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An inverse optimization approach for studying sustainability preferences in sourcing decisions

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ABSTRACT

Throughout many societies around the globe, there is growing awareness of the urgent need for the transition towards a sustainable economy. Research shows that buying firms have substantial leverage to initiate sustainable development by controlling the sustainable performance of their suppliers. In that context, this article presents a novel methodology based on inverse optimization to derive the implicit preferences of decision-makers in the trade-off between traditional sourcing objectives and sustainability in the supplier selection and order allocation process. The derived implicit preferences can then be used for further analyses to gain a better understanding of the characteristics of purchasing managers and sourcing situations that come with particularly high/low preferences placed on sustainability. Since the inverse optimization approach is computationally resource-intensive and consumes a significant amount of time, we present a scalable state-of-the-art cloud architecture that allows solving an arbitrary number of optimization programs in an acceptable amount of time. We demonstrate the feasibility of the proposed methodology in a real-world case. In doing so, we test how important sustainability aspects are in the supplier selection and order allocation decisions of one of the world's largest automotive parts manufacturers.

1. Introduction

Although the attention to green supply chain management has increased due to environmental regulation and consumer pressure on sustainability (Govindan et al., 2015) and even though the selection of suppliers plays a vital role in providing ecological improvements for firms (Mathiyazhagan et al., 2018; Liou et al., 2021), very little is known about how sustainability objectives actually affect sourcing decisions. From a general perspective, unsustainable supply chain links are slowing the transition towards a sustainable economy; that is, they harm natural environments and threaten human health and welfare – at least in the long run. From a firm perspective, unsustainable supply chain links increase the exposure of buying firms to future costs associated with their suppliers' social and/or environmental irresponsibility (Kalkanci and Plambeck, 2020; Zhang et al., 2021). These costs stem from compensation payments, damage to a brand's reputation, and supply disruptions, amongst others. Besides the possibility of hedging a buying firm against a variety of costs stemming from their suppliers' social and environmental irresponsibility, the consideration of sustainability in sourcing decisions offers numerous opportunities for purchasing companies, including the strengthening of their competitiveness, an increase in their corporate reputation, and encouragement of inter-organizational learning (Bai and Sarkis, 2010; Gopalakrishnan et al., 2012).

On the one hand, the supplier selection literature is rich on different approaches how to consider sustainability in purchasing decisions (e.g., Çalık, 2021; Chang et al., 2021; Karaer et al., 2020; Kellner et al., 2019; Lo et al., 2018; Lo et al., 2021; Xing et al., 2022). On the other hand, there is a lack of empirical examinations of how to determine to what extent decision-makers in purchasing departments have *actually* considered sustainability as an objective in past sourcing decisions. The need for studying preferences (also known as 'weights' in the objective function) of different objectives in sourcing decisions stems from the request in cleaner production literature (e.g., Sinha and Anand, 2018) that highlights the importance of selecting the right (i.e., socially and ecologically sustainable) suppliers, for instance, in the context of product development. However, direct approaches to determine preferences such as surveys and interviews may suffer from self-reporting biases among decision-makers and might not reveal the 'real' preferences. Greenwashing in the supply chain might be one aspect of why it is

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important to understand the real preferences in sourcing decisions.

In this context, our research presents a model that allows us to derive implicit preferences from real-world sourcing decisions. Our model builds on the multi-objective optimization model proposed by Kellner et al. (2019) and Kellner and Utz (2019). The model solves the multi-criteria supplier selection problem with the objectives of costs, logistics performance, supply risk, and sustainability in an a posteriori setting, i.e., it determines the entire set of efficient supplier portfolios, and we select the one nearest to the actual sourcing decision as the one from which we derive the implicit preferences.

Overall, this research contributes to the sustainable configuration of supply and value chains by proposing an approach that allows stakeholders to empirically study the extent to which companies *actually* integrate sustainability objectives into their sourcing decisions. In detail, we propose a methodology that combines inverse optimization and multi-objective programming to derive the sustainability preferences of purchasing managers (or 'decision-makers' in general) in the trade-off between traditional sourcing objectives and the suppliers' sustainability performances in the supplier selection and order allocation process. This means that we derive and analyze ex-post to what extent decision-makers in purchasing departments have *actually* considered sustainability as an objective in past sourcing decisions, i.e., what sustainability preferences decision-makers are implicitly placing on different purchasing objectives when opting for a certain supplier portfolio. In this context, a supplier portfolio refers to the selected suppliers and the proportions of the purchasing company's total demand ordered from these sources. The derived implicit preferences can then be used to carry out further analyses. One advantage of using derived implicit preferences is that they are derived from real-world decision situations, that is, they are measured after the decision has been made and, thus, do not suffer from self-reporting biases. Another advantage of applying inverse optimization is its ability to explicitly include actual constraints that represent the decision situation realistically. This eases the incorporation of domain knowledge and thus inverse optimization offers the promise of models with enhanced prediction accuracy and interpretability, compared with, for instance, common black-box machine learning methods (Gupta and Zhang, 2022). In general, our research is based on the key assumption of a rationally acting decision-maker who needs to balance four purchasing objectives: costs, logistics performance, supply risk, and sustainability.

Since applying the inverse optimization approach to derive the purchasing managers' sustainability preferences is, from a computational perspective, resource intensive and involves a certain amount of time to generate the optimal solutions, we present a scalable state-of-the-art cloud architecture that allows the user to solve an arbitrary number of optimization programs in an acceptable amount of time. We argue that the proposed architecture is generic enough to be used in many other future research projects that involve solving many optimization problems, such as in the case of applications based on inverse optimization.

We apply the suggested methodology to a real-world case from the automotive industry and analyze the derived implicit preferences to gain a better understanding of the characteristics of the purchasing managers and sourcing situations that come with particularly high/low preferences on sustainability. This allows us to demonstrate the method's applicability and to empirically test how important sustainability aspects are in the supplier selection and order allocation process of one of the world's largest automotive parts manufacturers. Specifically, we study a sample of 145 real-world purchasing cases and use the technique of inverse optimization to derive the implicit preference parameters of decision-makers in the trade-off between low purchasing costs, high logistics quality, low supply risk, and the suppliers' sustainability. We are not aware of any research that used inverse optimization in the supplier selection case before to derive implicit preferences from real-world decisions. For sure, there is research that analyzed sustainability considerations in purchasing decisions. For instance, Mansi and Pandey (2016) studied the impact of demographic characteristics of procurement professionals on sustainable procurement practices. However, these studies are typically based on questionnaires and might, therefore, suffer from self-reporting biases. This paper intends to present an alternative approach to the 'classical' self-reporting-based approach for studying sustainability preferences in sourcing decisions.

The remainder of the paper is organized as follows: Section 2 positions this research in the stream of related literature. Section 3 develops the general approach for estimating sustainability preferences in sourcing decisions based on inverse optimization. Section 4 presents the application of the proposed methodology to a real-world case. Section 5 discusses several aspects of the proposed approach and the results observed in the application case. Finally, Section 6 contains concluding remarks.

2. Related literature

Many scholars consider supplier selection as one of the most important decisions in purchasing and supply chain management (Golmohammadi and Mellat-Parast, 2012; Parthiban et al., 2013; Wetzstein et al., 2016). This explains, at least partly, why supplier evaluation and selection have been studied so intensively during the last decades. Comprehensive literature reviews in this area are presented, for instance, by Chai et al. (2013), Degraeve et al. (2000), and Ho et al. (2010). These reviews, among others, state that supplier selection decisions typically involve evaluating the performance of potential suppliers against a broad range of often conflicting criteria.

2.1. Supplier evaluation and selection

Popular evaluation criteria in supplier selection are cost, quality, on-time delivery, manufacturing capability, service level, performance history, technology, research and development, finance, flexibility to respond to unexpected demand changes, reputation, supply risk, and safety and environment (Ho et al., 2010; Kannan and Tan, 2002). Contemporary research (e.g., Saputro et al. (2024); Giannakis et al. (2020); Bai and Sarkis, 2010; Saputro et al. (2024); Giannakis et al. (2020); Ghadimi et al., 2018; Govindan et al., 2013; Govindan and Sivakumar, 2016; Liu et al., 2018; Ma et al., 2022; Rashidi et al., 2020; Schramm et al., 2020) shows that sustainability has become a more and more important aspect during the last decade. Over the years, many different approaches have been developed to solve the multi-criteria supplier selection problem including AHP, ANP, DEA, DEMATEL, ELECTRE, fuzzy set theory, genetic algorithms, mathematical programming, neural networks, PROMETHEE, and TOPSIS. Besides the aforementioned 'individual' decision-making approaches, several 'combined' techniques have been developed; e.g., ANP + TOPSIS, AHP + DEA, TOPSIS + DEMATEL, DEA + mathematical programming, and AHP + goal programming (Chai et al., 2013; Ho et al., 2010; Kaur and Singh, 2021; Nasr et al., 2021; Li et al., 2021; Tong et al., 2022).

Recently, Kellner et al. (2019) and Kellner and Utz (2019) combined multi-objective optimization, the Markowitz (1952, 1959) portfolio theory, and a posteriori decision-making to solve the multi-criteria supplier selection and order allocation problem considering costs, logistics performance, supply risk, and sustainability. The authors show that the combination of these individual techniques allows the user to visualize and analyze the different trade-offs that come with a particular supplier selection problem and to get a better understanding of the decision-making problem at hand, – which finally allows for a more informed decision-making process.

2.2. Sustainability in supplier selection

Environmental and social sustainability is a prominent topic in the current supplier selection literature (e.g., Chai et al., 2013; Chai and Ngai, 2020; Rashidi et al., 2020; Schramm et al., 2020). In this context, the literature on sustainable supplier selection and order allocation is mostly based on approaches to determine the subjective preferences (or weights) regarding the importance of sustainability for the decision-maker.

To overcome the limitation of relying decision-making of supplier evaluation on vague and subjective information, fuzzy-based approaches are frequently used to manipulate such vagueness and subjectivity (Li et al., 2019). Adding to this discussion, Li et al. (2019) extend the TOPSIS method for sustainable supplier selection by an integrated weighting method that considers both subjective and objective weights. Gören (2018) also proposes a decision framework for sustainable supplier selection and order allocation. The framework applies a fuzzy DEMATEL approach to calculate the preferences for sustainability criteria and uses these preferences as inputs in Taguchi Loss Functions for ranking. Jain and Singh (2020) use a Fuzzy Interference System (FIS) for evaluating the sustainability performance index value of each supplier in three sustainability dimensions, and suppliers are ranked for final selection. Nasr et al. (2021) apply the fuzzy best-worst method to select the most suitable suppliers according to economic, environmental, social, and circular criteria in sustainable closed-loop supply chains to minimize waste by circling back (repairing, reselling, or dismantling for parts). Also, they use a fuzzy goal programming approach where they transform the multi-objective mixed-integer linear programming into a single objective model. This is an important aspect since fuzzy methods are typically applied to reduce the dimension of objectives by determining fuzzy preferences and calculating one single performance index that is the basis of the ranking of the suppliers. Another approach to generating a single index is presented by Sinha and Anand (2018) who develop a sustainable supplier selection index from a sustainability perspective by analyzing the interrelationships between different attributes of suppliers and selecting the suppliers best on the index value.

Other studies combine fuzzy techniques with multi-objective programming. For instance, Mohammed et al. (2018) combine the fuzzy techniques with AHP to assign the relative weights for sustainability criteria, the fuzzy techniques with TOPSIS, and a multi-objective programming model. The model aims to minimize the costs of transportation, purchasing, and administration, the environmental impact (particularly CO_2 emissions), and the travel time of products, while maximizing the social impact and total purchasing value. Vahidi et al. (2018) propose a novel bi-objective two-stage mixed possibilistic-stochastic programming model to address the sustainable supplier selection and order allocation problem under operational and disruption risks. A mixed sustainability-resilience objective function is also introduced to select a resiliently sustainable supply base. Lo et al. (2018) also combine different steps in a model that integrates the best-worst method, a modified fuzzy TOPSIS, and fuzzy multi-objective linear programming to solve problems in green supplier selection and order allocation. Table 1 shows the diversity in the methodological approaches that have been proposed so far to support the supplier evaluation and selection process under sustainability considerations.

The methods in Table 1 have been conceptualized for stating preferences that are known before the optimization stage and are therefore input variables for the optimization. Based on these preferences, the decision-maker determines the optimal supplier portfolio. In contrast, the methodology proposed in this research is not an additional approach for selecting sustainable suppliers but an approach to derive implicit preferences from actual sourcing decisions. This means that the preferences used by the decision-maker are unknown to us. With our inverse optimization model, we aim to derive these preferences from actual sourcing decisions. The advantage of our approach is that it is not biased by the setting in which the decision-maker sets her/his preferences (such as in surveys, interviews, or AHP).

Table 1
Supplier selection and sustainability: methodological approaches.

Example	Methodological approach
Bai and Sarkis (2010)	Grey approach; grey system and rough set theory
Saputro et al. (2024)	AHP & quality function deployment; AHP & multi-objective programming
Giannakis et al. (2020)	ANP
Ghadimi et al. (2018)	Multi-agent systems approach
Jain and Singh (2020)	Fuzzy logic/numbers/inference systems, and/or fuzzy TOPSIS
Wang et al. (2020)	Multi-objective optimization
Liu et al. (2018)	ANP-VIKOR

2.3. Inverse optimization

The introduction of the notion of inverse optimization goes back to Burton and Toint (1992), who derived the travel costs based on the routes the users took in a network. Inverse optimization uncovers hidden decision-making strategies from observed decision data, i.e., it generally aims to infer unknown optimization models from decision data (Gupta and Zhang, 2022). Thus, inverse optimization can be used as a means for determining the preferences for certain objectives by assuming a general shape of the objective function and identifying the preference parameters that yield the actual decision (Rönnqvist et al., 2017). Actual decisions from decision-makers can be considered as optimal (near-optimal) solutions of an optimization model. Inverse optimization is applied to elicit this unknown model from observations. An overview of the theory and applications of inverse optimization is presented by Chan et al. (2022).

Inverse optimization has been used in several disciplines, such as in network optimization problems (Liu and Zhang, 2006; Zhang and Cai, 1998), radiation therapy planning (Babier et al., 2021; Chan et al., 2014), investment portfolio optimization (Bertsimas et al., 2012; Utz et al., 2014; Zagst and Pöschik, 2008), electricity demand forecasting (Saez-Gallego and Morales, 2018), auction mechanism design (Beil and Wein, 2003; Birge et al., 2017), biological systems (Burgard and Maranas, 2003; Terekhov et al., 2010), optimal control (Hempel et al., 2015; Westermann et al., 2020), capacitated vehicle routing problem (Chen et al., 2021), and determining the expediting engineering projects by studying how to schedule the number of labor in each process at the minimum cost to achieve an extremely short construction period goal (Peng and Liu, 2024). These contributions mainly focus on determining an objective function that makes the observed decisions, given the constraints of the problem, exactly optimal. Ahuja and Orlin (2001) show a general tool for inverse optimization with linear forward optimization problems that has been extended to be considered as conic (Iyengar and Kang, 2005; Zhang and Xu, 2010), discrete (Bulut and Ralphs, 2021; Schaefer, 2009), and nonlinear (Chow et al., 2014).

A relatively new stream of literature considers so-called data-driven inverse optimization. In principle, the inverse optimization model is applied to a decision in multiple instances, i.e., with different input parameter values (Mohajerin et al., 2018). Data-driven inverse optimization increases the likelihood of finding an optimization model that has true predictive power for future decisions in unseen instances (Gupta and Zhang, 2022). The approach mitigates three key sources of noise in the observations: measurement errors, bounded rationality of the decision-maker, and model specification mismatch (Aswani et al., 2018; Mohajerin et al., 2018). Also, in this direction, Gupta and Zhang (2024) suggest a framework that constructs surrogate models that minimize the decision prediction error. This error is defined as the difference between the optimal solutions of the original and the surrogate optimization problems.

3. A novel approach to derive implicit preferences in sourcing decisions

This section presents a novel approach for deriving the extent to which purchasing managers actually included sustainability as an objective in the supplier selection process. The underlying idea is to measure the importance of sustainability based on the preference a decision-maker attributes to sustainability in an actual sourcing decision. This preference, which we refer to as *sustainability preference*, determines the importance of sustainability in the sourcing decision compared to traditional supplier selection objectives, such as low purchasing costs. To determine the decision-maker's sustainability preference in a certain purchasing case, we employ inverse optimization to deduce how the different purchasing objectives have been related to each other to achieve the optimal solution. To put it more technically, we aim to determine the weighting parameters, that is the preference parameters of a specific decision-maker's objective function. In the following subsection (Section 3.1), we derive the general shape of the objective function. In Section 3.2, we show how the inverse optimization approach may be implemented.

3.1. Objective function in the inverse optimization model

The basic assumption for our model is that a decision-maker selects the supplier portfolio that maximizes her/the company's expected utility of the overall logistics performance. The *logistics performance* relates to the expected service experienced by the purchasing company. It is a combination of different purchasing objectives such as low costs, high supplier reliability, timeliness, and sustainability. In practice, the logistics performance is often deemed to be high when the share of the deliveries meeting the 'six Rs of Logistics' is high, i.e., the **R**ight Product is delivered in the **R**ight Quantity and the **R**ight Condition at the **R**ight Time, at the **R**ight Place, and at the **R**ight Price.

The formal setting of our model is as follows: For each supplier i and each time t, each purchasing objective j can be described as a random variable $\omega_{i,j}^{(t)}, i = 1, \ldots, n, j = 1, \ldots, J$. This means that the logistics performance is uncertain ex-ante. Moreover, the available suppliers perform differently concerning the single purchasing objectives; that is, some suppliers perform better concerning costs or sustainability than other suppliers, for instance. The exact performance of each supplier for the single objectives is not exactly known at the time when the decision needs to be made, however, it can be described in terms of expected performance values and typical deviations from these performance scores.

For one decision situation, assume that the supplier portfolio P contains n suppliers. Let $\boldsymbol{x} \in \mathbb{R}^n$ with $\sum_{i=1}^n x_i = 1$ be a vector of the weights of portfolio P, reflecting the order shares placed at the available suppliers. The random variable of the purchasing objective j of portfolio P in time t is then defined as $\omega_{j,P}^{(t)} = \sum_{i=1}^n x_i * \omega_{i,j}^{(t)}$, where $\omega_{i,j}^{(t)}$ is the random variable describing logistic objective j and supplier i. We define the overall logistics performance $L_P^{(t)}$ of a supplier portfolio P in time t as a linear combination of the random variables of the different $j = 1, \ldots, J$ purchasing objectives $L_P^{(t)} = \sum_{j=1}^J \delta_j * \omega_{j,P}^{(t)}$, where δ_j is the weight of purchasing objective j in the linear combination. The expected value of $L_P^{(t)}$ is finite if the random variables of the purchasing objectives have finite expected values. It can be calculated as the weighted sum of the n x 1 vector of expected values $\mu_j^{(t)} = E\left[\omega_j^{(t)}\right]$:

$$\mu_P^{(t)} = E\left[L_P^{(t)}\right] = \sum_{j=1}^J \delta_j * \boldsymbol{x}^T \mu_j^{(t)} . \tag{1}$$

Accordingly, the variance of $L_P^{(t)}$ is defined as

$$\left(\sigma_P^{(t)}\right)^2 = Var\left[L_P^{(t)}\right] = Var\left[\sum_{j=1}^J \delta_j * \omega_{j,P}^{(t)}\right] = \sum_{j=1}^J \delta_j^2 Var\left[\omega_{j,P}^{(t)}\right] + 2 * \sum_{j<k} \delta_j \delta_k Cov\left[\omega_{j,P}^{(t)}, \omega_{k,P}^{(t)}\right], \tag{2}$$

where $Cov\left[\omega_{j,P}^{(t)}, \omega_{k,P}^{(t)}\right]$ represents the covariance between purchasing objectives j and k. If the random variable of one purchasing objective is deterministic, the variance of this random variable equals zero. For the sake of clarity, we drop the time index (t) in the following since we consider a portfolio decision on a particular date t_0.

We follow the mean-variance approach as a standard practice in multi-criteria decision making (Hosseininasab and Ahmadi, 2015; Kellner et al., 2019; Talluri et al., 2010; Utz et al., 2014) and determine

$$\Psi\left(\mu_P, \sigma_P^2, \lambda^*\right) = -\sigma_P^2 + \lambda^* \mu_P \tag{3}$$

as the general version of the objective function that the manager applied in the purchasing decision. In (3), λ^* represents the decision-maker's risk tolerance (i.e., the preference parameter) regarding the expected logistics performance. If varied over the non-negative portion of the real line, maximizing Ψ causes expected utility to generate one candidate for an optimal solution in the 'logistics performance risk'-'expected logistics performance' space for each value of the risk tolerance parameter λ^*. This risk tolerance parameter indicates how important expected logistics performance is compared to logistics performance risk. The higher λ^*, the higher the additional logistics performance risk a decision-maker is willing to take for one additional unit of expected logistics performance. That is, a high number of λ^* means that a decision-maker evaluates expected logistics performance as more important than logistics performance risk. A small number of λ^* characterizes a decision-maker who mainly wants to minimize logistics performance risk. This objective function will be central to our inverse optimization process.

Substituting μ_P from Equation (1) and σ_P^2 from Equation (2) in Equation (3) results in

$$\Psi\left(\mu_P, \sigma_P^2, \lambda\right) = -\sum_{j=1}^J \delta_j^2 Var\left[\omega_{j,P}\right] - 2 * \sum_{j<k} \delta_j \delta_k Cov\left[\omega_{j,P}, \omega_{k,P}\right] + \lambda^* * \sum_{j=1}^J \delta_j * \boldsymbol{x}^T \mu_j. \tag{4}$$

In this paper, we assume that all processes j are deterministic except the first one. This means that $Var\left[\omega_{j,P}\right] = 0$ and $Cov\left[\omega_{j,P}, \omega_{k,P}\right] = 0$ for $j > 1$. Costs and sustainability are typical examples of deterministic purchasing objectives. Costs are usually predefined in the supplier's/vendor's offer and therefore fixed for the decision situation. Moreover, while the future sustainability of a supplier could be interpreted as a stochastic quantity, the persistence of sustainability assessments of firms is high, that is, these measures are rather stable on a year-to-year basis. Therefore, we also consider it as being deterministic in our general model specification. It should be noted that the approach is also able to include additional nondeterministic (i.e., quadratic) objectives. For this paper, without losing generalizability, we stick to the case with one quadratic and J linear objectives. Thus, Equation (4) results in

$$\Psi\left(\mu_P, \sigma_P^2, \lambda^*\right) = -\delta_1^2 Var\left[\omega_{1,P}\right] + \lambda^* * \sum_{j=1}^J \delta_j * \boldsymbol{x}^T \mu_j . \tag{5}$$

Dividing the entire equation by δ_1^2 and using $\lambda_j = \frac{\lambda^* * \delta_j}{\delta_1^2}$ yields

$$\Psi\left(\mu_P, \sigma_P^2, \lambda\right) = -Var\left[\omega_{1,P}\right] + \sum_{j=1}^J \lambda_j * \boldsymbol{x}^T \mu_j . \tag{6}$$

The preference functional (6) is to be maximized to find the supplier portfolio that maximizes the decision-maker's expected utility. The optimal solution depends on the preference parameters λ_j since the J risk tolerance parameters $\lambda = (\lambda_1, \ldots, \lambda_J)$ give a parameterization of the $(J+1)$-dimensional set of candidates for optimal solutions (i.e., the pareto-efficient or nondominated surface) in criterion space. To specify this set of possible optimal solutions, multi-criteria decision-making problems have a criterion space beside the decision space (i.e., the feasible region S). In the criterion space $Z \subset \mathbb{R}^{J+1}$, the dimension $J+1$ is the number of objectives.

3.2. Inverse optimization process

In the decision situation described above, each decision-maker has her own set of λ-values. This section explains how the decision-makers' preferences λ between the objectives from Equation (6) can be derived using an inverse optimization process.

The notation of a specific sourcing decision is the following: Let $I = \{1, \ldots, n\}$ be the set of suppliers that launched a bid. The vector $\hat{x} = (\hat{x}_1, \ldots, \hat{x}_2, \ldots, \hat{x}_3)$ represents the weights that are attributed to the single suppliers in the actual sourcing decision. Note that, in the context of the supplier selection and order allocation problem, $\hat{x}$ represents the percentage share of the buying firm's overall demand that is sourced from the available suppliers. Also, note that the portfolio composition vector $\hat{x}$ adds always up to 1 to ensure that the buying firm's overall demand is satisfied.

In the proposed approach, one obtains *implicit* preferences derived from a supplier portfolio composition vector for a given purchasing case k. This approach differs from regular optimization as follows: In regular optimization, an objective function with fixed parameters exists, and the goal is to find the point in the feasible region that optimizes this objective function. In inverse optimization, we start with a point $\hat{x}$ in the feasible region, that is, with the actual sourcing decision in terms of the percentage order shares assigned to the available suppliers. For this point $\hat{x}$ that represents the optimal solution for the decision-maker, we aim to derive the parameters of the objective function. To do so, our endeavor is to identify the closest efficient point to $\hat{x}$ for the feasible region of the problem.[1] For this closest efficient point, which we refer to as x, we retrieve the values of preference parameters in Equation (6) that would have generated x when optimizing the objective function. These preference parameters refer to the closest efficient point only. However, we consider them to be the *implicit* parameters for $\hat{x}$ in the actual supplier decision case. In summary, we apply the following four steps to determine λ in Ψ:

1. Begin with a given sourcing decision $\hat{x}$ for the purchasing case k. This vector indicates the percentage shares of the buying firm's overall demand sourced from the individual suppliers.
2. Compute the efficient set for the given purchasing case k by either using the method presented by Hirschberger et al. (2013) or by solving a large number of quadratic optimization problems with objective function Ψ over a grid of varying λ parameters. The result is the $(J+1)$-criterion efficient set, which we refer to as $\mathcal{E}$.
3. Find the $x \in \mathcal{E}$ closest to $\hat{x}$ (in Euclidean norm) from the set of all efficient portfolio composition vectors $\mathcal{E}$.
4. Derive risk tolerance parameters λ^x as the implicit preference parameters from the x-vector that is closest to $\hat{x}$.

Fig. 1 illustrates the process of the inverse optimization approach.

With n suppliers having submitted a bid for a specific supplier decision k, the mathematical expression of the inverse optimization process is as follows:

$$\min_{\lambda} \|x - \hat{x}\| \tag{7a}$$

$$\text{s.t. } x \in \mathcal{E}(\lambda) \tag{7b}$$

where $\mathcal{E}(\lambda)$ is the nondominated set of a particular purchasing case derived from the optimization model

$$\max_{x} \Psi(x, \Sigma, \Omega, \lambda) \tag{8a}$$

$$\text{s.t. } G(x) \leq 0 \tag{8b}$$

$$H(x) = 0 \tag{8c}$$

where $G(x)$ and $H(x)$ are sets of real-valued functions in x that represent (non-)linear constraints, Σ represents the covariance matrix of the first (random) purchasing objective, and Ω is the matrix including all vectors of the expected values of the J purchasing objectives. The solution x of the outer minimization problem (7) is the efficient portfolio corresponding to portfolio $\hat{x}$.

4. Application

In this section, we show the feasibility of the proposed methodology. Therefore, we empirically analyze the preferences of decision-makers concerning sustainability versus traditional purchasing objectives in the supplier selection and order allocation process based on a real-world data set. The goal is to investigate how important sustainability aspects are in the actual sourcing decisions of one of the world's largest automotive parts manufacturers.

4.1. Collaborating firm

The investigated sample comprises the most critical purchasing cases in the calendar years 2019 and 2020 of one of the world's largest automotive parts manufacturers. This firm, which is a multinational multi-billion-dollar revenue Tier-1 supplier, provided us with deep insights into its current sourcing practices and processes, and into critical key performance indicators, including the sustainability and the logistics quality of its complete supplier base during the last three years, the associated supply risk, and the real-world purchasing costs. There are several reasons why we view the sample data as exceptionally useful.

1. *Industry*: The automotive industry is one of the world's largest industries by revenue. On their websites and in their annual reports, many car manufacturers claim that they will make sustainability a strategic priority in the upcoming years. This includes the composition of the product portfolio but also the design and the implementation of business processes. As the automotive sector is characterized by complex value chains and a deeply structured supplier base, the integration of sustainability aspects into the sourcing process is an essential element for guaranteeing that sustainable practices cover the complete value chain.
2. *Supply chain position and firm size*: The collaborating firm is a Tier-1 supplier. Tier-1 suppliers are firms that supply parts, modules, and systems directly to the original equipment manufacturers (OEMs). They typically source a wide range of raw materials from a variety of other firms to produce the products offered to their customers. Due to the size of the collaborating firm and its position in the supply chain, we have the chance to gain representative industry insights without being limited to a certain geographical region, product and raw material group (e.g., mechanics vs. electronics), customer/OEM group, and Tier-2 sub-supplier group. The collaborating firm has an active supplier base of more than 17,000 suppliers and operates more than 100 production facilities in more than 60 countries to supply virtually any automotive OEM. The employees who are responsible for the sourcing decisions show great diversity concerning their gender, age, and seniority.
3. *Sample size*: In this research, we study the preferences of decision-makers concerning different purchasing objectives for one firm. This approach assures the comparability of the single observations. To be specific: if we tried to compare the purchasing decisions of several firms, problems might arise concerning the measurement of the single objectives. Different firms will use different approaches for measuring the logistics quality, the supply risk, and the sustainability of their suppliers. Thus, the attribution of preference will be affected by the factors that determine the suppliers' scores at the single

[1] We search for the closest efficient point since $\hat{x}$ is not necessarily efficient.

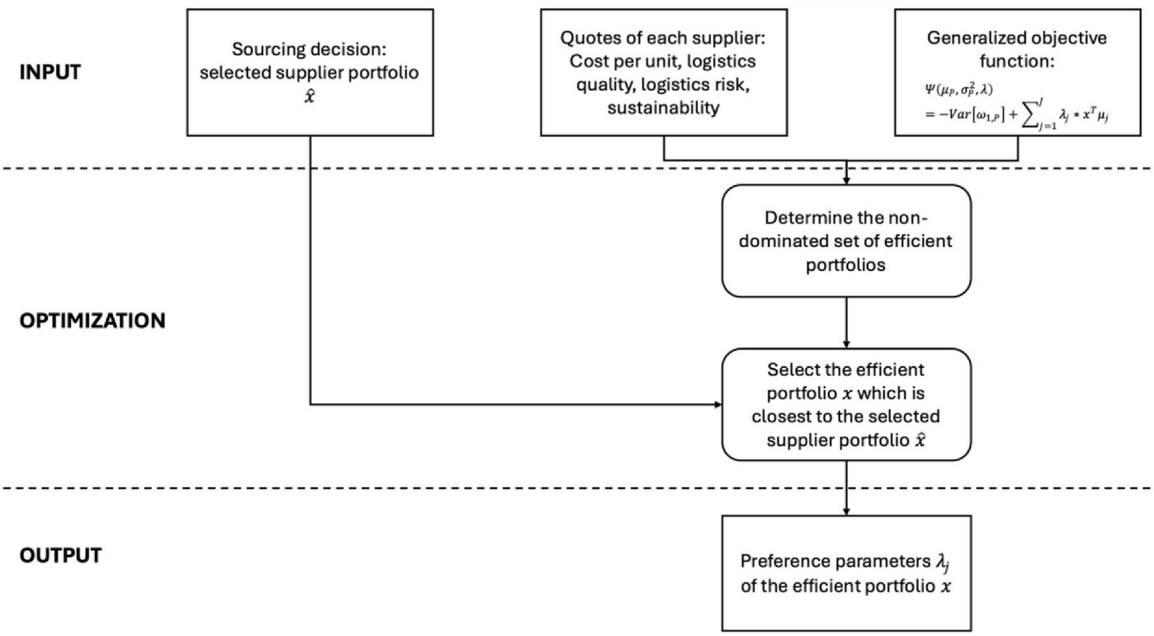

Fig. 1. Process of the inverse optimization approach.

objectives. The advantage of the single-case approach is that the measurement of the single objectives is the same across all purchasing cases studied.

4.2. Data collection

From the great number of sourcing decisions that are made every year in the collaborating firm, we concentrate on those that have been classified as 'critical cases' by the collaborating firm. These decisions are the best-documented ones and typically have a high and long-term impact on the firm. Specifically, we study the firm's most critical sourcing decisions in the calendar years 2019 and 2020. There are different reasons why a purchasing case may be classified as 'critical,' including cases of no competition or a lifetime purchase volume exceeding a certain eight-digit Euro value. According to a senior purchasing manager working at the collaborating firm, the critical sourcing decisions are representative of the majority of the purchasing cases, with the exception that they typically involve a greater purchase volume. That is, the critical purchasing cases are representative of the diversity of all purchasing processes concerning the geographical location of the production facilities for which the raw materials are sourced, the raw material group and the potential suppliers/Tier-2 suppliers, and the decision-makers.

Between January 2019 and December 2020, there were a total of 591 critical purchasing cases. Not all purchasing cases can be used for our analyses: For 42 (7.1%) of all critical purchasing cases no sourcing decision was made. In 50 (8.5%) cases, no supplier placed a quote. And in 173 (29.3%) cases, there was only one supplier to choose from.[2] After having eliminated these purchasing cases from the initial list, it was necessary to further reduce the set of the remaining 326 purchasing cases because, for some suppliers, not enough information was available for the quality and sustainability of the logistics. The final sample of valid purchasing cases consists of 145 cases (24.5% of the 591 critical purchasing cases in 2019–2020).

4.3. Sample description

For each purchasing case $k \in K = \{1, \ldots, 145\}$ of the final sample, we derive the decision-makers' preferences for the objectives 'purchasing costs,' 'logistics quality,' 'supply risk,' and 'sustainability.' These four objectives fit the general model introduced in Section 3 (cf., Equations (4)–(6)) with two deterministic purchasing objectives (costs and sustainability) and one non-deterministic (logistics quality, see below). Each purchasing case is characterized by two types of data: (a) metadata describing the setting of the purchasing case, and (b) data used for deriving the decision-makers' preferences. The meta-information includes the calendar year the sourcing decision was made, the person who was responsible for the sourcing decision (gender, age, seniority), the geographical location of the production facility supplied, and the purchasing volume (target price in Euro). The data used for deriving the decision-maker's preferences for the different objectives in a specific purchasing case k includes:

1. Supplier $i \in I = \{1,\ldots,n\}$: In each purchasing case, there are between two and eight suppliers (Tier-2 sub-suppliers) providing quotes for the demand of the collaborating firm.
2. The supplier's selling prices c_i^k: For the further analyses, the suppliers' selling prices (quotes) have been normalized, with the highest quote per purchasing case being set to 1 and all other quotes adapted accordingly, that is, divided by the highest quote.
3. The supplier's logistics quality l_i^k: Following the collaborating firm's practice, a certain supplier's overall logistics quality l_i^k is measured with the average logistics quality this supplier achieved during the last twelve months before the purchasing decision. The logistics quality of a certain sub-supplier in a certain month indicates, in turn, the percentage share of the deliveries that meet the following five of the six Rs of logistics in this month: The **R**ight Product is delivered in the **R**ight Quantity and the **R**ight Condition at the **R**ight Time, and at the **R**ight Place.
4. The supply risk $\sum_{ij}^k = Cov\left[l_i^k, l_j^k\right]$: Supply risk refers to the fact that the logistics quality of the single suppliers is typically not constant over time but can vary to a more or less significant degree from one month to another. The variability in the logistics quality of the suppliers is measured with the variance of the monthly logistics

[2] The single-quote cases are partly due to a supplier's monopoly for a certain raw material, or the supplier is dictated by the OEM.

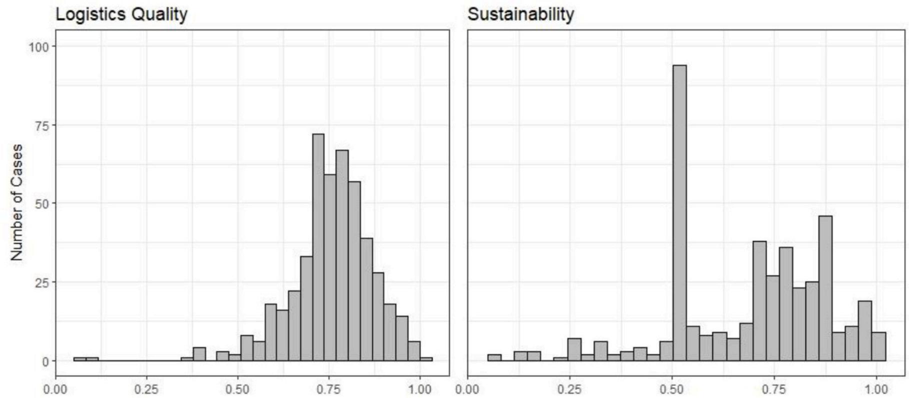

Fig. 2. Histograms for the logistics and sustainability performance of the available suppliers across all studied purchasing cases.

quality achieved. Transferring the ideas of the Markowitz (1952, 1959) portfolio theory to sourcing decisions in supplier selection, the overall supply risk is measured with the variance of the logistics quality of the supplier portfolio as a whole. This implies that the overall supply risk can be reduced by (a) opting for suppliers with a low variation in the service offered (low standard deviation), or (b) by assembling suppliers who 'compensate' each other, that is, when one supplier shows a bad logistics quality, the other(s) perform well – and vice versa. Or, to put it technically, the desirable situation is achieved when the logistics qualities of the single suppliers are negatively correlated. As stated in prior research (e.g., Hosseininasab and Ahmadi, 2015; Kellner et al., 2019), some suppliers are, for different reasons, simultaneously affected by certain supply disruptions, and assembling a supplier portfolio of similar suppliers may be crucial for when such disruptions occur. There are various reasons for why two or more suppliers may break down simultaneously, including situations where the suppliers are supplied by the same sub-supplier, and/or a natural disaster occurs and the suppliers are geographically located close to each other, and/or the suppliers use the same means of transport, which breaks down or is delayed. In accordance with Markowitz's portfolio theory, these interactions in the logistics quality between two suppliers i and j are measured with the covariance $Cov\left[l_i^k, l_j^k\right]$.

5. The supplier's sustainability ϑ_i^k: The sustainability of the suppliers is indicated with a sustainability score ranging from 0 (poor) to 1 (excellent). A specificity of this research compared to others is that the suppliers' sustainability is not reported based on self-made sustainability performance indicators. Instead, the sustainability performance scores ϑ_i^k originate from a self-assessment questionnaire based on the Global Automotive Sustainability Guiding Principles. These principles have been specified by 'Drive Sustainability,' which is a partnership between ten leading OEMs (e.g., BMW, Daimler, Ford, Honda, Scania, Toyota, and Volkswagen) aiming to drive sustainability across the automotive supply chain by fostering an aligned approach within the industry. The self-assessment questionnaire upon which the sustainability scores ϑ_i^k are based was established in 2014. At present, it represents the common standard for the sustainability rating of suppliers in the automotive industry. Even if the approach of determining the sustainability performance of the suppliers based on a self-assessment questionnaire is not as sophisticated as other approaches that have been proposed in literature (e.g., AHP/ANP, DEA, PROMETHEE, TOPSIS), it enjoys some important advantages (Kellner and Utz, 2019): First, the assessment of the sustainability of third parties (as in the case of a purchasing company rating the sustainability of its suppliers) is challenging as good information of the suppliers' performance in the different areas of sustainability is necessary. We argue that it is easier for a company to concentrate on its sustainability performance (self-assessment) and communicate the results in a standardized way. Moreover, the Global Automotive Sustainability Guiding Principles are a standardized approach for the assessment of the sustainability performance of suppliers in the automotive industry. Based on a questionnaire containing almost 60 items, suppliers are asked to provide information about their practices in different sustainability domains. The answers are then aggregated and an overall sustainability score is calculated. The fact that the sustainability performance is measured consistently (i.e., same questions and same rating) across the whole industry allows for a better comparability of the potential suppliers.
6. The actual sourcing decision ($\hat{x}^k$, the 'optimal solution'): the actual sourcing decision made by the person responsible for the purchasing case.
7. Constraints: in each purchasing case, $G(x)$ includes $x_i \geq 0\ \forall i$ to ensure that all weights are non-negative and $H(x)$ the constraint $\sum_{i=1}^{n} x_i = 1$ to ensure that the sum of the weights equals one.

Table 2 in Appendix A lists all parameters, formulas, and procedures included in the order allocation models. This table shows the objective function, which indicates that the four criteria for supplier evaluation are (1) the suppliers' selling prices, (2) the suppliers' logistics quality, (3) the supply risk, and (4) the suppliers' sustainability performance. Besides, budget constraints and overall logistics quality constraints are taken into account. These are the criteria that the collaborating company uses to evaluate its (potential) suppliers. An overview of the sample composition is presented in Table 3 in Appendix B. About one-third of the investigated sourcing decisions have been made by female decision-makers (53), most of the decision-makers are between 25 and 45 years old, and the majority of the decision-makers are purchasing managers. The histograms in Fig. 2 give an overview of the logistics and sustainability performance of the available suppliers across all studied purchasing cases. These histograms indicate that the purchasing managers can select from a broad range of different supplier characteristics.

4.4. Implementation of the inverse optimization process

A central element in our analyses are the implicit preference parameters λ_μ^x, λ_c^x, and λ_ϑ^x. As explained above, these parameters indicate, for a given sourcing decision, the relative importance the decision-maker attributed to the objectives 'low purchasing costs' (λ_c^x), 'high logistics quality' (λ_μ^x), and 'high sustainability' (λ_ϑ^x), where the objective 'low supply risk' serves as the benchmark. The higher the λ-value, the greater the relative importance of the corresponding purchasing objective is compared to the objective 'low supply risk.' To facilitate further analyses, we study λ-values in the interval ranging from 0 to 3, that is, $\lambda \in [0;3]$. We opted for this interval because our pre-experimental testing showed that, for the investigated sample, all implicit preference parameters $(\lambda_\mu, \lambda_c, \lambda_\vartheta)$ are located in this range.[3] Thus, a λ-value of 0 for the objective 'low purchasing costs,' for instance, indicates a situation where the decision-maker gave absolute preference to the purchasing objective 'low supply risk' when compared to the objective 'low purchasing cost.' A λ-value of 3 for 'logistics quality' indicates a situation where the decision-maker gave high preference to the objective 'high logistics quality' compared to 'low supply risk.' Appendix C contains more details on the calculation of the implicit preferences.

Since the inverse optimization approach is, from a computational perspective, resource-intensive and involves a certain amount of time to generate the optimal solutions, we developed a scalable state-of-the-art cloud architecture that allows us to solve an arbitrary number of (quadratic) optimization programs in an acceptable amount of time. Appendix C explains this architecture in detail.

4.5. Summary statistics for the implicit preference parameters

Table 3 in Appendix B presents descriptive statistics for the three implicit preference parameters λ_μ, λ_c, and λ_ϑ. For each preference parameter, we indicate the minimum, the mean, and the maximum across the whole sample and per investigated variable. These summary statistics indicate differences in the importance the decision-makers attributed to purchasing costs, logistics quality, and sustainability. Influencing factors might include the decision-maker's age, gender, and seniority, the distance of the decision-maker's office location to the supplied plant, and the purchase volume measured in Euro.

Table 3 shows that there is, across all variable characteristics, a noticeable variability in the preference parameters λ_μ, λ_c, and λ_ϑ, ranging from 0 to 2.259. This indicates that there is a certain variability in the preferences the decision-makers attributed to the single purchasing objectives. As a consequence, we continue with a per-variable analysis. When doing this, we focus on the mean λ-values, since the mean λ-values indicate whether there are sub-groups in the investigated sample that tend to place more importance on purchasing costs, logistics quality, and sustainability than other sub-groups.

Concerning the *calendar year* the decision was made, we notice an increase in the mean λ-value referring to purchasing cost and a (slight) decrease in logistics quality and sustainability from 2019 to 2020. This indicates that, in 2020, the decision-makers placed, compared to risk, more importance on the aspect of 'low purchasing costs' than in the previous year and less importance on 'high logistics quality' and 'high sustainability.' Concerning the *gender* of the decision-makers, the mean and maximum values of the implicit preference parameters of the aspects of 'purchasing costs' and 'logistics quality' are higher in the female sample than in the male one. The preferences of males for high sustainability were slightly greater than the preferences of females. As for the decision-makers' *age*, the classes '35–45 years' and '> 45 years' show higher mean values on the purchasing objective 'high sustainability' than the classes '< 25 years' and '25–35 years.' Furthermore, the figures in Table 3 indicate that the classes '35–45 years' and '> 45 years' placed less importance on high logistics quality. Assuming that the *seniority* of the decision-maker might affect the importance attributed to the different purchasing objectives, we compare the corresponding λ-values. Each decision-maker of the investigated sample belongs to one out of three groups: Purchasing Manager, Senior Purchasing Manager, or Head of Purchasing. According to the results presented in Table 3, the Purchasing Managers placed, on average, noticeably more importance on the aspect of 'purchasing cost' than decision-makers belonging to the groups 'Senior Purchasing Manager' and 'Head of Purchasing.' As for logistics quality, we do not notice a specific trend. Concerning sustainability, the group 'Head of Purchasing' ranked this preference the lowest. We also control for the distance between the decision-makers location to that of the plant in which the sourcing decision is implemented. It might be the case that the further away the plant for which the sourcing decision is made, the more or less important the different purchasing objectives are. Therefore, we calculate the great-circle *distance* between the office location of the decision-maker and the plant to be supplied. The summary statistics in Table 3 do not indicate that the distance affects the implicit preference parameters. Finally, the *purchasing volume* measured in Euro appears to not influence the importance the decision-makers place on the single purchasing objectives.

We further test the figures in Table 3 for statistical inference. Therefore, we use pairwise Wilcoxon rank-sum tests to test whether one λ-value is different from another. We use this non-parametric test as we cannot assume a specific distribution of the implicit preference parameters. Appendix D presents the p-values that result from the application of this test. A given λ-value is classified as 'significantly greater' than another if the corresponding p-value is below 10% (in the table in Appendix D, this is indicated by bold letters). According to the test results, females placed significantly more importance on the purchasing objective 'high logistics quality' than males did. In addition, purchasing managers placed significantly more importance on the aspect of 'purchasing cost' than senior purchasing managers.

4.6. Differences in the implicit preference parameters λ

The mean λ-values in the last row of Table 3 indicate that, overall, the decision-makers placed, compared to risk, more importance on purchasing cost than on logistics quality and sustainability. In this section, we go into more detail by focusing directly on the differences in the implicit preference parameters the decision-makers attributed to the different purchasing objectives. The idea is to understand whether the decision-makers' preferences differ significantly in favor of a certain purchasing objective. In addition, we intend to learn whether the preference ranking for the different purchasing objectives differs depending on the gender, age, and seniority of the decision-maker, the distance from the decision-maker's office location to the supplied plant, and the purchasing volume.

To check whether a given λ-value is significantly greater or less than another, we again apply the pairwise Wilcoxon rank-sum test. Our findings, in terms of the resulting p-values, are summarized in Table 5 in Appendix E. Again, we classify a given λ-value as 'significantly greater' or as 'significantly less' than another if the corresponding p-value is below 10% (in Table 5, this is indicated by bold letters). As shown in Table 5, we check for each variable characteristic whether the implicit preference for low purchasing cost is significantly less/greater than for high logistics quality ($\lambda_c < \lambda_\mu / \lambda_c > \lambda_\mu$), whether the implicit preference for low purchasing cost is significantly less/greater than for high sustainability ($\lambda_c < \lambda_\vartheta / \lambda_c > \lambda_\vartheta$), and whether the implicit preference for high sustainability is significantly less/greater than for high logistics quality ($\lambda_\vartheta < \lambda_\mu / \lambda_\vartheta > \lambda_\mu$).

[3] We conducted optimization runs with different combinations of preference parameters $\lambda_\mu, \lambda_c, \lambda_\vartheta \in [0;20]$. Due to the constraints on the weights, the grid $\lambda_\mu \times \lambda_c \times \lambda_\vartheta \in [0;3] \times [0;3] \times [0;3]$ covers all efficient portfolios. Extending the upper bounds of the preference parameter ranges does not add new efficient portfolios in our application case.

The numbers in the last row of Table 5 indicate that, across all 145 purchasing cases, the responsible persons placed significantly more importance on the sourcing objective 'low purchasing cost' than on 'high logistics quality' and on 'high sustainability.' The pairwise comparison for logistics quality and sustainability does not reveal any significant differences. This preference ranking does not only apply to the whole sample but also to a great share of the investigated purchasing cases.

5. Discussion

5.1. Summary of the application case findings

Having analyzed the real-world sourcing decisions, we arrive at the following conclusions.

1. The way of implementing the inverse optimization process generated a good match between the vector $\hat{x}$, which represents the actual sourcing decisions, and the x-vector that is closest to $\hat{x}$ in Euclidean norm. Thus, we can accurately derive the implicit preference parameters for the different objectives in the different purchasing cases.
2. Across the 145 purchasing cases, there is a noticeable variability in the preferences the decision-makers attributed to the four purchasing objectives, independent of the person's characteristics and the purchasing volume.
3. There are subgroups in the investigated sample that tend to place more importance on purchasing costs, logistics quality, and sustainability than other subgroups.
4. Across the 145 investigated purchasing cases, the decision-makers placed significantly more importance on low purchasing cost than on high logistics quality and high sustainability. Concerning the direct comparison of the ranking of logistics quality and sustainability, the results do not show any significant differences.

Interestingly, the senior purchasing manager with whom we worked most closely in this project admitted that while she was not surprised that cost is across all purchasing cases the dominating sourcing objective, there is no significant superiority when comparing logistics quality and sustainability. Even more interesting is that her assumption could be confirmed that due to the COVID-19 pandemic in 2020, the objective of low purchasing costs received even more attention than one year before.

5.2. Possible additional analyses

In the previous sections, we presented a series of analyses to study the implicit preference parameters of decision-makers derived from the inverse optimization approach. In general, there are additional ways to statistically investigate the set of implicit preference parameters. For instance, the implicit preference parameters could be used to analyze whether specific characteristics of decision-makers, such as gender and seniority, have an impact on the importance of purchasing objectives in sourcing decisions. For carrying out such analyses, one can apply regression models. Another more sophisticated analysis could ha differences-in-differences setting to elicit whether one decision-maker increased the importance of sustainability objectives to a higher extent than the other one. This might be interesting after a change in the strategy of a department or business area, or after a change in the head of the department.

In summary, the methodology proposed provides figures that act as a basis for a wide range of empirical analyses of the importance decision-makers attribute to sustainability in sourcing decisions. Since the implicit preference parameters are derived from actual sourcing decisions, they do not suffer from self-reporting biases of the decision-makers, as survey or interview answers would.

5.3. Contribution, implications, scope, and applicability of this research and of the methods used

Overall, the contribution of this research is twofold: (1) First, this research contributes to the sustainable configuration of supply and value chains by proposing an approach that allows different kinds of stakeholders (researchers, purchasers, analysts, decision-makers) to empirically study the extent to which companies have *actually* integrated sustainability objectives into their sourcing decisions. To do this, the proposed methodology derives implicit preferences of the decision-maker(s) for the different sourcing objectives from past sourcing decisions. These preferences can then be used to carry out further analyses. Thus, the proposed methodology is not another approach for selecting sustainable suppliers but an approach to derive implicit preferences from actual sourcing decisions. The benefit of this approach is that it is based on actual sourcing decisions and is thus not biased by the setting in which the decision-maker sets her/his preferences (such as in surveys, interviews, or AHP). Since there exists no benchmark on the preferences (since they are subjective), we cannot determine whether our approach is empirically better or worse than existing approaches to determine preferences. Moreover, we do not measure stated preferences but implicit preferences. An advantage of using implicit purchasing preferences is that they are derived from real-world decision situations, that is, they are measured after the decision has been made and, thus, do not suffer from self-reporting biases. From an industry point of view, the application of the proposed methodology allows managers, among other things, to monitor whether the issued sourcing strategy (in terms of the preferences set on the different purchasing objectives) has actually been followed by the staff. Also, managers can identify what 'type' of staff (gender, age, seniority, location, etc.) is putting particular importance on the different purchasing objectives. From an academic perspective, the application of the proposed methodology allows scholars, among other things, to compare the preferences set on different purchasing objectives between industries, geographical regions, age groups, and more. This allows for deepening the understanding of the characteristics of the purchasing managers and sourcing situations that come with particularly high/low preferences on sustainability. (2) Another contribution of this research is the presented cloud architecture, which allows the user to solve an arbitrary number of optimization programs in an acceptable amount of time. We argue that the proposed architecture can be used in many other future projects that involve solving many optimization problems. Both industry/management and academia may build different applications on this architecture, for example, applications that involve inverse optimization or applications that aim to identify optimal solutions for a high number of parameter settings/scenarios.

5.4. Key assumptions and limitations

Even if the presented approach offers several benefits and innovative features for practitioners and scholars, some aspects should be considered when applying the presented methodology. In the following, we list the key assumptions of the study.

The first aspect refers to the assumptions concerning the objective function, which assumes that the decision-maker needs to balance four purchasing objectives: costs, logistics performance, supply risk, and sustainability. This objective function may be criticized since one might expect to include more, less, or other objectives. In addition, the aspect of 'supply risk' could be modeled differently, i.e., not based on the concepts of the investment portfolio theory. Our response to such critics is that the objective function, as presented above, is based on best practices and based on accepted research results (e.g., Hosseininasab and Ahmadi, 2015; Kellner et al., 2019; Kellner and Utz, 2019; Talluri et al., 2010). Also, it should be noted that objective functions may be modified and adapted according to the specificities of the company context. Thus, it is possible to extend the objective function by adding or

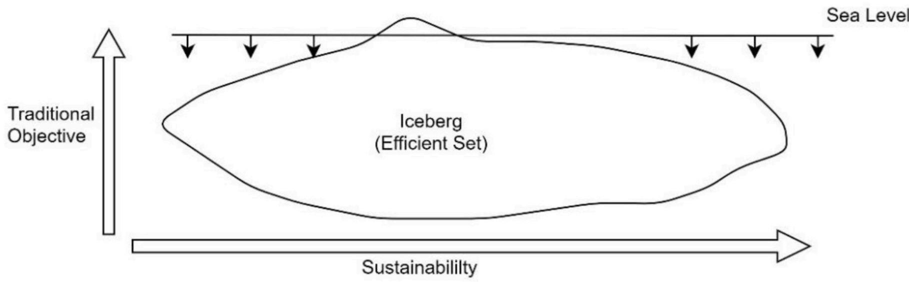

Fig. 3. Reducing the sea level.

removing specific aspects. Also, it is possible to integrate supply risk as a linear and not as a quadratic component in the objective function.

The second aspect refers to the constraints that are part of the decision-making/optimization problem. As shown in Table 2, three constraints have been considered in the real-world example, since no more constraints have been communicated to us by the collaborating firm. It is possible to extend the number of constraints in future applications of the proposed approach to reflect, for instance, situations where a certain number of suppliers needs to be part of the portfolio or to include a minimum number of suppliers that show certain characteristics.

The third aspect refers to the fact that the observed results depend on the data input and how exactly the different parameters, such as the sustainability indicators of the different suppliers, have been measured. Thus, problems might arise when trying to compare the preferences set on the different purchasing objectives between several companies since different companies might measure sustainability or supply risk in different ways. As for the real-world case in this article, this aspect is a minor problem since we assume that decision-makers used the same data values for assembling the different supplier portfolios that were fed into the optimization model.

Finally, we want to mention that we do not claim any generalizability of the results observed in the application case with 145 sourcing decisions, such as the importance men/women or certain age groups are putting on sustainability. Although the sample size is reasonable compared with other case studies, the results only illustrate the behavior of the decision-maker in the sample firm.

5.5. *A multi-criteria decision-making framework for sustainable supplier selection*

The intention of Section 4 was to present empirical evidence on the *status quo* concerning the importance decision-makers attribute to sustainability and traditional purchasing objectives in the purchase order allocations of one of the world's largest automotive parts manufacturers. Our results document, that in line with Ho et al. (2010) and despite the need for more sustainability in supply chains, the objective of 'low purchasing cost' is significantly more important than 'high sustainability.' The next step after measuring the *status quo* is the *search and application of methodologies that* support *solving the multi-criteria supplier selection problem under sustainability considerations*.

This section summarizes our key findings from applying a multi-criteria decision-making approach to analyze sensitivities between the considered objectives. This is an extension of the approach introduced by Kellner et al. (2019) and Kellner and Utz (2019), which supports purchasing managers in assembling supplier portfolios while making them aware of the trade-offs between the purchasing costs, the expected logistics quality, the supply risk, and the overall sustainability of the selected supplier base. The main idea is to model the supplier selection and order allocation problem as a multi-objective optimization problem and to solve it using an a posteriori approach. That means that, firstly, the complete sphere of optimal solutions is determined and, thereafter, the decision-maker can select the supplier portfolio that best matches the goals of the purchasing company – after having seen the complete set of optimal alternatives and after having studied all trade-offs that come with the decision-making problem at hand (Mavrotas, 2009). All the details on the implementation of this approach are presented in Appendix F.

The applied approach allowed us to carry out a series of sensitivity analyses. It is particularly interesting to see that the results of these analyses indicate that in the majority of the 145 purchasing cases, the sustainability of the actual sourcing decisions can be substantially improved with almost no deterioration in the traditional objectives. Based on these observations, we conclude that in the image of an iceberg (Fig. 3), methods ignoring the sustainability objective divide all possible supplier portfolios into those nondominated in traditional purchasing objectives (above sea level, i.e., visible to decision-makers) and those better in sustainability, but worse in the traditional purchasing objectives (below sea level and invisible to decision-makers). The applied method can be considered as a tool that allows decision-makers to reduce the sea level and, thus, to discover supplier portfolios that are close to traditionally efficient portfolios but with substantially improved sustainability. For this area, that is, slightly below the sea level, our results document a high potential to improve sustainability with low deterioration in traditional purchasing objectives. This pattern leads to situations where the increase in sustainability is, in percentage values, much greater than the increase in purchasing costs, for instance.

6. Conclusion

Research shows that buying firms have substantial leverage to initiate sustainable development by accounting for and controlling the sustainable performance of their suppliers (e.g., Gopalakrishnan et al., 2021; Wu and Pagell, 2011). This article presented a methodology based on inverse optimization to empirically study the importance decision-makers attribute implicitly and in reality to sustainability when opting for a certain supplier portfolio. In this regard, our paper fulfilled its intention of presenting an alternative approach to the 'classical' self-reporting-based approach for studying sustainability preferences in sourcing decisions. We applied the suggested methodology to study the most critical sourcing decisions of a major automobile parts manufacturer.

Future research may extend this study by making further use of the concepts of inverse optimization to deepen the understanding of the preferences decision-makers attribute to single purchasing objectives. This will allow the discovery of decision-maker, decision-situation, industry, region, and company-specific characteristics that contribute to certain behaviors. Another possibility is making use of the proposed decision-making approach to study sensitivities of typical purchasing situations – for instance, by focusing on certain industries or geographical regions.

CRediT authorship contribution statement

Florian Kellner: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sebastian Utz:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table 2
Parameters, formulas, and procedures included in the order allocation models.

Sets			
k	$1,\ldots,145$	Purchasing cases	
i	$1,\ldots,n$	Available suppliers	
j	$1,\ldots,J$	Objectives	
Decision Variables			
x_i^k	$\in [0;1]$	Supply share allocated to supplier *i* in purchasing case *k*	
Parameters			
$\hat{x}_i^k$	$\in [0;1]$	Supply share that was actually allocated to supplier *i* in purchasing case *k*	
c_i^k	$\in R^+$	Selling price of supplier *i* in purchasing case *k*	
l_i^k	$\in [0;1]$	Logistics quality of supplier *i* in purchasing case *k*	
$\sum_{ij}^k = Cov[l_i^k, l_j^k]$	$\in R$	Covariance of the logistics quality in suppliers *i* and *j*	
ϑ_i^k	$\in [0;1]$	Supplier *i*'s sustainability performance	
Objective			
$minimize\ \sum_{i,j} x_i^k * x_j^k * Cov[l_i^k, l_j^k] + \sum_i(\beta_c * x_i^k * c_i^k - \beta_\mu * x_i^k * l_i^k - \beta_\vartheta * x_i^k * \vartheta_i^k)$			(1)
Constraints			
$\sum_i x_i^k = 1$		Demand satisfaction	(2)
$\sum_i x_i^k * c_i^k \le Budget$		Budget constraint in purchasing case *k*	(3)
$\sum_i x_i^k * l_i^k \ge Logistics$		Assurance of the minimum desired logistics quality performance of the supplier portfolio	(4)
Procedure			
Step 1: Compute the efficient set for the purchasing case *k* over a grid of varying preference parameters β			
Increase β_c:			
Increase β_μ:			
Increase β_ϑ:			
Solve:			
Objective	Equation (1)		
Constraints	Equations (2)–(4)		
Record all relevant values, e.g.: x_i^k, β_c, β_μ, β_ϑ, $\sum_i x_i^k * c_i^k$, $\sum_i x_i^k * l_i^k$, $\sum_i x_i^k * \vartheta_i^k$			
Step 2: Identify the portfolio composition vector x that is closest to $\hat{x}$ in Euclidean norm			

Appendix B

Table 3
Summary information for the 145 investigated sourcing decisions (Nb. = Number of cases, Avg = Average).

Aspect	Variable	Characteristic	a) Nb.*, b) Avg	λ_c (Cost)			λ_μ (Logistics Quality)			λ_ϑ (Sustainability)		
				Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.
Decision Date	Calendar Year	2019	a) 73	0.000	0.071	1.305	0.000	0.082	2.259	0.000	0.049	1.061
		2020	a) 72	0.000	0.099	2.148	0.000	0.043	0.662	0.000	0.044	0.514
Decision-Maker	Gender	Female	a) 53	0.000	0.111	2.148	0.000	0.106	2.259	0.000	0.032	0.293
		Male	a) 92	0.000	0.069	1.305	0.000	0.038	0.427	0.000	0.055	1.061
	Age	<25 years	a) 16	0.000	0.097	0.649	0.000	0.113	0.662	0.000	0.036	0.293
		25–35 years	a) 47	0.000	0.057	1.895	0.000	0.078	2.259	0.000	0.019	0.211
		35–45 years	a) 58	0.000	0.096	1.305	0.000	0.042	0.427	0.000	0.055	1.061
		>45 years	a) 7	0.000	0.003	0.018	0.000	0.019	0.072	0.000	0.128	0.812
	Seniority	Purch. Manager	a) 110	0.000	0.107	2.148	0.000	0.047	0.662	0.000	0.048	1.061
		Senior Purch. Mngr.	a) 18	0.000	0.002	0.018	0.000	0.043	0.280	0.000	0.054	0.470
		Head of Purch.	a) 3	0.000	0.012	0.035	0.000	0.044	0.133	0.000	0.010	0.029
	Dist. Plant (km)	Quartile 1	b) 154	0.000	0.161	1.895	0.000	0.104	2.259	0.000	0.070	0.812
		Quartile 2	b) 593	0.000	0.042	0.547	0.000	0.036	0.662	0.000	0.042	0.514
		Quartile 3	b) 1050	0.000	0.024	0.649	0.000	0.065	0.613	0.000	0.053	1.061
		Quartile 4	b) 6581	0.000	0.110	2.148	0.000	0.044	0.375	0.000	0.021	0.211
Purchasing Vol.	Budget (Euro)	Quartile 1	b) 622,595	0.000	0.077	1.305	0.000	0.105	2.259	0.000	0.040	0.470
		Quartile 2	b) 2,897,450	0.000	0.131	2.148	0.000	0.034	0.280	0.000	0.036	0.514
		Quartile 3	b) 13,721,504	0.000	0.052	1.143	0.000	0.019	0.162	0.000	0.016	0.123
		Quartile 4	b) 95,166,639	0.000	0.083	1.895	0.000	0.096	0.662	0.000	0.099	1.061
Overall			a) 145	0.000	0.085	2.148	0.000	0.063	2.259	0.000	0.047	1.061

* If the total number of cases for a certain variable does not add up to 145, then this is due to missing information for some purchasing cases concerning this variable.

Appendix C

The process of inverse optimization, which is used to derive the decision-makers' preferences $(\lambda_\mu, \lambda_c, \lambda_\vartheta)$ for the individual purchasing objectives in the different purchasing cases, has been implemented mainly in Python and R. Following the procedure described in Section 3.2, we firstly take note of, for each purchasing case separately, the actual supplier portfolio composition vector $\hat{x}$, that is, the actual sourcing decision made by the responsible person concerning the percentage shares of the total demand that are sourced from the available suppliers (Step 1). Next, we compute the efficient set for the considered purchasing case (Step 2). To do this, we solve a large number of quadratic optimization problems with objective function Ψ over a grid of varying λ_μ, λ_c, and λ_ϑ parameters using Gurobi 9.1 with the default parameter settings and a flow control organizing the sequence of the calculations. In detail, we solve a large number of quadratic optimization problems over the grid from 0 to 3 for all preference parameters, since our pre-tests elicit that this range covers all efficient portfolios that we achieve by our inverse optimization. Since we intend to determine the distance of the actual sourcing decision from the efficient set as precisely as possible, a detailed (dense) representation of the efficient set is required. A dense representation of the efficient set can be achieved by opting for a dense grid of varying λ-values. This, however, implies an extensive computational study. For computing the 145 efficient sets that refer to the investigated purchasing cases, we incremented all λ-values 51 times in an iterative manner and solved the corresponding optimization problems. This implies that for each purchasing case, 132,651 (=51*51*51) quadratic optimization problems are solved to optimality. This also implies that the results reported below, which refer to our observations for the final sample as a whole, are based on the optimal solutions of 19,234,395 (=145*132,651) quadratic optimization programs.

Since solving almost 20 million quadratic optimization programs is, from a computational perspective, resource intensive and involves a certain amount of time to generate the optimal solutions, we developed a scalable state-of-the-art cloud architecture that allows us to solve an arbitrary number of (quadratic) optimization programs in an acceptable amount of time. The underlying idea of this architecture is to run the 19,234,395 quadratic optimization problems as a containerized application in a Kubernetes cluster. Fig. 4 gives an overview of this architecture.

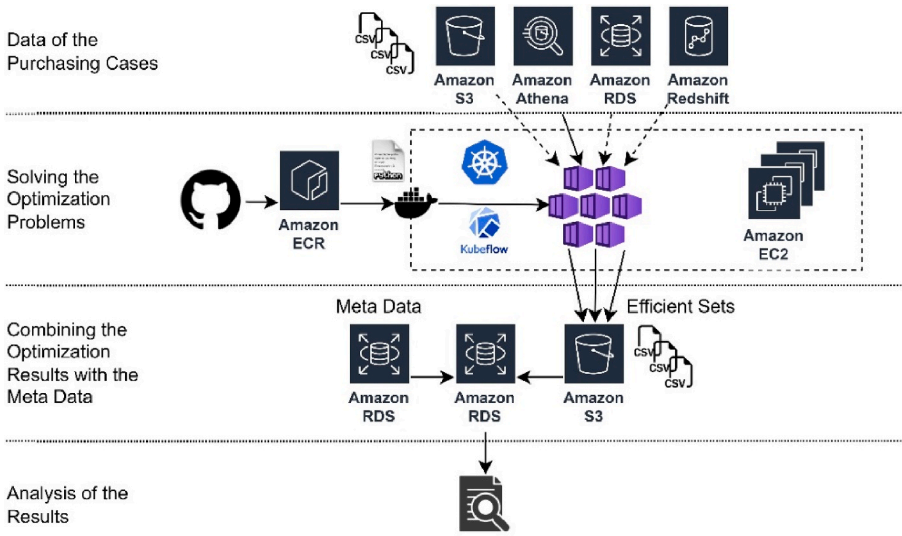

Fig. 4. Cloud architecture for solving the 19,234,395 quadratic optimization programs.

The first layer entitled 'Data of the Purchasing Cases' provides the data used for deriving the decision-makers' preferences. In our case, this data is stored as CSV files and made available for the next processing step through AWS Athena. Besides Athena, other AWS services can be used alternatively (e.g., S3, RDS, Redshift). At the heart of the proposed architecture is a Kubernetes cluster, which is managed using Kubeflow and is based on a couple of Amazon EC2 virtual computers. In detail, the cluster spins up, for each purchasing case separately, a Kubernetes Pod that contains the Gurobi optimization engine and a Python file that holds the logic for reading the base data, for solving the mathematical problem, and for writing persistently the solutions of the quadratic optimization problems. In this case, each Kubernetes Pod consists exactly of one Docker container, where the image is pulled from a container repository (ECR). The latter is filled by a continuous integration pipeline based on GitHub Actions. The results calculated inside the Kubernetes Pods are dumped to Amazon S3, from where the data is moved to a relational database (in this case, PostgreSQL) where the data is joined with the meta information of the purchasing cases. From there the data is retrieved to carry out the subsequent analyses. At this point, it should be noted that while we make use of AWS as the underlying cloud platform, other cloud service providers and the corresponding services can also be used. In the Azure case, this would primarily be Blob Storage, SQL Database, and Virtual Machines. In the GCP case, this would primarily be Cloud Storage, Cloud SQL, and Virtual Machine Instances. The implementation of this architecture took around two man-days. Using this architecture, we were able to solve the 19,234,395 quadratic optimization problems quickly. Depending on the underlying EC2 instances, it took around 9 min to complete all the steps shown in Fig. 4. For comparison: the overall computation time was about 8 h on a single Win10 64-bit PC equipped with an Intel i7-8550 CPU and 16 GB RAM. Finally, it is worth mentioning, that the proposed architecture is completely scalable, both vertically and horizontally, i.e., it is easily possible to upgrade the underlying EC2 instances in terms of the numbers of CPUs and RAM (vertical scaling) and to add additional Kubernetes Pods, for instance by adding additional EC2 instances (horizontal scaling). Thus, while the computation time will increase when more purchasing cases are to be analyzed or when the density is increased from 51 to higher numbers in the case of one single computer, the time for running the cloud architecture will remain constant (i.e., more or less 9 min) since the cluster can scale automatically the computing resources when there is a higher computation demand. In Step 3, we determine, for each purchasing case individually, the Euclidean distances of the actual sourcing decision $\hat{x}$ to each one of the 132,651 efficient supplier portfolios on the corresponding efficient set. We identify the portfolio composition vector x that is closest to $\hat{x}$ in Euclidean norm as the representative for the actual sourcing decision. Finally, in Step 4, we derive the preference parameters λ_μ^x, λ_c^x, and λ_ϑ^x as the implicit preference parameters from the x-vector that is closest to $\hat{x}$.

The approach of Steps 3 and 4, that is, the identification of the purchase order allocation x that is closest to the actual sourcing decision $\hat{x}$ and the derivation of the corresponding λ-values, is shown in Fig. 5. The figure shows, for a given purchasing case, a sample of 1000 alternatives out of the 132,651 efficient supplier portfolios, where each optimal supplier portfolio is represented by a line spanning from the leftmost axis over all other axes to the rightmost axis in the parallel coordinates plot. In the considered purchasing case, six suppliers (S_1 to S_6) provided quotes. From the left, the first vertical axis is a count number for the considered 1000 efficient supplier portfolios. The remaining six vertical axes range from 0 to 1 and the line of a respective case intersects the axis at the value of the portfolio share of the respective supplier in the efficient portfolio represented by this line. The red line indicates the supplier portfolio that has actually been selected, that is, the actual sourcing decision $\hat{x}$. In this $\hat{x}$, Supplier 1 has a share of about 0.7, Supplier 5 has a share of 0.3, and Suppliers 2, 3, 4, and 6 have a share of 0. For each efficient supplier portfolio, we measure for each potential supplier the distance between the respective component of $\hat{x}$ and the supplier share of the considered portfolios (in Fig. 5, some portfolios are highlighted with purple color for illustration. The distances between the red and the purple lines are used to calculate the overall Euclidean distance between vector $\hat{x}$ (red line) and a certain efficient supplier portfolio (purple line). As each efficient supplier portfolio originates from a certain combination of λ-values, we can derive λ_μ, λ_c, and λ_ϑ from the vector x that realizes the minimum Euclidean distance to $\hat{x}$.

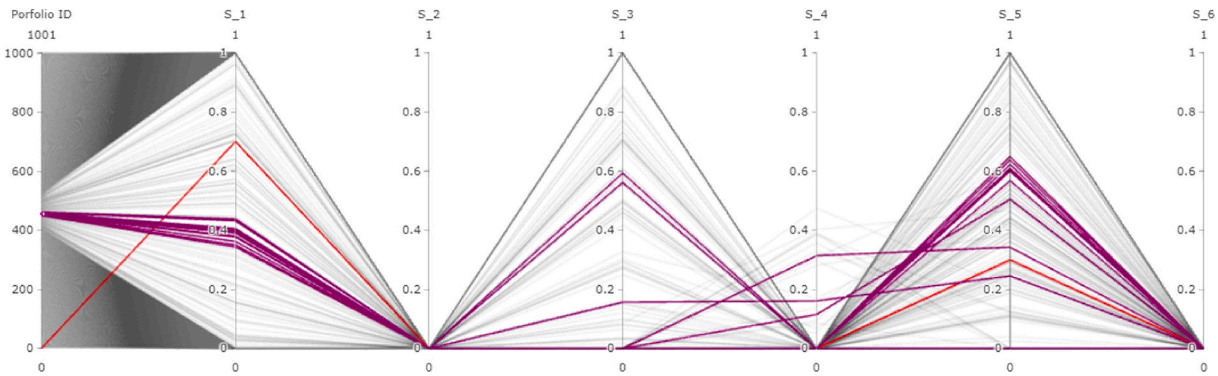

Fig. 5. Inverse optimization process: Steps 3 and 4.

In summary, we find that the dense representation of the efficient set allows us to achieve a good match between the actual sourcing decision $\hat{x}$ and the x-vector that is closest to $\hat{x}$: across all 145 purchasing cases, the minimum distance between $\hat{x}$ and the x-vector that is closest to $\hat{x}$ is 0.000, the median is 0.000, the mean is 0.127, and the maximum is 1.366. Fig. 6 presents a histogram of the distances between $\hat{x}$ and the x-vector that is closest to $\hat{x}$ over all purchasing cases of the final sample.

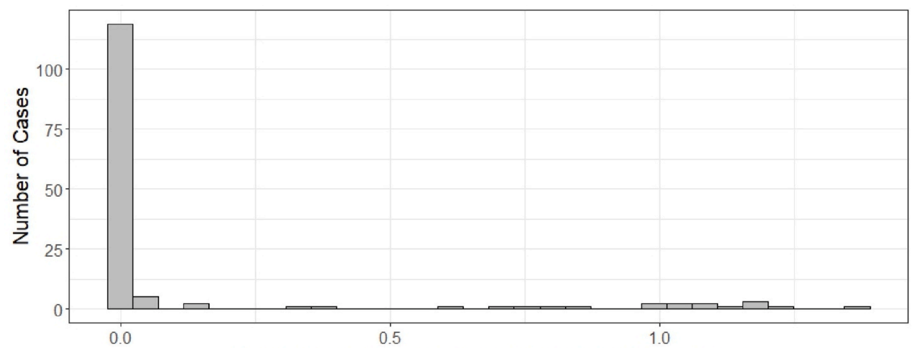

Fig. 6. Histogram for the distance (on the x-axis) between $\hat{x}$ and the x-vector that is closest to $\hat{x}$.

Appendix D

Table 4
Comparison of the λ-value using the pairwise Wilcoxon rank-sum test (Nb. = Number of cases, Avg = Average).

Aspect				λ_c (Cost)			λ_μ (Logistics Quality)			λ_ϑ (Sustainability)		
	Variable	Characteristic	a) Nb.*, b) Avg	Ch. 1	Ch. 2	Ch. 3	Ch. 1	Ch. 2	Ch. 3	Ch. 1	Ch. 2	Ch. 3
Decision Date	Calendar Year	2019	a) 73									
		2020	a) 72	0.425			0.617			0.978		
Decision-Maker	Gender	Female	a) 53									
		Male	a) 92	0.183			**0.069**			0.148		
	Age	<25 years	a) 16									
		25–35 years	a) 47	0.437			0.980			1.000		
		35–45 years	a) 58	0.437	0.437		0.980	0.980		1.000	1.000	
		>45 years	a) 7	0.263	0.437	0.437	0.980	0.980	0.980	1.000	1.000	1.000
	Seniority	Purch. Manager	a) 110									
		Senior Purch. Mngr.	a) 18	**0.021**			0.893			0.361		
		Head of Purch.	a) 3	0.865	0.892		0.893	0.893		0.545	0.545	
	Dist. Plant (km)	Quartile 1	b) 154									
		Quartile 2	b) 593	1.000			1.000			1.000		
		Quartile 3	b) 1050	**0.081**	**0.026**		1.000	1.000		0.822	0.665	
		Quartile 4	b) 6581	0.292	0.149	1.000	1.000	1.000	1.000	0.822	0.665	1.000
Purchasing Vol.	Budget (Euro)	Quartile 1	b) 622,595									
		Quartile 2	b) 2,897,450	1.000			1.000			1.000		
		Quartile 3	b) 13,721,504	1.000	1.000		1.000	1.000		1.000	1.000	
		Quartile 4	b) 95,166,639	1.000	0.994	0.896	1.000	1.000	1.000	1.000	1.000	1.000

The numbers in the last nine columns show the p-values of the pairwise Wilcoxon rank-sum tests between the characteristic (Ch. 1, Ch. 2, Ch. 3) indicated by the column and the characteristic indicated by the row. For instance, Ch. 1 in the decision date group means the calendar year 2019. The null hypothesis is that the

characteristic indicated by the column has a greater λ-value than the characteristic indicated by the row.
* If the total number of cases for a certain variable does not add up to 145, then this is due to missing information for some cases with respect to this variable.

Appendix E

Table 5
Differences in the implicit preference parameters (Nb. = Number of cases, Avg = Average).

Aspect	Variable	Characteristic	a) Nb.*, b) Avg	$\lambda_c < \lambda_\mu$	$\lambda_c < \lambda_\vartheta$	$\lambda_\vartheta < \lambda_\mu$	$\lambda_c > \lambda_\mu$	$\lambda_c > \lambda_\vartheta$	$\lambda_\vartheta > \lambda_\mu$
Decision Date	Calendar Year	2019	a) 73	0.510	0.510	0.510	1.000	1.000	1.000
		2020	a) 72	0.125	**0.007**	0.903	1.000	1.000	0.292
Decision-Maker	Gender	Female	a) 53	0.220	0.220	0.530	1.000	1.000	1.000
		Male	a) 92	0.261	**0.081**	0.766	1.000	1.000	0.704
	Age	<25 years	a) 16	0.984	0.984	0.718	1.000	1.000	1.000
		25–35 years	a) 47	0.869	0.869	0.869	1.000	1.000	1.000
		35–45 years	a) 58	0.280	**0.066**	0.809	1.000	1.000	0.579
		>45 years	a) 7	0.477	0.394	0.724	1.000	1.000	0.983
	Seniority	Purch. Manager	a) 110	0.377	0.196	0.694	1.000	1.000	0.921
		Senior Purch. Mngr.	a) 18	**0.072**	**0.094**	0.391	1.000	1.000	1.000
		Head of Purch.	a) 3	1.000	1.000	1.000	1.000	1.000	1.000
	Dist. Plant (km)	Quartile 1	b) 154	1.000	0.941	1.000	0.619	0.691	0.426
		Quartile 2	b) 593	1.000	0.679	1.000	0.804	0.804	0.394
		Quartile 3	b) 1050	**0.015**	**0.031**	0.258	1.000	1.000	1.000
		Quartile 4	b) 6581	0.164	0.164	0.386	1.000	1.000	1.000
Purchasing Vol.	Budget (Euro)	Quartile 1	b) 622,595	0.158	**0.041**	0.752	1.000	1.000	0.757
		Quartile 2	b) 2,897,450	1.000	1.000	1.000	1.000	1.000	1.000
		Quartile 3	b) 13,721,504	1.000	1.000	1.000	0.682	0.682	0.682
		Quartile 4	b) 95,166,639	**0.036**	**0.020**	0.567	1.000	1.000	1.000
Overall			a) 145	**0.085**	**0.021**	0.717	1.000	1.000	0.851

* If the total number of cases for a certain variable does not add up to 145, then this is due to missing information for some purchasing cases with respect to this variable.

Appendix F

Introduction to the multi-criteria supplier selection model

The applied multi-criteria decision-making approach solves the following optimization model with four different objective functions

$$\min \sigma_P^2 = x^T \sum x \tag{9}$$

$$\min c_P = c^T x \tag{10}$$

$$\max \mu_P = \mu^T x \tag{11}$$

$$\max \vartheta_P = \vartheta^T x \tag{12}$$

$$\text{s.t. } x \in S \tag{13}$$

where σ_P^2 measures the supply risk of supplier portfolio P, c_P are the average per-unit purchasing costs of the portfolio, μ_P is the average logistics quality, and ϑ_P is the average supplier sustainability of the portfolio. Model (9)–(13) is presented in multi-criteria format. The first two objective functions are to be minimized, while the latter two are to be maximized over the feasible region S, that is, the possible combinations of different possible suppliers. In multi-criteria decision-making, the feasible region S is referred to the decision space and contains all possible portfolio vectors $x \in S \subset \mathbb{R}^n$ with $n \in \mathbb{N}$ is the number of suppliers submitting a bid for the purchasing case. The criterion space of Model (9)–(13) with four objectives is

$$Z = \left\{ z \in \mathbb{R}^4 \;\middle|\; z_1 = \sigma_P^2, z_2 = c_P, z_3 = \mu_P, z_4 = \vartheta_P, x \in S \right\}. \tag{14}$$

Since z_1, z_2 are to be minimized and z_3, z_4 are to be maximized, a $\bar{z} \in Z$ is nondominated in Model (9)–(13) if and only if there exists no $z \in Z$ such that $z_1 \le \bar{z}_1$, $z_2 \le \bar{z}_2$, $z_3 \ge \bar{z}_3$, $z_4 \ge \bar{z}_4$ with $z \ne \bar{z}$.

Sensitivity analysis

A major benefit of the proposed approach is that the user gains an overview of the decision-making problem at hand as well as deeper insights into it. This allows her to make a more informed decision by considering and balancing multiple aspects in the purchase order allocation problem. In the following, we will provide a comprehensive summary of the sensitivities of traditional portfolio objectives for changes in portfolio sustainability. These sensitivities indicate the additional 'costs' incurred in terms of higher purchasing costs, lower logistics quality, and higher supply risk when increasing the sustainability of the supplier portfolio.

Table 6 shows the sensitivities for three different portfolios (the minimum purchasing costs portfolio, the maximum logistics quality portfolio, and the minimum supply risk portfolio) and five panels, where each panel represents a certain level of portfolio sustainability. For establishing these five panels, we determine, for each purchasing case separately, the difference between the maximum sustainability achievable in this purchasing case and the sustainability of the respective actual supplier portfolio (i.e., the reference value for the portfolio sustainability is the sustainability of the actual portfolio decision). We refer to this difference as 'sustainability gap' for each purchasing case k. Panel 1 shows the average relative change in purchasing costs, logistics quality, and sustainability over the 145 purchasing cases for the minimum purchasing costs portfolio, the maximum logistics quality portfolio, and the minimum supply risk portfolio compared to the actual sourcing decision when there are no further sustainability requirements – which reflects the initial situation. In the cases of Panels 2 through 5, we show the same figures but with increased sustainability requirements, which means that only those portfolios can be selected that cover a certain percentage of the sustainability gap, namely 10%, 20%, 50%, and 100%. Note that 100% sustainability gap coverage (Panel 5) forces the decision-makers to choose those supplier portfolios that maximize the overall portfolio sustainability in each purchasing case. This results in only one portfolio, the maximum sustainability portfolio, and therefore we report only one portfolio in this panel.

The numbers in Table 6 are average relative changes in the portfolio characteristics (purchasing costs, logistics quality, and supply risk) when moving from the actual portfolio decision to a portfolio with a better sustainability. For instance, the rows 4–6 of Panel 1 (Column 'All') read as follows: Compared with the actual portfolio decision, the maximum logistics quality portfolio (*Max. Log. Quality*) with the same portfolio sustainability level as the actual portfolio decision has on average 8% higher purchasing costs, 4% better logistics quality, and 28% higher supply risk. The respective three rows in Panel 3 (Column 'All') show the average relative changes in each portfolio characteristic for the portfolio with the highest logistics quality among all portfolios covering additional 20% of the sustainability gap. These portfolios are on average 10% more expensive than the actual portfolio, have a 3% higher logistics quality than the actual portfolios, and observe a 30% higher risk.

A comparison of Panel 1 and Panel 3 shows that covering additional 20% of the sustainability gap imposes only marginal deterioration of the portfolio characteristics (purchasing costs, logistics quality, and supply risk) for the three considered portfolios. These results show the main benefit of the application of the multi-criteria decision-making framework with sustainability as an additional objective. Applying this framework elicits portfolios that increase the portfolio sustainability substantially without serious costs on the traditional three objectives. The results for the portfolios that reduce the sustainability gap by 50% show that even this group, although its relative changes are consistently worse than those of the no-increase in sustainability portfolios, performs acceptably in the traditional characteristics compared to a substantial improvement in sustainability. Panel 5 shows the averages of the maximum sustainability portfolio. Achieving maximum possible sustainability comes with an 21% increase in purchasing costs, a 2% reduction in logistics quality, and a 251% increase in supply risk.

These overall results might be biased by the size of the possible improvement in sustainability. For instance, low improvement potential might exist for decision situations where all possible suppliers have similar sustainability or the actually selected suppliers already show very high sustainability. Therefore, we try to capture this bias in two ways: First, we group the average relative changes by the size of the sustainability gap and present these numbers for different ranges of the sustainability gap in Columns 5–8 in Table 6. The sustainability gaps range between 0.00 and 0.73. In about one third of the sourcing decisions (51 cases), the sustainability gap is 0, that is, sustainability cannot be improved compared to the actual sourcing decision. For the further analyses, we subdivided the other 94 sourcing cases into tertiles as a function of the sustainability gap. The lower and the upper bounds of these tertiles are shown in Table 6 in the rows titled 'LB' and 'UB.' Second, we group the average relative changes by the sustainability of the actual portfolio and present these numbers separated by quartiles of the actual sustainability in Columns 10–13 in Table 6.

The results indicate that the average relative changes do not show a clear structure based on the possible biases. Thus, we apply line-wise correlation tests between the relative changes and the sustainability gap (actual sustainability). The correlation coefficients of these tests are presented in Columns 9 and 14, respectively, with the corresponding p-values being represented by asterisks. For supply risk, we find no indication that the relative changes are influenced by the level of the sustainability gap or by the actual sustainability. However, purchasing costs and logistics quality deteriorate strongly with higher sustainability gaps and lower levels of sustainability.

Table 6
Sensitivity analysis (LB/UB: lower/upper bound, Obs: Observations, CC: Correlation Coefficient).

Portf.	Objective		All	Sustainability gap					Act. sustainability				
		LB	All	0.00	0.00	0.08	0.22	CC	0.06	0.56	0.75	0.85	CC
		UB		0.00	0.08	0.22	0.73		0.56	0.75	0.85	1.00	
		Obs	145	51	31	31	32		36	36	36	37	
Panel 1: No increase in the sustainability													
Min. Purch. Cost	Purch. Cost		−5	0	−7	−8	−8	−0.1***	−6	−7	−5	−1	0.0***
	Log. Qual.		−1	0	0	0	−4	−0.2***	−2	−2	0	0	0.1***
	Suppl. Risk		133	4	55	525	36	0.0***	36	472	24	5	0.0***
Max. Log. Quality	Purch. Cost		8	0	−3	17	23	0.3***	20	11	1	2	−0.4***
	Log. Qual.		4	1	3	8	5	0.3***	5	5	4	1	−0.2***
	Suppl. Risk		28	0	40	46	42	0.1***	27	46	36	3	0.0***
Min. Supply Risk	Purch. Cost		15	1	16	24	27	0.2***	18	25	16	2	−0.2***
	Log. Qual.		0	0	−1	2	−1	0.1***	0	0	0	0	−0.1***
	Suppl. Risk		−26	−8	−16	−38	−54	−0.6***	−50	−28	−18	−10	0.5***
Panel 2: 10% sustainability gap reduction													
Min. Purch. Cost	Purch. Cost		−3	0	−4	−5	−5	0.0***	−3	−5	−3	0	0.0***
	Log. Qual.		−1	0	0	0	−4	−0.2***	−2	−2	0	0	0.1***
	Suppl. Risk		130	1	53	518	32	0.0***	26	472	22	1	0.0***
Max. Log. Quality	Purch. Cost		9	0	0	17	23	0.3***	20	11	3	2	−0.4***
	Log. Qual.		3	0	2	7	5	0.3***	4	5	3	1	−0.2***
	Suppl. Risk		26	1	39	44	36	0.1***	22	46	35	2	0.0***
Min. Supply Risk	Purch. Cost		15	1	17	23	27	0.2***	17	23	16	2	−0.2***
	Log. Qual.		0	0	−2	2	−1	0.1***	0	0	0	0	−0.1***

(*continued on next page*)

Table 6 (*continued*)

Portf.	Objective		All	Sustainability gap					Act. sustainability				
		LB	All	0.00	0.00	0.08	0.22	CC	0.06	0.56	0.75	0.85	CC
		UB		0.00	0.08	0.22	0.73		0.56	0.75	0.85	1.00	
		Obs	145	51	31	31	32		36	36	36	37	
	Suppl. Risk		−23	−5	−11	−33	−52	−0.6***	−46	−22	−14	−8	0.4***
Panel 3: 20% sustainability gap reduction													
Min. Purch. Cost	Purch. Cost		−1	0	−1	−2	−2	0.0***	−1	−3	0	0	−0.1***
	Log. Qual.		−1	0	−1	0	−5	−0.2***	−2	−3	0	0	0.1***
	Suppl. Risk		132	1	54	518	41	0.0***	28	479	24	0	0.0***
Max. Log. Quality	Purch. Cost		10	0	3	18	24	0.3***	21	12	5	2	−0.3***
	Log. Qual.		3	0	1	7	4	0.3***	3	4	3	0	−0.2***
	Suppl. Risk		30	1	42	57	38	0.1***	24	59	36	2	0.0***
Min. Supply Risk	Purch. Cost		15	1	17	23	27	0.2***	17	24	16	2	−0.2***
	Log. Qual.		0	0	−2	2	−1	0.1***	0	0	0	0	−0.1***
	Suppl. Risk		−17	−4	−3	−17	−49	−0.4***	−43	−8	−8	−7	0.3***
Panel 4: 50% sustainability gap reduction													
Min. Purch. Cost	Purch. Cost		5	0	9	7	8	0.1***	7	4	8	2	−0.2***
	Log. Qual.		−2	0	−2	0	−6	−0.1***	−3	−3	0	0	0.1***
	Suppl. Risk		163	−1	85	530	142	0.1***	89	518	47	2	−0.1***
Max. Log. Quality	Purch. Cost		13	0	11	20	26	0.2***	22	14	12	3	−0.3***
	Log. Qual.		1	0	0	5	1	0.2***	1	2	2	0	−0.1***
	Suppl. Risk		71	−1	79	168	83	0.1***	69	150	61	4	0.0***
Min. Supply Risk	Purch. Cost		16	1	18	25	28	0.2***	19	26	17	2	−0.2***
	Log. Qual.		−1	0	−2	1	−3	0.0***	−2	−1	0	0	0.0***
	Suppl. Risk		27	−3	45	112	−25	0.0***	−15	100	26	−2	0.0***
Panel 5: Maximum (100% sustainability gap reduction)													
Min. Purch. Cost	Purch. Cost		21	0	25	25	46	0.2***	28	29	24	4	−0.2***
	Log. Qual.		−2	0	−3	1	−5	−0.1***	−3	−2	0	−1	0.0***
	Suppl. Risk		251	−1	230	657	280	0.1***	283	540	168	19	−0.1***

Columns 5–8 and 10–13 indicate the average relative changes (in %) in the min. purchasing costs, max. logistics quality, and min. supply risk achievable over all 145 purchasing cases compared to the actual sourcing decisions, when setting the sustainability increase to the level indicated in the respective panel. Columns 9 and 14 contain the results of a correlation test (i.e., the coefficient and its significance level) for each row between the relative changes and the sustainability gap/actual sustainability.
*p-value < 0.1.
**p-value < 0.05.
***p-value < 0.01.

Data availability

The data that has been used is confidential.

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