominantly available for large listed companies (MSCI KLD, 2022) and typically do not cover SMEs.

ESG indices offer a key advantage by distilling complex, multidimensional sustainability data into simplified, manageable metrics (Atkinson et al., 1997; Mayer, 2008). These ratings are derived by rating agencies from company disclosures and public data via sophisticated methodologies (Drempetic et al., 2020). However, ESG ratings often conflate aspirational commitments with actual performance, which raises concerns about their reliability and interpretability (Ferrazzi and Tueske(2022)). These concerns are echoed in recent studies that underscore inconsistencies and a lack of transparency across rating systems. For instance, Berg et al. (2022) find weak correlations between different ESG scores issued by the agencies, which indicates limited comparability. Building on this, Benuzzi et al. (2025) show that ESG performance assessments are highly sensitive to methodological choices, such as indicator selection, weighting, and aggregation. Del Vitto et al. (2023) employ machine learning techniques to replicate ESG ratings from Refinitiv. They reveal that, although ESG scores can be approximated with reasonable accuracy, a portion of the variance remains unexplained, which suggests the presence of opaque, proprietary adjustments. Similarly, Billio et al. (2021) demonstrate that ESG ratings often diverge significantly across providers, leading to inconsistent investment signals and undermining the reliability of ESG-based financial decisions. Sahin et al. (2023) add to this discussion by pointing out to the instability of ESG scores. They note that providers like Refinitiv may retroactively alter published scores without disclosure, further undermining their transparency and credibility. Collectively, these insights highlight the need for transparent and standardized scoring frameworks. This is an objective our methodology directly aims to addresses through its use of expert-informed optimization and clearly defined scoring functions.

ESG assessments typically rely on data from company reports on sustainability policies, surveys, and public sources. Berg et al. (2022) demonstrate that discrepancies in ESG scores arise from differences in information sources, metrics, different measurement techniques, and weighting schemes. A more recent review on ESG rating (Agosto & Tanda, 2025) confirm inconsistencies between multiple methodologies, when employing diverse sustainability data aggregation techniques. ESG scores are skewed towards large firms due to their greater disclosure capacity of sustainability related information (Giese et al., 2019). Drempetic et al. (2020) argue that this size bias reflects better availability of resources and more advanced sustainability practices in larger firms. As most ESG frameworks are designed for large firms, their applicability to SMEs remains limited. Research on ESG scoring of SMEs is also lagging. Cantele et al. (2018) argue that existing studies focus heavily on US-based large firms and classical ratings (e.g., MSCI KLD), rather than assessing sustainability practices. Cardoni and Kiseleva (2025) further highlight this gap by examining the ESG communication strategies of SMEs. To capture SMEs transition to sustainability, Mure et al. (2024) suggest focusing on self-reported questionnaire, which is tested in context specific banking sector. Though such an approach has advantages as it allows to consider industry-specific sustainability policies, its background on self-reported data raises major critique. While environmental factors may be quantified and tested, social and governance factors are more qualitative, which makes their assessment more subjective. In their study of European SMEs Ortiz-Martínez et al. (2022) provide arguments that there is a strong influence of country and sector when reporting and verification of non-financial information based on the Global Reporting Initiative. Yang et al (2025) investigate material ESG issues following SASB ESG score methodology. Their findings suggest that ESG communication in SMEs is fragmented and shaped more by internal capabilities, availability of financial resources than by strategic integration. This reinforces the need for structured and externally validated ESG assessment frameworks.

To bridge this gap, scholars have begun developing alternative methodologies tailored for SMEs. For instance, Ozkan et al. (2023) propose a neural network-based model that estimates environmental (E) scores for SMEs using satellite data from the Copernicus programme. Their approach bypasses the need for firm-level disclosure by training a model on large companies' environmental ratings and applying it to SMEs. However, it is limited to environmental performance. Liang et al. (2023) construct a sector-specific credit rating model for sustainable agricultural supply chain finance, integrating heterogeneous evaluation information and managing misclassification risk through a three-way decision framework.[3] D'Amato et al. (2022) further demonstrate that ESG scores can be predicted using Random Forest algorithms trained on structural financial data, such as balance sheet and income statement variables. Other approaches include Moody's ESG score predictor, which combines firm-level characteristics (e.g., size, location, industry) with country-level data to generate ESG scores (Moody's, 2021), though it lacks detailed sustainability inputs. Barro et al. (2025) propose a multicriteria decision analysis (MCDA) framework to evaluate the ESG performance of European-listed SMEs. Their approach identifies sector-specific leaders and laggards by applying predefined weights to ESG indicators based on expert judgment and stakeholder relevance. In contrast, our methodology is based on a more flexible, data-driven optimization framework that determines indicator weights by minimizing the deviation between expert rankings and predicted scores, particularly suited to SMEs with heterogeneous disclosure practices. Moreover, differently from MCDA-based methods, our model incorporates multiple mapping functions (logistic, hyperbolic tangent, and cumulative distribution), which cater to different scoring scenarios, especially in sectors with limited standardised reporting. In another recent study, Momtaz and Parra (2025) find that both internal ESG signals (e.g., voluntary disclosures) and external certifications positively influence SME financial performance, though they act as informational substitutes. While Momtaz and Parra (2025) focus on the financial outcomes of ESG disclosure, our work complements this

[3] Although focused on creditworthiness rather than ESG scoring, Liang et al. (2023) highlight the importance of combining sustainability indicators with risk-sensitive classification. This is particularly relevant for SMEs in environmentally dependent sectors.

by addressing the methodological challenge of ESG scoring itself, particularly for SMEs with limited or inconsistent disclosure. Along similar lines, Zanin (2022) demonstrates that ESG scores in general positively influence corporate credit ratings. Using a multivariate ordinal logit regression model, the study confirms the predictive value of ESG indicators in financial risk assessment. This underscores the need for robust, transparent, and statistically grounded ESG scoring methodologies such as the one proposed in this paper.

These examples of sustainability/ESG scoring methodologies indicate that major challenges remain. Since SMEs are largely exempt from compulsory sustainability reporting under the CSRD, the scope of sustainability-related information provided is and will remain limited. This is influenced by the needs of companies for green investment financing and voluntary information disclosures reflecting their strategic aspirations and values. Survey-based methodologies, if implemented, have high administration costs. Self-reported data are broadly considered to have significant drawbacks related to reliability, potentially leading to greenwashing. Score predictor-type methodologies may produce biased results, significantly deviating from actual company practices. The importance of SMEs for economies and their role in promoting sustainability policies, combined with the existing gap in providing solutions to SMEs, highlights the need for a firm-level sustainability index and ranking for SMEs. This should address methodological challenges and existing information limitations.

4 Research design

Our research design is depicted in Fig. 1, which illustrates three primary stages: data collection, methodology development, and methodology application. This section is organized as follows: Sect. 4.1 details our data collection strategy, Sect. 4.2 outlines the steps involved in developing the ESG rating and scoring methodology, and Sect. 4.3 evaluates the methodology's application on SMEs from the European Union.

4.1 Data collection

We used a structured assessment framework – referred to as a 'questionnaire' – to collect data on selected ESG components from publicly available online sources. These sources included company websites, sustainability reports, and third-party web pages. The framework was thoroughly tested to ensure that the necessary information was accessible and could be quantified. The collected data were subsequently converted into a binary format. Specifically, each question pertaining to a specific indicator was analysed and evaluated as either YES (coded as 1) or NO (coded as 0). The final ESG index, specifically designed for SMEs, consists of 15 indicators for meat and dairy industry and 16 indicators for agricultural firms. These include five environmental indicators: greenhouse gas emissions, energy, water, waste management, and sustainable practices; six social indicators (seven social indicators for agricultural companies): (food safety), working conditions, qualifications, ecological environment, corporate social responsibility, employee development, and equality and anti-discrimination; and four governance indicators: business ethics breaches, sustainability reporting, green supply chain, and gender diversity. The questionnaires for both meat and dairy and agriculture are depicted in Table 1, Panels A and B, respectively. This table provides detailed information on the indicators and their coding.

The proposed ESG sustainability index and ranking methodology were tested on a set of companies. 20 SMEs from the meat and dairy industry across European countries were

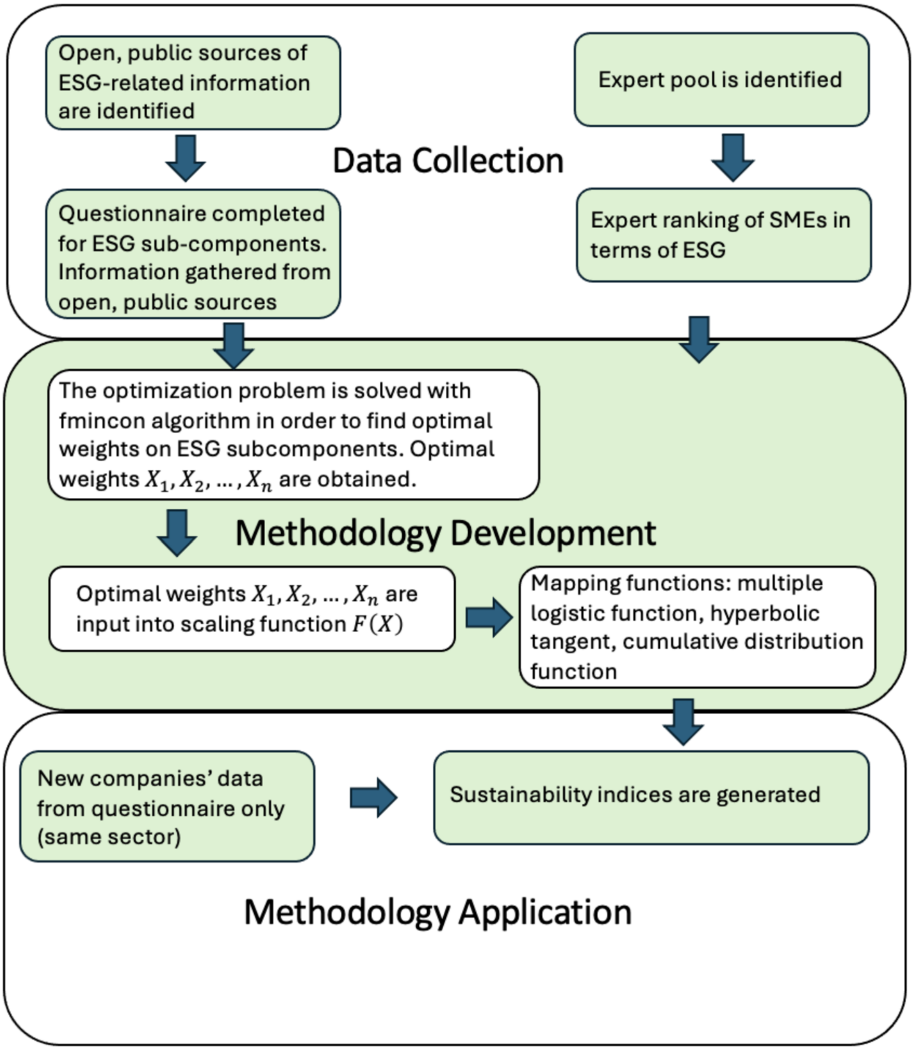

Fig. 1 Research design flow chart diagram**.** Figure 1 summarizes the research methodology, which is structured in three main stages: data collection, methodology development, and application. This flowchart helps readers understand the structure and logic of the ESG scoring framework. It illustrates how raw data from public sources is transformed into sustainability scores through expert input, optimization, and mapping functions

selected based on their voluntary disclosure of sustainability information in public sources. The decision to focus initially on the meat and dairy industry was motivated by its high environmental and social impact, as well as its regulatory complexity. This sector is among the most scrutinized in terms of sustainability due to its significant greenhouse gas emissions, water and energy usage, and animal welfare concerns. Moreover, it benefits from substantial support packages and regulatory oversight within the European Union, which makes it a relevant and policy-sensitive context for ESG evaluation. The ESG indicators selected for this study were aligned with the SASB framework to ensure sector-specific materiality (SASB,

Table 1 Description of the questionnaire of ESG indicators

Indicator	Description
A. Meat and dairy industry	
1	Greenhouse Gases: a) Are greenhouse gases monitored? b) Nitrious Oxide c) Sulfur Dioxide d) CO2 e) L-R or S-R strategy/analysis to reduce scope 1 emissions
2	Energy Management: a) Total energy consumed b) Percentage or amount of renewable energy c) Is it aimed to minimize energy consumption through certain operations? d) Are there quantifiable targets for the reduction of energy usage? e) Are efficient strategies applied in advancing energy management? f) Are energy consumption trends routinely monitored?
3	Water Management: a) Total water withdrawn b) Description of water management risks or discussion/applications of strategies to reduce those risks c) Are efficient strategies applied in enhancing water conservation?
4	Waste Management: a) Is the quantity of waste ensured to be minimized from its operations? b) Is waste monitored and recorded?
5	Sustainable practices: a) Has environmental policy or vision b) Has sustainable investments c) Uses sustainable finance options (grants) for sustainability projects d) Has sustainable packaging solutions
6	Working Environment: a) Were there no safety incidents? b) Is there safety policy in the website/report regarding working environment? c) Is there safety programs/initiatives to reduce safety incidents or increase secure working environment?
7	Qualifications: Are products qualified? Information provided on the website or in the report
8	Ecological Environment: a) Are products free from antibiotics or ensures natural ingredients? b) Is supply chain ecological (website, report) c) Is the environmentally and/or animal friendly farming is assured?
9	Corporate Social Responsibility: Are there any corporate social responsibility activities supporting local communities?
10	Employee Development: Are there investments in employee training?
11	Equality and Anti-discrimination: Equality and/or anti-discrimination policy published on the website or in sustainability report

Table 1 (continued)

Indicator	Description
12	Were there no business ethics breaches? a) Taxes b) Court cases c) Complaints of employees d) Environmental offenses e) Product/services complaints f) Unethical trading
13	Sustainability reporting a) Does the company have a sustainability section on the website? b) Strategic sustainability aim mentioned in the company's website c) Does the company track measurement indicators with respect to sustainability? d) Does the company have a sustainability report?
14	Green supply chain Is there sustainable supply chain information on the website or in the sustainability report?
15	Gender Diversity a) Is there information about gender diversity in management or overall published on the company's website or in the report? b) Is there a policy on gender diversity on the company's website or in the report?
B. Agriculture	
1	Greenhouse Gases: a) Are greenhouse gases monitored? b) Nitrious Oxide c) Sulfur Dioxide d) CO2 e) L-R or S-R strategy/analysis to reduce scope 1 emissions f) Does the company provide information on fleet fuel used per year or at least some trace about the fleet usage g) fleet fuel used percentage by renewable fuel
2	Energy Management: a) Does the company provide operational energy consumed b) Does the company provide percentage grid electricity c) Percentage renewable provided information e) Does the company at least has some policy or strategy for the use of energy?
3	Water Management: a) Total water withdrawn b) Total water consumed c) Description of water management risks or discussion/applications of strategies to reduce those risks d) Number of incidents of non-compliance with respect to water quality permits etc
4	Waste Management: a) Is the quantity of waste ensured to be minimized from its operations or the damage done recreated? b) Is waste monitored and recorded?
5	Sustainable practices: a) Has environmental policy or vision b) Has sustainable investments c) Uses sustainable finance options (grants) for sustainability projects d) Has sustainable packaging solutions?

Table 1 (continued)

Indicator	Description
6	Food Safety: a) Has environmental policy or vision b) Has sustainable investments c) Uses sustainable finance options (grants) for sustainability projects d) Has sustainable packaging solutions?
7	Working Environment: a) Were there no safety incidents? b) Is there safety policy in the website/report regarding working environment? c) Is there safety programs/initiatives to reduce safety incidents or increase secure working environment?
8	Qualifications: Are products qualified? Information provided on the website or in the report
9	Ecological Environment: a) Are products free from antibiotics or ensures natural ingredients? b) Is supply chain ecological (website, report or Social Media) c) Is the environmentally and/or animal/plants friendly farming is assured?
10	Corporate Social Responsibility: Are there any corporate social responsibility activities supporting local communities?
11	Employee Development: Are there investments in employee training?
12	Equality and Anti-discrimination: Equality and/or anti-discrimination policy published on the website or in sustainability report
13	Were there no business ethics breaches? a) Taxes b) Court cases c) Complaints of employees d) Environmental offenses e) Product/services complaints f) Unethical trading
14	Sustainability reporting a) Does the company have a sustainability section on the website? b) Strategic sustainability aim mentioned in the company's website c) Does the company track measurement indicators with respect to sustainability? d) Does the company have a sustainability report?
15	Green supply chain Is there sustainable supply chain information on the website/ social media or in the sustainability report?
16	Gender Diversity a) Is there information about gender diversity in management or overall published on the company's website or in the report? b) Is there a policy on gender diversity on the company's website or in the report?

This panel A presents the Environmental, Social, and Governance (ESG) indicators used to evaluate the sustainability performance of SMEs in the meat and dairy industry. The framework includes five environmental indicators: greenhouse gas emissions, energy use, water management, waste management, and sustainable practices; six social indicators: working conditions, product qualifications, ecological considerations, corporate social responsibility, employee development, and equality and anti-discrimination; and four governance indicators: business ethics, sustainability reporting, green supply chain practices, and gender diversity. All responses are coded as binary variables (Yes=1, No=0), which ensures consistency and comparability across firms. The questionnaire is aligned with the SASB materiality framework

This panel B presents the Environmental, Social, and Governance (ESG) indicators used to evaluate the sustainability performance of SMEs in the agricultural industry. The framework includes five environmental indicators: greenhouse gas emissions, energy use, water management, waste management, and sustainable practices; seven social indicators: food safety, working conditions, product qualifications, ecological considerations, corporate social responsibility, employee development, and equality and anti-discrimination; and four governance indicators: business ethics, sustainability reporting, green supply chain practices, and gender diversity. All responses are coded as binary variables (Yes=1, No=0), which ensures consistency and comparability across firms. The questionnaire is aligned with the SASB materiality framework

2025b). A similar approach was used for the selection of 18 agricultural firms. To determine the weight coefficients for the indicators, we evaluated the initially collected data with input from four sustainability experts. The experts came from diverse departments, including consulting (1 expert), financial services (2 experts), and manufacturing (1 expert). While their formal roles were account manager, sales manager, CEO, and compliance officer, they were actively involved in designing sustainability strategies, developing policies, and overseeing sustainability practices. For the agricultural sample, we consulted a panel of five experts with diverse professional backgrounds and direct involvement in sustainability-related roles. The panel included an account manager, a senior pricing associate, a technical sales manager in agricultural technologies, a sustainability and human resources director at a dairy company, and a sustainability manager at an investment firm. All experts were selected based on their sector-specific knowledge, practical experience with ESG implementation, and familiarity with sustainability disclosures in the agricultural domain. This selection of experts helped conduct a balanced and well-informed evaluation process. The experts scored each firm on each criterion. Specifically, they evaluated the companies on a scale of 1 to 5, with 1 indicating the lowest and 5 the highest level of sustainability performance. Based on these expert evaluations, companies were ranked accordingly, with rank 1 representing the highest sustainability score, and rank 20 (or 18 for the agricultural group) the lowest. These expert evaluations were subsequently used to generate benchmark rankings, which served as the foundation for determining the optimal weights of ESG indicators through the optimization process described in Sect. 4.2.

Panel A of Table 2 provides a sample of 20 anonymised SMEs selected by industry and ranked by experts based on collected information on 15 selected environmental, social, and governance indicators. These 20 companies span across 13 countries. The company with the smallest revenue is in Greece, generating approximately EUR 3.08 million per annum, while the largest, based in Lithuania, reports EUR 31.5 million. In terms of the workforce size, the smallest company is in Norway, employing between 11 and 20 people, whereas the largest also in Lithuania, has 216 employees. Finally, the highest-ranked company by experts is in Norway, while the lowest-ranked is in Greece. Panel B of Table 2 provides an overview of 18 agricultural SMEs from 9 European countries, each evaluated for their sustainability performance. These firms vary significantly in size and scale, with employee counts ranging from as few as 4 to as many as 190. The smallest company by revenue is based in France, reporting just EUR 74,700 annually, while the largest, located in Belgium, reports EUR 23.99 million.

Based on the companies' indicators and rankings (see Table 3), we observe a clear non-linear relationship between the ESG questionnaire scores and the rankings. For example, a company with a higher score may have a lower rank, which indicates that linear regression is not appropriate for determining weights due to the absence of linear dependence.

4.2 Methodology development

This section outlines the approach used to develop an Environmental, Social, and Governance (ESG) scoring methodology tailored to SMEs, which addresses key challenges such as data availability and model construction. It details the steps taken to create the ESG index and ranking. Overall, this section offers valuable insights for designing a tailored ESG index and ranking methodology for SMEs, while overcoming specific challenges.

The main procedures for building a sustainability index and subsequently ranking include choosing appropriate sustainability indicators, weighing the selected indicators, aggregating

Table 2 Experts ranking of SMEs

Company no	Country	Industry	Company revenue	Number of employees	Expert rank
A. Meat and dairy industry					
1	Lithuania	Meat	31.5 M EUR	159	4
2	Lithuania	Meat	12 M EUR	216	14
3	Denmark	Meat	11.21 M EUR	34	11
4	Denmark	Meat	4.69 M EUR	32	8
5	Sweden	Meat	13.98 M EUR	21–50	18
6	Norway	Meat	< 4.7 M EUR	74	6
7	Norway	Meat	9 M EUR	31	1
8	Norway	Meat	5.91 M EUR	11 to 20	9
9	Norway	Meat	< 4.7 M EUR	30	10
10	Norway	Meat	16.88 M EUR	200	15
11	Greece	Dairy	3.08 M EUR	25	17
12	Greece	Dairy	6.2 M EUR	25	20
13	Portugal	Dairy	4.67 M EUR	25	16
14	France	Dairy	4.67 M EUR	25	19
15	United Kingdom	Dairy	17.29 M EUR	87	7
16	Austria	Dairy	13.27 M EUR	54	5
17	Slovakia	Dairy	7.57 M EUR	31	12
18	Cyprus	Dairy	12.15 M EUR	200	13
19	Spain	Dairy	28.78 M EUR	134	2
20	Germany	Dairy	< 5 M EUR	< 25	3
B. Agriculture					
1	France	Agro	74.7 K EUR	4	7
2	Italy	Agro	5 M EUR	5–9	5
3	Denmark	Agro	5 M EUR	5–9	3

Table 2 (continued)

Company no	Country	Industry	Company revenue	Number of employees	Expert rank
4	Netherlands	Agro	5 M EUR	60	4
5	Germany	Agro	6.1 M EUR	19	1
6	Lithuania	Agro	1 M EUR	21	10
7	Italy	Agro	11 M EUR	49	15
8	Belgium	Agro	< 5 M EUR	49	7
9	Belgium	Agro	23.99 M EUR	9	9
10	Italy	Agro	2 M EUR	9	8
11	Lithuania	Agro	1.6 M EUR	9	13
12	Lithuania	Agro	2.2 M EUR	56	11
13	Lithuania	Agro	0.6 M EUR	53	6
14	Latvia	Agro	13.14 M USD	190	2
15	Estonia	Agro	14 M USD	57	14
16	Estonia	Agro	9.4 M USD	13	17
17	Estonia	Agro	7.53 M USD	5	16
18	Latvia	Agro	10.31 M USD	48	12

Panel A describes the meat and dairy sample and presents the expert-assigned sustainability rankings for SMEs based on their ESG disclosures. It covers 20 SMEs in the meat and dairy industry. Each company is anonymized and listed with its country, revenue, number of employees, and expert rank (where 1 is the highest sustainability performance and 20 is the lowest). These rankings were derived from expert evaluations using the questionnaire of ESG indicators defined in Table 1. This table provides a benchmark against which the model's predicted rankings are later compared. This table was sourced from https://www.europages.com; https://www.zoominfo.com; https://www.rekvizitai.lt

Panel B describes the agricultural sample and presents the expert-assigned sustainability rankings for SMEs based on their ESG disclosures. It covers 18 SMEs in the agricultural industry. Each company is anonymized and listed with its country, revenue, number of employees, and expert rank (where 1 is the highest sustainability performance and 18 is the lowest). These rankings were derived from expert evaluations using the questionnaire of ESG indicators defined in Table 1. This table provides a benchmark against which the model's predicted rankings are later compared. This table was sourced from https://www.europages.com; https://www.zoominfo.com; https://www.rekvizitai.lt

those indicators into a composite index (Meadows, 1998), and finally, giving scores and ranks for the companies. Sustainability-related information selection for the choice of appropriate indicators was based on the following conceptual framework:

1. *Disclosure*. SMEs in general are not subject to compulsory sustainability information disclosure. Companies engaged in sustainability-related activities disclose the information on a voluntary basis. As a result, the availability of standardized ESG data is limited. To overcome this, we rely on voluntarily disclosed information that is publicly accessible through company websites, sustainability reports, media coverage, registry sources, and third-party providers. This approach ensures the ESG indicators used in the scoring model are grounded in real-world, observable practices.

Table 3 Analysis of the questionnaire for SMEs

Company No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
A. Meat and dairy industry															
1	0.80	0.50	1.00	1.00	1.00	0.33	1.00	1.00	0.00	0.00	0.00	0.83	0.75	1.00	0.00
2	0.00	0.50	0.00	0.50	0.75	0.33	0.00	1.00	0.00	0.00	0.00	0.67	0.50	1.00	0.00
3	0.00	0.67	0.67	0.50	0.75	0.33	1.00	0.33	0.00	1.00	0.00	1.00	0.50	1.00	0.00
4	0.20	0.33	0.00	0.00	0.75	0.33	1.00	1.00	0.00	0.00	0.00	1.00	0.50	1.00	0.50
5	0.00	0.00	0.00	0.50	0.25	0.33	1.00	0.00	1.00	1.00	0.00	1.00	0.50	0.00	0.00
6	0.20	0.50	0.00	0.50	0.75	0.33	0.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	0.50
7	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00
8	0.60	0.50	0.33	0.50	0.75	0.33	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	0.00
9	0.20	0.50	0.67	1.00	0.75	0.33	1.00	0.33	1.00	0.00	0.00	1.00	0.50	0.00	0.00
10	0.20	0.00	0.00	0.50	0.50	0.33	1.00	0.00	0.00	1.00	1.00	1.00	0.50	0.00	1.00
11	0.00	0.00	0.00	0.50	0.50	0.33	1.00	0.00	0.00	1.00	1.00	1.00	0.50	0.00	0.00
12	0.00	0.00	0.00	0.50	0.75	0.33	1.00	0.00	0.00	0.00	0.00	1.00	0.50	0.00	0.00
13	0.00	0.00	0.00	0.00	0.25	0.33	1.00	0.00	0.00	1.00	0.00	1.00	0.50	1.00	0.00
14	0.00	0.00	0.00	0.00	0.75	0.33	1.00	0.00	1.00	0.00	0.00	1.00	0.50	0.00	0.00
15	0.40	0.67	0.00	0.00	0.75	0.67	1.00	1.00	1.00	0.00	0.00	0.83	0.75	1.00	0.00

Table 3 (continued)

Company No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
16	0.60	0.67	0.00	0.00	0.50	0.33	1.00	1.00	0.00	1.00	0.00	1.00	0.75	1.00	0.50
17	0.80	0.33	0.00	0.50	0.75	0.33	1.00	0.00	1.00	1.00	0.00	1.00	0.75	0.00	0.00
18	0.20	0.50	0.67	0.50	0.50	0.33	1.00	0.00	1.00	0.00	0.00	1.00	0.50	0.00	0.00
19	0.80	1.00	1.00	1.00	0.75	1.00	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00	0.50
20	1.00	1.00	1.00	1.00	0.50	0.33	1.00	1.00	0.00	0.00	0.00	1.00	1.00	1.00	0.50

Company No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
B. Agriculture																
1	0.14	0	0	0.50	0.75	1	0.33	1	1	0	0	0	1	0.5	1	0
2	0.14	0	0	0.5	0.5	1	1	1	0.67	1	1	1	1	0.5	1	1
3	0.14	0.25	0	1	0.5	1	1	1	1	0	0	0	1	0.5	1	1
4	0.14	0.25	0	0	0.75	1	1	1	1	0	1	1	1	0.5	1	1
5	0.57	0.75	0	0	0.75	1	1	1	1	1	0	0	1	1	1	0
6	0	0	0	0.5	0.75	0.5	1	1	1	0	0	0	0.83	0.5	1	0
7	0	0	0	0	0.25	0.5	0	0	1	0	0	0	0.83	0	0	0
8	0.14	0.25	0	0.5	0.75	1	0.33	1	1	0	0	0	1	0.5	1	0
9	0.00	0	0	0	1	1	0.33	1	1	1	0	0	1	0.5	1	0
10	0.00	0.50	0	0	1	1	0.33	1	1	0	1	0	1	0.5	1	0
11	0.00	0	0	0	0.25	1	0.33	1	1	0	0	0	1	0	0	0
12	0.00	0	0	0	1	1	0.33	1	1	1	0	0	0.83	0.5	1	0
13	0.29	1	0	0	0.5	1	0.33	1	1	0	0	0	1	0.5	1	0

Table 3 (continued)

Company No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
14	0.43	0.75	0.25	1	0.75	1	0.33	1	1	1	1	0	1	0.75	1	0
15	0.00	0	0	0	0.25	1	0	0	0.33	0	0	0	1	0	0	0
16	0.00	0	0	0	0.5	0	0.33	0	0	0	0	0	1	0	0	0
Company No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
17	0.00	0	0	0	0	0	0.33	0	0	0	0	0	1	0	0	0
18	0.29	0.25	0.25	0	0.75	0	0	0	0	0	0	0	1	0	0	0

Panel A displays the raw ESG indicator scores for each SME that operates in the meat and dairy industry, based on publicly available data. Each row represents a company, and each column corresponds to a specific ESG indicator (X1 to X15). The firms are ranked by a panel of experts from 1 (highest sustainability performance) to 20 (lowest), and these expert rankings serve as the benchmark for the optimization model that calculates ESG scores and predicted rankings. The scores are normalized between 0 and 1, which indicates the presence or absence of sustainability practices. Each indicator consists of multiple sub-questions, and the score is calculated as the proportion of sub-questions answered ‘Yes’. For example, for the first company and first indicator, a score of 0.80 indicates that 4 out of 5 sub-questions were answered affirmatively. This data forms the input for the optimization model that calculates ESG scores and rankings

Panel B displays the raw ESG indicator scores for each SME that operates in the agricultural industry, based on publicly available data. Each row represents a company, and each column corresponds to a specific ESG indicator (X1 to X16). The firms are ranked by a panel of experts from 1 (highest sustainability performance) to 18 (lowest), and these expert rankings serve as the benchmark for the optimization model that calculates ESG scores and predicted rankings. The scores are normalized between 0 and 1, which indicates the presence or absence of sustainability practices. Each indicator consists of multiple sub-questions, and the score is calculated as the proportion of sub-questions answered ‘Yes’. For example, for the first company and first indicator, a score of 0.14 indicates that 1 out of 7 sub-questions were answered affirmatively. This data forms the input for the optimization model that calculates ESG scores and rankings

2. *Materiality*. Sustainability challenges can vary significantly across industries. For example, water usage may be critical in agriculture but less so in software development. We adopt a sector-specific approach, in which indicator selection is aligned with the SASB framework. This emphasizes industry-specific materiality. An advantage of this approach is that the ESG dimensions assessed reflect the actual sustainability risks and opportunities faced by SMEs in sectors such as meat, dairy, and agriculture. The materiality principle thus ensures that the scoring system captures relevant sustainability performance metrics in each context.
3. *Quantifiability*. For the ESG scoring model to be robust and comparable across firms, indicators must be measurable consistently and objectively. In other words, sustainability measurement should be quantifiable to provide for comparisons of metrics and evaluations of the environmental, social, and governance dimensions. To this end, all indicators were initially operationalized as binary variables (Yes $=1$, No $=0$), based on the presence or absence of specific sustainability practices or disclosures. This principle supports the use of optimization algorithms and mapping functions in later stages of the methodology, where the sustainability indices are developed.

Since sustainability indicator integration is a highly subjective procedure (Morse et al., 2001), in this paper these indicators are framed according to the ESG components. ESG index (score) structure was suggested with the focus of aligning to the SASB framework. Based on it a set of criteria to assess specific sustainability practices was developed on each of the three components – environmental, social, and governance – to align with SASB standards. Firstly, the environmental part covers energy management, water conservation, waste management, intention toward green initiatives, green technology adaptation, and sustainable green practices (Yacob, 2019). Secondly, the social part covers the health & safety of employees, aid for employee further education activities, fair remuneration of employees, and fair & respectful treatment of employees, regardless of gender or ethnic background (Lindgreen et al., 2009). Thirdly, the governance part covers corruption, lobbying, executive remuneration, and tax disclosure. Environmental and social parts are basically about stakeholders, whereas the governmental part ensures managers act on the shareholder's side (Edmans, 2023).

With the indicators defined, the next critical step involves determining their relative importance and aggregating them into a composite ESG index. Several methods for this process have been proposed in previous research. One common approach is equal weighting, which assumes that all indicators carry the same level of importance (Nardo et al., 2005). Alternatively, Van Haaster et al. (2017) introduced the public opinion method, where stakeholder preferences assign higher weights to indicators of greater concern. More advanced techniques, such as regression analysis, assess the relationships between variables using statistical methods (Kleinbaum et al., 2013). While regression analysis is effective across a broad range of indicators, it is limited by multicollinearity – an issue often encountered in sustainability assessments (Nardo et al., 2005).

Aggregation methods are essential for combining indicator scores into a composite index, but they come with limitations, particularly in sustainability assessments where multicollinearity is common. One dominant method is additive aggregation, such as a weighted arithmetic mean. This method sums the contributions of all indicators to produce a total score, implying that no synergies or conflicts exist among the indicators (Nardo et al., 2005). A less common approach is the weighted geometric mean (Gan et al., 2017), which, unlike additive methods, only allows partial compensation between indicators, due to the inequality property inherent to the geometric mean (Beliakov et al., 2007). Non-compensatory aggregation methods (Gan et al., 2017) offer an alternative when substitution between sub-components of sustainability is not acceptable. These methods are particularly valuable in scenarios where compensation is inappropriate, as they prioritize the properties of aggregation functions (Pollesch, 2015) and multi-criteria decision-making frameworks (Martel, 1998).

To determine the relative importance of each ESG indicator, we incorporated expert input into the optimization framework. Experts were asked to evaluate each SME based on the full set of ESG indicators, assigning scores that were then used to generate a benchmark ranking. These rankings served as the target vector in our constrained nonlinear optimization model, which determined the indicator weights to minimize the deviation between expert rankings and model-predicted scores. As discussed in Sect. 4.1, the expert panel consisted of professionals with direct experience in sustainability strategy and implementation, selected from consulting, financial services, and manufacturing sectors. For the agricultural sample, a separate group of domain-specific experts was consulted. This diversity was intended to capture a broad range of perspectives and reduce individual bias. Our approach strikes a balance between compensatory and non-compensatory techniques by incorporating expert opinions, expressed as varying indicator weights. Indicators with higher weights are deemed more important, allowing for some indicators to offset others, while others may not hold enough influence to compensate for weaker indicators. Our research design employs mapping functions to derive company sustainability scores expressed as percentages. We selected three distinct sigmoidal functions for this purpose: the multiple logistic function (MLF), the shifted hyperbolic tangent function (HTF), and the normal cumulative distribution function (CDF). The MLF is characterized by its smooth S-shaped curve. It offers balanced scaling across the full range of scores, with the lowest gradient at the midpoint and steeper slopes at the extremes. This makes it effective for distinguishing between SMEs with very high or very low sustainability performance. However, it offers less differentiation among those clustered around the average. Moreover, the MLF minimizes distortion at the tails; hence, it is deemed a robust choice for datasets with outliers. In contrast, the HTF exhibits the highest gradient at the at the midpoint, where it is highly sensitive to small differences in average-performing SMEs. This allows for finer differentiation among SMEs in the middle of the distribution. Thus, the HTF becomes effective when most firks fall within a moderate performace range. However, its effectiveness diminishes at the extremes. Finally, the CDF is particularly suited for datasets with relatively more dispersed scores. Its gradient characteristics make it particularly effective in differentiating among SMEs across the broader range of the score distribution, especially at the extremes.

Following the mapping of indicators, the next step involves aggregating them into a composite ESG index. To determine the relative importance of each indicator, we conducted a constrained nonlinear optimization using the Sequential Quadratic Programming (SQP) algorithm (please refer to Appendix A for more detailed explanations). Specifically, we applied the SQP algorithm to minimize that objective function, which is defined as a mean square error penalty function. This function calculates the sum of squared differences between the model-predicted rankings, Q, and the expert rankings, R, for company i and criterion j as follows:

$$f\left(W_j\right) = \sum_{i=1}^{n} \left(\sum_{j=1}^{m} Q_{ij} W_j - R_i \right)^2 \tag{1}$$

The weights W_j, $j = 1, 2, \ldots, m$ are constrained to be positive for all j. The optimal weights W_j are obtained by minimizing the objective function $f\left(W_j\right)$.

4.3 Methodology application

The optimization problem is set up using an initial guess for the weights, which are assumed randomly distributed. The optimal weights are found separately using the fmincon algorithm for E, S and G. Table 4 shows the optimal weights.

In Panel A (meat and dairy SMEs) and Panel B (agricultural SMEs) of Table 4, rank 1 corresponds to the highest-performing firm, while rank 20 (or rank 18 for agriculture) indicates the lowest. For computational consistency with the optimization algorithm, these ranks are inverted. For instance, for the meat and dairy industry (agriculture), the inversion is calculated as $21 - rank(k)$ ($19 - rank(k)$ for agriculture) where $rank(k)$ is the original assigned rank of the k-th SME. Consequently, an inverted rank of 20 (18) corresponds to the best-performing SME in the meat and dairy industry (agriculture), and an inverted rank of 1 to the lowest.

According to expert evaluations, certain indicators are deemed more influential than others, with environmental and governance indicators highlighted as more critical than social ones in this study. For the meat and dairy industry, using the optimal weights assigned to each of the 15 indicators and the corresponding company scores, predicted rankings can be computed for each company across the Environmental (E), Social (S), and Governance (G) categories. For instance, for the first company, the environmental score (E) is calculated as: $\widehat{R}_{E,1} = f_{E,1}(X) = 5.0351X_1 + 10.9785X_2 + 0.001X_3 + 0.001X_4 + 5.7566X_5 = 15.2759$. The same computation procedure is applied to the agricultural firm sample in Panel B. Each company's expert rankings and predicted rankings $f(X)$ are provided in Table 5, accompanied by detailed explanatory notes to support interpretation.

The Root Mean Square Error (RMSE) was calculated separately for the Environmental (E), Social (S), and Governance (G) dimensions for both the meat and dairy industry and agricultural companies. For the meat and dairy industry, RMSE values are as follows: $RMSE(\widehat{R}_E) = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \widehat{R}_i{}^2}{N}} = 2.3458$, $RMSE(\widehat{R}_S) = 3.2979$, and $RMSE(\widehat{R}_G) = 2.87$. For the agricultural industry, RMSE values are: $RMSE(\widehat{R}_E) = 2.4517$, $RMSE(\widehat{R}_S) = 2.4991$, and $RMSE(\widehat{R}_G) = 1.4214$. These results indicate that, depending on the industry and ESG dimension, the model-predicted rankings deviate from expert assessments by an average of approximately 1.42 to 3.30 positions. This relatively narrow range suggests a strong level of agreement.

Further, the minimum and maximum predicted ranks were identified for the Environmental dimension (Social and Governance dimensions), detailed in the explanatory notes to Table 5 (Panels A and B). These values were used to construct a linear scaling function, denoted as $F(X)$, which is defined in Eq. 2:

$$F_i\left(\hat{R}_i\right) = \left(\frac{\hat{R}_i - \hat{R}_{min}}{\hat{R}_{max} - \hat{R}_{min}} - \frac{1}{2}\right) \cdot 6 \quad (2)$$

The intuition behind the linear scaling function is to transform raw predicted rankings into a standardized range that facilitates comparison and further mathematical processing. This transformation rescales the predicted rankings to a standardized range between -3 and + 3. Specifically, the function yields $F\left(\widehat{R}_{max}\right) = \left(\frac{\widehat{R}_{max} - \widehat{R}_{min}}{\widehat{R}_{max} - \widehat{R}_{min}} - \frac{1}{2}\right) \bullet 6 = 3$ and $F\left(\widehat{R}_{min}\right) = \left(\frac{\widehat{R}_{min} - \widehat{R}_{min}}{\widehat{R}_{max} - \widehat{R}_{min}} - \frac{1}{2}\right) \bullet 6 = -3$. The scaled values $F\left(\widehat{R}_i\right)$ for each company, across

Table 4 The optimal weights on ESG indicators for E, S and G

ESG indicator No	ESG indicator weight, W_i
A. Meat and dairy industry	
1 (E)	5.0351
2 (E)	10.9785
3 (E)	0.0010
4 (E)	0.0010
5 (E)	5.7566
6 (S)	8.1821
7 (S)	2.1174
8 (S)	9.3473
9 (S)	0.1800
10 (S)	0.9365
11 (S)	0.0010
12 (G)	0.0010
13 (G)	10.2717
14 (G)	4.7947
15 (G)	3.8398
B. Agriculture	
1 (E)	10.8696
2 (E)	3.6092
3 (E)	0.0010
4 (E)	5.8745
5 (E)	8.5096
6 (S)	4.6540
7 (S)	5.1560
8 (S)	1.8658
9 (S)	1.0817
10 (S)	1.0787
11 (S)	1.7691
12 (S)	0.0010
13 (G)	3.5569
14 (G)	13.5624
15 (G)	0.0010
16 (G)	3.6609

Panel A presents the weights assigned to each ESG indicator for the meat and dairy sample, determined through a constrained nonlinear optimization algorithm (fmincon in MATLAB). The optimal weights for the five environmental indicators, six social indicators, and four governance indicators are determined separately. The algorithm calculates the weights based on the expert assessments of the companies, assigning higher or lower values to reflect their relative importance as expressed in the rankings. These weights reflect the relative importance of each indicator in predicting sustainability performance, as judged by experts

Panel B presents the weights assigned to each ESG indicator for the agricultural sample, determined through a constrained nonlinear optimization algorithm (fmincon in MATLAB). The optimal weights for the five environmental indicators, seven social indicators, and four governance indicators are determined separately. The algorithm calculates the weights based on the expert assessments of the companies, assigning higher or lower values to reflect their relative importance as expressed in the rankings. These weights reflect the relative importance of each indicator in predicting sustainability performance, as judged by experts

Table 5 Expert ranks and predicted ranks for SMEs

Company no	Predicted rank by E,$\widehat{R}_{E,i} = f_{E,i}(X)$	Predicted rank by S,$\widehat{R}_{S,i} = f_{S,i}(X)$	Predicted rank by G,$\widehat{R}_{G,i} = f_{G,i}(X)$	Expert rank,R_i
A. Meat and dairy industry				
1	5.7241	6.8079	8.5007	4
2	11.1928	8.9500	11.0688	14
3	9.3257	12.1600	11.0684	11
4	12.0526	6.8400	9.1485	8
5	19.5603	15.0700	15.8632	18
6	10.1857	7.8400	4.0127	6
7	2.1060	1.3500	2.0928	1
8	8.1714	18.3000	5.9326	9
9	10.1846	12.9200	15.8632	10
10	17.1142	15.2500	12.0234	15
11	18.1212	15.2500	15.8632	17
12	16.682	16.1800	15.8632	20
13	19.5608	15.2500	11.0684	16
14	16.6825	16.0000	15.8632	19
15	7.3129	3.8700	8.5007	7
16	7.7450	5.90000	6.5806	5
17	9.0310	15.0700	13.2952	12
18	11.6242	16.0000	15.8632	13
19	- 0.0380	0.2400	4.0130	2
20	2.1060	6.8400	4.0127	3
B. Agriculture				
1	10.8412	9.3030	10.3391	11
2	8.7138	15.2494	14	13
3	12.5533	12.7576	14	15
4	8.8062	14.5277	14	14
5	15.2847	13.8363	17.1204	17
6	9.3194	10.4306	9.7345	8
7	2.1274	3.4087	2.9522	3
8	11.7435	9.3030	10.3391	11
9	8.5096	10.3817	10.3391	9
10	10.3141	11.0721	10.3391	10
11	2.1274	9.3030	3.5569	5
12	8.5096	10.3817	9.7345	7
13	11.0161	9.3030	10.3391	12
14	19.6377	12.1508	13.7298	16
15	2.1274	5.0109	3.5569	4

Table 5 (continued)

Company no	Predicted rank by E,$\widehat{R}_{E,i} = f_{E,i}(X)$	Predicted rank by S,$\widehat{R}_{S,i} = f_{S,i}(X)$	Predicted rank by G,$\widehat{R}_{G,i} = f_{G,i}(X)$	Expert rank,R_i
16	4.2548	1.7015	3.5569	1
17	0	1.7015	3.5569	2
18	10.4369	0	3.5569	6

Panel A compares the expert-assigned ranks with those predicted by the model for each company across the Environmental (E), Social (S), and Governance (G) dimensions in the meat and dairy industry. The "Expert Rank" column adjusts the original rank so that higher values represent better performance, consistently with the model's scoring logic. The similarity between predicted and expert ranks demonstrates the model's effectiveness in capturing sustainability performance. While some discrepancies arise due to the non-linear nature of the problem, in general the methodology is robust. Specifically, using the optimal weights assigned to each of the 15 indicators and the corresponding company scores, predicted rankings can be computed for each company across the Environmental (E), Social (S), and Governance (G) categories. For instance, for the first company, the environmental score (E) is calculated as: $\widehat{R}_{E,1} = f_{E,1}(X) = 5.0351X_1 + 10.9785X_2 + 0.001X_3 + 0.001X_4 + 5.7566X_5 = 15.2759$. The corresponding predicted rank is $21 - f_{E,1}(X) = 5.7241$. Next, the social score (S) is computed as: $\widehat{R}_{S,1} = f_{S,1}(X) = 8.1821X_6 + 2.1174X_7 + 9.3473X_8 + 0.18X_9 + 0.9365X_{10} + 0.001X_{11} = 14.1921$. This results in a predicted rank of $21 - f_{S,1}(X) = 6.8079$. Finally, the governance score (G) is calculated as $\widehat{R}_{G,1} = f_{G,1}(X) = 0.001X_{12} + 10.2717X_{13} + 4.7947X_{14} + 3.8398X_{15} = 12.4993$. The resulting predicted ranking is $21 - f_{G,1}(X) = 8.5007$. The minimum and maximum predicted ranks for the Environmental dimension (Social and Governance dimensions) are: $\widehat{R}_{E,min} = -0.0380$ and $\widehat{R}_{E,max} = 19.5608$ ($\widehat{R}_{S,min} = 0.2400$ and $\widehat{R}_{S,max} = 18.3000$, $\widehat{R}_{G,min} = 2.0928$ and $\widehat{R}_{G,max} = 15.8632$), respectively. The Root Mean Square Error (RMSE) was calculated separately for the Environmental (E), Social (S), and Governance (G) dimensions for both the meat and dairy industry as follows: $RMSE(\widehat{R}_E) = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \widehat{R}_i)^2}{N}} = 2.3458$), $RMSE(\widehat{R}_S) = 3.2979$, and $RMSE(\widehat{R}_G) = 2.87$

Panel B compares the expert-assigned ranks with those predicted by the model for each company across the Environmental (E), Social (S), and Governance (G) dimensions in the agricultural industry. The "Expert Rank" column adjusts the original rank so that higher values represent better performance, consistently with the model's scoring logic. The similarity between predicted and expert ranks demonstrates the model's effectiveness in capturing sustainability performance. While some discrepancies arise due to the non-linear nature of the problem, in general the methodology is robust. The minimum and maximum environmental (social, governance) scores are $\widehat{R}_{E,min} = 0$ and $\widehat{R}_{E,max} = 19.6377$ ($\widehat{R}_{S,min} = 0$ and $\widehat{R}_{S,max} = 15.2494$, $\widehat{R}_{G,min} = 2.9522$ and $\widehat{R}_{G,max} = 17.1204$), respectively. The Root Mean Square Error (RMSE) for the entire sample of agricultural companies is calculated separately for the Environmental (E), Social (S), and Governance (G) indicators as follows: $RMSE(\widehat{R}_E) = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \widehat{R}_i)^2}{N}} = 2.45166$), $RMSE(\widehat{R}_S) = 2.4991$, and $RMSE(\widehat{R}_G) = 1.4214$

the Environmental (E), Social (S), and Governance (G) dimensions are presented in columns 2, 3, and 4 of Table 6, respectively.

The sustainability index values are calculated by means of a multiple logistic function (MLF), outlined in Eq. 3.

$$S_{MLF}(F(X)) = \frac{1}{1 + e^{-F(X)}} \tag{3}$$

This function transforms the scaled scores into values bounded between 0 and 1, with a smooth S-shaped curve that highlights differences at the tails while compressing values near the center. The resulting sustainability scores based on the MLF are reported in column 2 of Tables 7, 8, and 9. To assess the robustness of our scoring approach, we also apply two alternative mapping functions. The first is the shifted hyperbolic tangent function (HTF), defined in Eq. 4 below.

Table 6 The scaled values for the environmental, social, and governance indices

Company no	Environmental, $F_E(\widehat{R}_i)$	Social, $F_S(\widehat{R}_i)$	Governance, $F_G(\widehat{R}_i)$
A. Meat and dairy industry			
1	− 1.2360	− 0.8180	− 0.2080
2	0.4382	− 0.1063	0.9110
3	− 0.1334	0.9601	0.9108
4	0.7014	− 0.8073	0.0743
5	2.9998	1.9269	3.0000
6	0.1299	− 0.4751	− 2.1635
7	− 2.3436	− 2.6312	− 3.0000
8	− 0.4868	3.0000	− 1.3269
9	0.1296	1.2126	3.0000
10	2.2510	1.9867	1.3269
11	2.5593	1.9867	3.0000
12	2.1187	2.2957	3.0000
13	3.0000	1.9867	0.9108
14	2.1188	2.2359	3.0000
15	− 0.7496	− 1.7940	- 0.2080
16	− 0.6173	− 1.1196	− 1.0446
17	− 0.2236	1.9269	1.8811
18	0.5703	2.2359	3.0000
19	− 3.0000	− 3.0000	− 2.1633
20	− 2.3436	− 0.8073	− 2.1645
B. Agriculture			
1	0.3124	0.6603	0.12823
2	− 0.3376	3.000	1.6786
3	0.8355	2.0196	1.6786
4	− 0.3094	2.7160	1.6786
5	1.6700	2.4440	3.0000
6	− 0.1526	1.1040	− 0.1278
7	− 2.3500	− 1.6588	− 3.0000
8	0.5880	0.6603	0.1282
9	− 0.4000	1.0848	0.1282
10	0.1513	1.3564	0.1282
11	− 2.3500	0.6603	− 2.7439
12	− 0.4000	1.0848	− 0.1278
13	0.3658	0.6603	0.1282
14	3.0000	1.7808	1.5641
15	− 2.3500	− 1.0284	− 2.7439
16	− 1.7000	− 2.3305	− 2.7439

Table 6 (continued)

Company no	Environmental, $F_E(\widehat{R}_i)$	Social, $F_S(\widehat{R}_i)$	Governance, $F_G(\widehat{R}_i)$
17	– 3.0000	– 2.3305	– 2.7439
18	0.1888	– 3.0000	– 2.7439

Panel A shows how the raw predicted ranks are transformed into a standardized scale ranging from -3 to + 3 using a linear scaling function for the meat and dairy industry. The linear scaling function is given by $F(\widehat{R}_i) = \left(\frac{\widehat{R}_i - \widehat{R}_{min}}{\widehat{R}_{max} - \widehat{R}_{min}} - \frac{1}{2}\right) * 6$. This normalization is essential for applying mapping functions that convert scaled values into final sustainability scores. The scaled values ensure that the scoring system is consistent across companies and dimensions. For instance, for the Environmental dimension, the function calculates the following value for company 1: $F(5.7241) = \left(\frac{5.7241-(-0.038)}{19.5608-(-0.038)} - \frac{1}{2}\right) * 6 = -1.236\left(\widehat{R}_{min} = -0.038; \widehat{R}_{max} = 19.5608\right)$

Panel B shows how the raw predicted ranks are transformed into a standardized scale ranging from -3 to + 3 using a linear scaling function for the agricultural industry. The linear scaling function is given by $F(\widehat{R}_i) = \left(\frac{\widehat{R}_i - \widehat{R}_{min}}{\widehat{R}_{max} - \widehat{R}_{min}} - \frac{1}{2}\right) * 6$. This normalization is essential for applying mapping functions that convert scaled values into final sustainability scores. The scaled values ensure that the scoring system is consistent across companies and dimensions. For instance, for the Environmental dimension, the function calculates the following value for company 1: $F(10.8412) = \left(\frac{10.8412-0}{19.6377-0} - \frac{1}{2}\right) * 6 = 0.3124\left(\widehat{R}_{min} = 0, 0; \widehat{R}_{max} = 19.6377\right)$

$$S_{HTF}(F(X)) = \frac{\tanh(F(\mathrm{X})) + 1}{2} \tag{4}$$

Like the MLF, this function maps values to the [0,1] interval but is more sensitive to differences near the midpoint of the distribution. The HTF-based scores are presented in column 3 of Tables 7, 8, and 9. The second alternative is the cumulative distribution function (CDF) of the standard normal distribution, shown in Eq. 5:

$$S_{CDF}(F(X)) = \Phi(F(X)) = \int_{-\infty}^{F(X)} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \tag{5}$$

This function also produces values between 0 and 1 and caters to the relative standing of firms across a normally distributed range of scores. The CDF-based results are listed in column 4 of Tables 7, 8, and 9.

The standard deviations of the scores across these three methods are relatively small (not exceeding 0.078), which indicates that the mapping functions are both stable and well-suited to the data. A graphical comparison of the three functions is provided in Fig. 2, which illustrates their respective scaling behaviors and vindicates their appropriateness for transforming ESG scores.

Table 7 Sustainability values for E and descriptive statistics

Company no	Sustainability index (MLF),$S_{MLF}\left(F_E\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF),$S_{HTF}\left(F_E\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF),$S_{CDF}\left(F_E\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
A. Meat and dairy industry					
1	0.2251	0.0778	0.1082	0.1371	0.078
2	0.6078	0.7061	0.6694	0.6611	0.050
3	0.4667	0.4337	0.4469	0.4491	0.017
4	0.6685	0.8026	0.7585	0.7432	0.068
5	0.9526	0.9975	0.9986	0.9829	0.026
6	0.5324	0.5646	0.5517	0.5496	0.016
7	0.0876	0.0091	0.0095	0.0354	0.045
8	0.3807	0.2742	0.3132	0.3227	0.054
9	0.5323	0.5644	0.5515	0.5494	0.016
10	0.9047	0.9890	0.9878	0.9605	0.048
11	0.9282	0.9941	0.9948	0.9723	0.038
12	0.8927	0.9858	0.9829	0.9538	0.053
13	0.9526	0.9975	0.9987	0.9829	0.026
14	0.8927	0.9858	0.9829	0.9538	0.053
15	0.3209	0.1825	0.2268	0.2434	0.071
16	0.3504	0.2254	0.2685	0.2814	0.064
17	0.4443	0.3900	0.4115	0.4153	0.027

Table 7 (continued)

Company no	Sustainability index (MLF),$S_{MLF}\left(F_E\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF),$S_{HTF}\left(F_E\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF),$S_{CDF}\left(F_E\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
18	0.6388	0.7578	0.7158	0.7041	0.060
19	0.0474	0.0025	0.0014	0.0171	0.026
20	0.0876	0.0091	0.0095	0.0354	0.045
B. Agriculture					
1	0.5775	0.6513	0.6226	0.6171	0.037
2	0.4164	0.3373	0.3678	0.3738	0.040
3	0.6975	0.8417	0.7983	0.7792	0.074
4	0.4233	0.3501	0.3785	0.3840	0.037
5	0.8416	0.9658	0.9525	0.9200	0.068
6	0.4619	0.4243	0.4394	0.4419	0.019
7	0.0871	0.0090	0.0094	0.0352	0.045
8	0.6429	0.7642	0.7217	0.7096	0.062
9	0.4013	0.3100	0.3446	0.3520	0.046
10	0.5378	0.5751	0.5601	0.5577	0.019
11	0.0871	0.0090	0.0094	0.0352	0.045
12	0.4013	0.3100	0.3446	0.3520	0.046
13	0.5904	0.6752	0.6427	0.6361	0.043
14	0.9526	0.9975	0.9987	0.9829	0.026

Table 7 (continued)

Company no	Sustainability index (MLF), $S_{MLF}\left(F_E\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF), $S_{HTF}\left(F_E\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF), $S_{CDF}\left(F_E\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
15	0.0871	0.0090	0.0094	0.0352	0.045
16	0.1545	0.0323	0.0446	0.0771	0.067
17	0.0474	0.0025	0.0013	0.0171	0.026
18	0.5471	0.5933	0.5749	0.5718	0.023

In Panel A, the sustainability index based on the logistic function is given by $S_{MLF}(F(X)) = \frac{1}{1+e^{-F(X)}}$ for the meat and dairy industry. For example, for company 1, the environmental sustainability index is given by $S_{MLF}\left(F_E\left(\widehat{R}_1\right)\right) = \frac{1}{1+e^{-(-1,236)}} = 0.2251$. The sustainability index based on the hyperbolic tangent function is defined by $S_{HTF}(F(X)) = \frac{\tanh(F(X))+1}{2}$. For instance, for company 1, the environmental sustainability index is calculated as $S_{HTF}\left(F_E\left(\widehat{R}_1\right)\right) = \frac{\tanh(-1.236)+1}{2} = 0.0778$. Further, the sustainability index based on the cumulative distribution function of a standard normal distribution is defined by $S_{CDF}(F(X)) = \Phi(F(X)) = \int_{-\infty}^{F(X)} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$. For example, for company 1, the resulting score is calculated as $S_{CDF}\left(F_E\left(\widehat{R}_1\right)\right) = \Phi(-1.236) = \int_{-\infty}^{-1.236} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt = 0.1082$

In Panel B, the sustainability index based on the logistic function is given by $S_{MLF}(F(X)) = \frac{1}{1+e^{-F(X)}}$ for the agricultural industry. For example, for company 1, the environmental sustainability index is given by $S_{MLF}\left(F_E\left(\widehat{R}_1\right)\right) = \frac{1}{1+e^{-(0.31236346)}} = 0.5775$. The sustainability index based on the hyperbolic tangent function is defined by $S_{HTF}(F(X)) = \frac{\tanh(F(X))+1}{2}$. For instance, for company 1, the environmental sustainability index is calculated as $S_{HTF}\left(F_E\left(\widehat{R}_1\right)\right) = \frac{\tanh(0.31236346)+1}{2} = 0.6513$. Further, the sustainability index based on the cumulative distribution function of a standard normal distribution is defined by $S_{CDF}(F(X)) = \Phi(F(X)) = \int_{-\infty}^{F(X)} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$. For example, for company 1, the resulting score is calculated as $S_{CDF}\left(F_E\left(\widehat{R}_1\right)\right) = \Phi(0.31236346) = \int_{-\infty}^{0.31236346} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt = 0.6226$

Table 8 Sustainability values for S and descriptive statistics

Company no	Sustainability index (MLF),$S_{MLF}(F_S(\widehat{R}_i))$	Sustainability index (HTF),$S_{HTF}(F_S(\widehat{R}_i))$	Sustainability index (CDF),$S_{CDF}(F_S(\widehat{R}_i))$	Mean	Standard deviation
A. Meat and dairy industry					
1	0.3062	0.1630	0.2067	0.2281	0.073
2	0.4734	0.4470	0.4577	0.4594	0.013
3	0.7231	0.8722	0.8315	0.8089	0.077
4	0.3085	0.1659	0.2097	0.2281	0.073
5	0.8729	0.9792	0.9730	0.9417	0.060
6	0.3834	0.2789	0.3174	0.3265	0.053
7	0.0672	0.0052	0.0043	0.0255	0.036
8	0.9526	0.9975	0.9987	0.9829	0.026
9	0.7708	0.9187	0.8874	0.8590	0.078
10	0.8794	0.9815	0.9765	0.9458	0.058
11	0.8794	0.9815	0.9765	0.9458	0.058
12	0.9085	0.9900	0.9892	0.9625	0.047
13	0.8794	0.9815	0.9765	0.9458	0.058
14	0.9034	0.9887	0.9873	0.9598	0.049
15	0.1426	0.0269	0.0364	0.0686	0.064
16	0.2461	0.0963	0.1314	0.1579	0.078
17	0.8729	0.9792	0.9730	0.9417	0.060

Table 8 (continued)

Company no	Sustainability index (MLF),$S_{MLF}\left(F_S\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF),$S_{HTF}\left(F_S\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF),$S_{CDF}\left(F_S\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
18	0.9034	0.9887	0.9873	0.9598	0.049
19	0.0474	0.0025	0.0014	0.0171	0.026
20	0.3085	0.1659	0.2097	0.2281	0.073
B. Agriculture					
1	0.6593	0.7893	0.7455	0.7314	0.066
2	0.9526	0.9975	0.9987	0.9829	0.026
3	0.8828	0.9827	0.9783	0.9479	0.056
4	0.9380	0.9956	0.9967	0.9768	0.034
5	0.9201	0.9925	0.9927	0.9685	0.042
6	0.7510	0.9010	0.8652	0.8391	0.078
7	0.1599	0.0350	0.0486	0.0812	0.069
8	0.6593	0.7893	0.7455	0.7314	0.066
9	0.7474	0.8975	0.8610	0.8353	0.078
10	0.7952	0.9378	0.9125	0.8818	0.076
11	0.6593	0.7893	0.7455	0.7314	0.066
12	0.7474	0.8975	0.8610	0.8353	0.078
13	0.6593	0.7893	0.7455	0.7314	0.066
14	0.8558	0.9724	0.9625	0.9302	0.065

Table 8 (continued)

Company no	Sustainability index (MLF),$S_{MLF}\left(F_S\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF),$S_{HTF}\left(F_S\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF),$S_{CDF}\left(F_S\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
15	0.2634	0.1134	0.1519	0.1762	0.078
16	0.0886	0.0094	0.0099	0.0360	0.046
17	0.0886	0.0094	0.0099	0.0360	0.046
18	0.0474	0.0025	0.0013	0.0171	0.026

In Panel A, the sustainability index based on the logistic function is given by $S_{MLF}(F(X)) = \frac{1}{1+e^{-F(X)}}$ for the meat and dairy industry. For example, for company 1, the social sustainability index is given by $S_{MLF}\left(F_S\left(\widehat{R}_1\right)\right) = \frac{1}{1+e^{-(-0.8180))}} = 0.306\ 2$. The sustainability index based on the hyperbolic tangent function is defined by $S_{HTF}(F(X)) = \frac{\tanh(F(\mathrm{X}))+1}{2}$. For instance, for company 1, the social sustainability index is calculated as $S_{HTF}\left(F_S\left(\widehat{R}_1\right)\right) = \frac{\tanh(-0.8180)+1}{2} = 0.1630$. Further, the sustainability index based on the cumulative distribution function of a standard normal distribution is defined by $S_{CDF}(F(X)) = \Phi(F(X)) = \int_{-\infty}^{F(X)} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$. For example, for company 1, the resulting score is calculated as $S_{CDF}\left(F_S\left(\widehat{R}_1\right)\right) = \Phi(-0.8180) = \int_{-\infty}^{-0.8180} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt = 0.2067$

In Panel B, the sustainability index based on the logistic function is given by $S_{MLF}(F(X)) = \frac{1}{1+e^{-F(X)}}$ for the agricultural industry. For example, for company 1, the social sustainability index is given by $S_{MLF}\left(F_S\left(\widehat{R}_1\right)\right) = \frac{1}{1+e^{-(0.66034073))}} = 0.6593$. The sustainability index based on the hyperbolic tangent function is defined by $S_{HTF}(F(X)) = \frac{\tanh(F(\mathrm{X}))+1}{2}$. For instance, for company 1, the social sustainability index is calculated as $S_{HTF}\left(F_S\left(\widehat{R}_1\right)\right) = \frac{\tanh(0.66034073)+1}{2} = 0.7893$. Further, the sustainability index based on the cumulative distribution function of a standard normal distribution is defined by $S_{CDF}(F(X)) = \Phi(F(X)) = \int_{-\infty}^{F(X)} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$. For example, for company 1, the resulting score is calculated as $S_{CDF}\left(F_S\left(\widehat{R}_1\right)\right) = \Phi(0.12823083) = \int_{-\infty}^{0.12823083} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt = 0.7455$

Table 9 Sustainability values for G and descriptive statistics

Company No	Sustainability index (MLF),$S_{MLF}\left(F_G\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF),$S_{HTF}\left(F_G\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF),$S_{CDF}\left(F_G\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
A. Meat and dairy industry					
1	0.4482	0.3975	0.4176	0.4211	0.026
2	0.7132	0.8608	0.8189	0.7976	0.076
3	0.7132	0.8608	0.8188	0.7976	0.076
4	0.5186	0.5371	0.5296	0.5284	0.009
5	0.9526	0.9975	0.9987	0.9829	0.026
6	0.1031	0.0130	0.0153	0.0438	0.051
7	0.0474	0.0025	0.0014	0.0171	0.026
8	0.2097	0.0658	0.0923	0.1226	0.077
9	0.9526	0.9975	0.9987	0.9829	0.026
10	0.7903	0.9342	0.9077	0.8774	0.077
11	0.9526	0.9975	0.9987	0.9829	0.026
12	0.9526	0.9975	0.9987	0.9829	0.026
13	0.7132	0.8608	0.8188	0.7976	0.076
14	0.9526	0.9975	0.9987	0.9829	0.026
15	0.4482	0.3975	0.4176	0.4211	0.026
16	0.2603	0.1102	0.1481	0.1728	0.078
17	0.8677	0.9773	0.9700	0.9383	0.061

Table 9 (continued)

Company No	Sustainability index (MLF),$S_{MLF}\left(F_G\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF),$S_{HTF}\left(F_G\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF),$S_{CDF}\left(F_G\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
18	0.9526	0.9975	0.9987	0.9829	0.026
19	0.1031	0.0130	0.0153	0.0438	0.051
20	0.1031	0.0130	0.0153	0.0438	0.051
B. Agriculture					
1	0.5320	0.5638	0.5510	0.5489	0.016
2	0.8427	0.9663	0.9534	0.9208	0.068
3	0.8427	0.9663	0.9534	0.9208	0.068
4	0.8427	0.9663	0.9534	0.9208	0.068
5	0.9526	0.9975	0.9987	0.9829	0.026
6	0.4681	0.4364	0.4492	0.4512	0.016
7	0.0474	0.0025	0.0013	0.0171	0.026
8	0.5320	0.5638	0.5510	0.5489	0.016
9	0.5320	0.5638	0.5510	0.5489	0.016
10	0.5320	0.5638	0.5510	0.5489	0.016
11	0.0604	0.0041	0.0030	0.0225	0.033
12	0.4681	0.4364	0.4492	0.4512	0.016
13	0.5320	0.5638	0.5510	0.5489	0.016
14	0.8269	0.9580	0.9411	0.9087	0.071

Table 9 (continued)

Company No	Sustainability index (MLF),$S_{MLF}\left(F_G\left(\widehat{R}_i\right)\right)$	Sustainability index (HTF),$S_{HTF}\left(F_G\left(\widehat{R}_i\right)\right)$	Sustainability index (CDF),$S_{CDF}\left(F_G\left(\widehat{R}_i\right)\right)$	Mean	Standard deviation
15	0.0604	0.0041	0.0030	0.0225	0.033
16	0.0604	0.0041	0.0030	0.0225	0.033
17	0.0604	0.0041	0.0030	0.0225	0.033
18	0.0604	0.0041	0.0030	0.0225	0.033

In Panel A, the sustainability index based on the logistic function is given by $S_{MLF}(F(X)) = \frac{1}{1+e^{-F(X)}}$ for the meat and dairy industry. For example, for company 1, the governance sustainability index is given by $S_{MLF}\left(F_G\left(\widehat{R}_1\right)\right) = \frac{1}{1+e^{-(-0.2080)}} = 0.4482$. The sustainability index based on the hyperbolic tangent function is defined by $S_{HTF}(F(X)) = \frac{\tanh(F(X))+1}{2}$. For instance, for company 1, the governance sustainability index is calculated as $S_{HTF}\left(F_G\left(\widehat{R}_1\right)\right) = \frac{\tanh(-0.2080)+1}{2} = 0.3975$. Further, the sustainability index based on the cumulative distribution function of a standard normal distribution is defined by $S_{CDF}(F(X)) = \Phi(F(X)) = \int_{-\infty}^{F(X)} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$. For example, for company 1, the resulting score is calculated as $S_{CDF}\left(F_G\left(\widehat{R}_1\right)\right) = \Phi(-0.2080) = \int_{-\infty}^{-0.2080} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt = 0.4176$

In Panel B, the sustainability index based on the logistic function is given by $S_{MLF}(F(X)) = \frac{1}{1+e^{-F(X)}}$ for the agricultural industry. For example, for company 1, the governance sustainability index is given by $S_{MLF}\left(F_G\left(\widehat{R}_1\right)\right) = \frac{1}{1+e^{-(0.12823083)}} = 0.5320$. The sustainability index based on the hyperbolic tangent function is defined by $S_{HTF}(F(X)) = \frac{\tanh(F(X))+1}{2}$. For instance, for company 1, the governance sustainability index is calculated as $S_{HTF}\left(F_G\left(\widehat{R}_1\right)\right) = \frac{\tanh(0.12823083)+1}{2} = 0.5638$. Further, the sustainability index based on the cumulative distribution function of a standard normal distribution is defined by $S_{CDF}(F(X)) = \Phi(F(X)) = \int_{-\infty}^{F(X)} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$. For example, for company 1, the resulting score is calculated as $S_{CDF}\left(F_G\left(\widehat{R}_1\right)\right) = \Phi(0.12823083) = \int_{-\infty}^{0.12823083} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt = 0.5510$

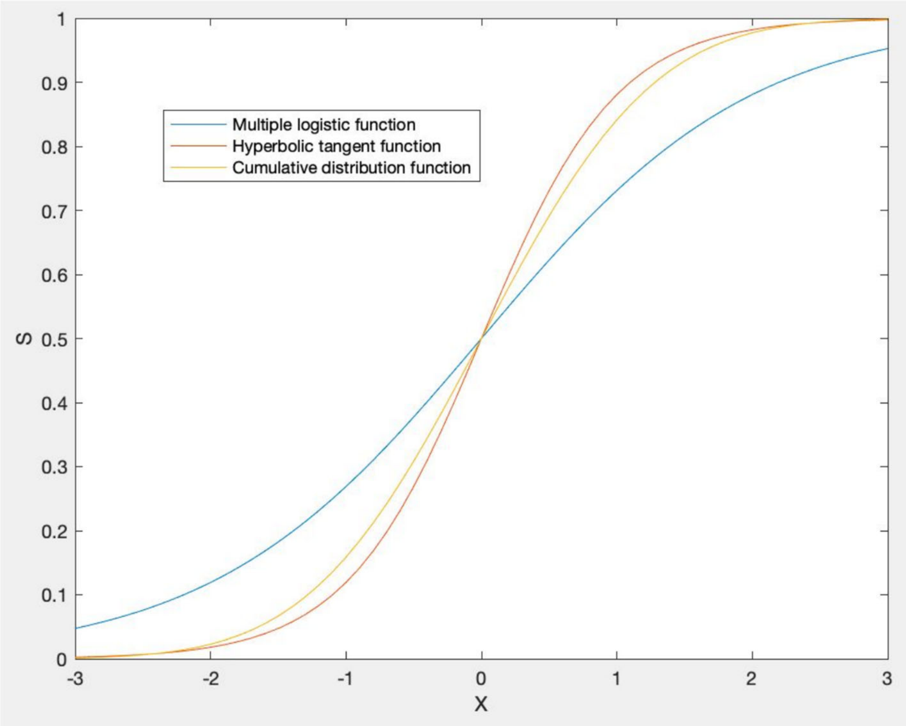

Fig. 2 Multiple logistic function (MLF), hyperbolic tangent function (HTF), and normal cumulative distribution function (CDF). Figure 2 illustrates the cumulative probability functions for the multiple logistic (MLF), shifted hyperbolic tangent (HTF), and normal (CDF) distributions. These distributions were employed to construct the E, S, and G scores for SMEs. These functions were used to convert scaled ranks into sustainability scores. The figure compares the shapes of the three functions. MLF offers smooth, balanced scaling, ideal for distinguishing extremes. HTF is steepest at the center, which makes it effective for differentiating average performers. CDF is based on the normal distribution and works well across a wide range of scores. This figure helps readers understand the rationale behind using multiple scoring methods and how each function contributes to the ESG scoring of SMEs

5 Conclusions

Small and medium-sized enterprises (SMEs) are vital drivers of economic growth, with increasing potential to lead sustainability initiatives. This study addresses a critical gap in the availability of tailored sustainability assessments for SMEs, which underscores the need for developing firm-level sustainability indices and rankings designed specifically for their unique needs and challenges. Existing sustainability metrics exhibit considerable diversity, presenting an opportunity for innovation in methodologies designed specifically for SMEs. In response to growing significance of climate challenges and sustainability policies, this paper contributes to the body of knowledge on ESG rating and scoring methodologies, focusing on the unique complexities of evaluating SME sustainability.

Unlike larger corporations, SMEs are not mandated to disclose sustainability information under regulations like the CSRD, making the development of appropriate ESG metrics even more pressing. The methodology presented in this paper selects relevant sustainability indicators based on criteria such as disclosure, materiality, and quantifiability, relying on publicly accessible data. Built on the SASB framework, the methodology organizes ESG components into environmental (e.g., energy management), social (e.g., employee health and safety), and governance (e.g., executive remuneration) dimensions. These indicators are carefully weighted and aggregated into a composite index using advanced optimization techniques. Various scoring methods, including logistic, hyperbolic tangent, and cumulative distribution, ensure robust metrics for measuring SME sustainability performance.

While tailored primarily to the meat and dairy, and agricultural industries, the methodology is adaptable to other industries. It identifies key sustainability factors for developing targeted ESG scoring systems for SMEs. The selection of companies across Europe was based on voluntary sustainability disclosures, as the lack of mandatory reporting currently limits automated data collection. In conclusion, this study not only advances the development of ESG scoring methodologies for SMEs but also informs policy discussions on improving sustainability disclosures that are customized to the unique operational contexts of SMEs. It underscores the importance of creating supportive frameworks that incentivize voluntary sustainability reporting from SMEs.

While the proposed ESG scoring methodology offers an adaptable, innovative, and structured framework, it is essential to recognize its limitations. One significant limitation is that the ESG index is currently based on just 15 or 16 criteria. This relatively narrow scope may not capture the full spectrum of environmental, social, and governance factors relevant to assessing a company's overall ESG performance. Consequently, the index might overlook some critical aspects that could influence the sustainability and ethical standing of the companies evaluated. Nevertheless, the methodology is designed with flexibility in mind. As more information becomes publicly available and companies disclose additional ESG-related data, the index can be expanded to incorporate a broader range of criteria. This would allow for the construction of more comprehensive indices, providing a more holistic view of a company's ESG performance. Second, the reliance on voluntary disclosures limits its applicability until broader adoption occurs. Third, sector-specific tailoring of ESG criteria requires careful validations and often depends on expert opinions, which introduces subjectivity. This is a common limitation in similar methodologies. Fourth, it should be acknowledged that methodology focuses on the status quo in the sustainability performance of SMEs. Specifically, the proposed ESG scoring framework assesses companies based on their existing practices and disclosures without necessarily accounting for their plans, potential for improvement, or ongoing sustainability initiatives.

In summary, while the present ESG index has its limitations due to the restricted number of criteria, it lays a solid foundation for a robust and expandable scoring system. As the availability of ESG data improves, this methodology can be refined and expanded, enhancing its comprehensiveness and utility in assessing corporate sustainability and governance practices.

Moving forward, the dynamic nature of sustainability policies suggests ongoing evolution and potential regulatory changes that could spur advancements in methodologies for assessing SME sustainability performance and refining ESG scoring systems. Future research could explore enhanced approaches that adapt to evolving regulatory landscapes and industry-specific aspects, ultimately promoting more comprehensive sustainability assessments for SMEs. A promising direction for future research is to apply the methodology to large, listed companies. Given their more extensive disclosure requirements, such an extension would allow for a comparative analysis between SMEs and larger firms, offering more in-depth insights into the robustness, scalability, and generalizability of the ESG scoring model. This would also help evaluate how ESG performance varies across firm sizes and regulatory environments, thereby contributing the broader debate on sustainability assessment frameworks.

Appendix A

To determine the relative importance of each indicator, we employed a constrained nonlinear optimization approach using the Sequential Quadratic Programming (SQP) algorithm via MATLAB's fmincon function (MathWorks, 2025). This is a flexible, robust, and efficient approach to solve complex optimization problems with both equality and inequality, linear and nonlinear constraints, as well as nonlinear objective functions (Nocedal and Wright, 2006). Specifically, our problem consists of minimizing the Mean Square Error between the predicted company rankings (based on weighted indicator scores) and the expert-provided rankings. The optimization yields the optimal weights for the selected ESG indicators (15 indicators for the meat and dairy industry, and 16 for agricultural firms). Here, the company rankings are treated as vectors to be optimized. This approach is designed to find the local minimum of a scalar objective function under specified constraints. The mathematical formulation of the objective function and its constraints is outlined in Eq. 6:

$$\min_{X} f(X)\ subject\ to \begin{cases} c(X) \leq 0 \\ ceq(X) = 0 \\ A \cdot X \leq b \\ Aeq \cdot X = beq \\ lb \leq X \leq ub \end{cases} \tag{6}$$

$f(X)$ represents an objective function specifically formulated to minimize the discrepancy between predicted and expert-assigned company rankings. The optimization problem is subject to a set of constraints. The constraints, which include both equality and inequality functions, determine the feasible solution space. Specifically, $c(X)$ defines nonlinear inequality constraints, $ceq(X)$ represents nonlinear equality constrains, $A \bullet X$ defines linear inequality constraints, and $Aeq \bullet X$ specifies linear equality constraints. Lastly, lb and ub establish the lower bounds and upper bounds for each coordinate of search space (Nocedal and Wright, 2006). Within the optimization procedure, the function fmincon iteratively searches for the local minimum of the scalar objective function, adjusting the weights assigned to ESG indicators to best approximate expert rankings. The rankings are treated as vectors within a bounded range, typically normalized between 0 and 1.

The optimization process involves several key steps. First, we load the indicator matrices for the Environmental (E), Social (S), and Governance (G) dimensions and construct the target ranking vector R, where R_i represents the expert rank for firm i with $i = 1, 2, \ldots, n$ (where $n = 20$ for the meat and dairy industry, and $n = 18$ for agriculture). Next, we form the predictor matrix Q by concatenating selected columns from E, S, and G block matrices. The total number of columns in Q, denoted m, is the sum of the indicators across the three ESG dimensions, $m = m_E + m_S + m_G$, where m_E is the number of indicators in the Environmental category, m_S is the number of indicators in the Social category, and m_G is the number of indicators in the Governance category. Specifically, $m_E = 5$ (greenhouse gases, energy management, water management, waste management, and sustainable practices), $m_S = 6$ for the meat and dairy industry ($m_S = 7$ for agriculture): working environment, qualifications, ecological environment, corporate social responsibility, employee development, equality and anti-discrimination, and (food safety), and $m_G = 4$ (business ethics breaches, sustainability reporting, green supply chain, and gender diversity). Thus, the final predictor matrix has dimensions 20×15 for the meat and dairy industry (20 SMEs and 15 ESG indicators), and 18×16 for agriculture (18 SMEs and 16 ESG indicators). The optimal weights W_j were obtained by minimizing the objective function $f(W_j)$, outlined in Eq. 1. We used the following code to solve the optimization problem:

E:

```
clear all
E = load('E.txt', '-ascii');
R = E(:,7);
R=21-R; % Invert expert ranks: 21 - rank(k) for meat/dairy sample
Q(:,1) = E(:,2);
Q(:,2) = E(:,3);
Q(:,3) = E(:,4);
Q(:,4) = E(:,5);
Q(:,5) = E(:,6);
Aeq = ones(1, 5);
beq = 1;
fun = @(W) sum(sum((Q * W' - R).^2));
initialWeights = rand(1, 5);
options = optimoptions('fmincon', 'Algorithm', 'sqp');
weights = fmincon(fun, initialWeights, [], [], [], [], 0.001*ones(1,5), [], [], options);
disp('Optimal Weights:');
disp(weights);
predictedRankings = Q * weights';
disp('Predicted Rankings:');
disp(predictedRankings);
for k = 1:20
   E = E + abs((R(k)-predictedRankings(k))/R(k));
end
E = E/20;
E
```

S:

```
clear all
S = load('S.txt', '-ascii');
E = load('E.txt', '-ascii');
R = E(:,7);
R=21-R; % Invert expert ranks: 21 - rank(k) for meat/dairy sample
Q(:,1) = S(:,2);
Q(:,2) = S(:,3);
Q(:,3) = S(:,4);
Q(:,4) = S(:,5);
Q(:,5) = S(:,6);
Q(:,6) = S(:,7);
Aeq = ones(1, 6);
beq = 1; % Equality constraint vector
fun = @(W) sum(sum((Q * W' - R).^2));
initialWeights = rand(1, 6);
options = optimoptions('fmincon', 'Algorithm', 'sqp');
weights = fmincon(fun, initialWeights, [], [], [], [], 0.001*ones(1,6), [], [], options);
disp('Optimal Weights:');
disp(weights);
predictedRankings = Q * weights';
disp('Predicted Rankings:');
```

```
disp(predictedRankings);E = 0;
for k = 1:20
   E = E + abs((R(k)-predictedRankings(k))/R(k));
end
E = E/20;
E
```

```
G:
clear all
G = load('G.txt', '-ascii');
E = load('E.txt', '-ascii');
R = E(:,7);
R=21-R; % Invert expert ranks: 21 - rank(k) for meat/dairy sample
Q(:,1) = G(:,2);
Q(:,2) = G(:,3);
Q(:,3) = G(:,4);
Q(:,4) = G(:,5);
Aeq = ones(1, 4);
beq = 1;
fun = @(W) sum(sum((Q * W' - R).^2));
initialWeights = rand(1, 4);
options = optimoptions('fmincon', 'Algorithm', 'sqp');
weights = fmincon(fun, initialWeights, [], [], [], [], 0.001*ones(1,4), [], [], options);
disp('Optimal Weights:');
disp(weights);
predictedRankings = Q * weights';
disp('Predicted Rankings:');
disp(predictedRankings);E = 0;
for k = 1:20
   E = E + abs((R(k)-predictedRankings(k))/R(k));
end
E = E/20;
E
```

Declarations

Conflict of interest Tautvydas Ragulskis declares that he has no conflict of interest. Valdonė Darškuvienė declares that she has no conflict of interest. Renatas Kizys declares that he has no conflict of interest. Dalius Misiūnas declares that he has no conflict of interest.

Ethical approval All procedures involving human participants (a total of nine experts across the two industry samples) were conducted in accordance with the ethical standards of the institutional and/or national research committee, and the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The identities of the experts have been anonymized appropriately. This article does not include any studies involving animals.

Informed consent Informed consent was obtained from all individual participants (all nine experts) involved in the study, with their identities suitably anonymized.

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