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Reliable estimation of suppliers' total cost of ownership: An imprecise data envelopment analysis model with common weights☆

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A B S T R A C T

Total cost of ownership (TCO) is a management accounting technique that evaluates the total cost of a business partnership using a time-consuming activity-based costing procedure. Studies have suggested that TCO-based data envelopment analysis (DEA) can effectively estimate the results of TCO with substantially less effort and time; however, its adoption in practice is limited due to certain shortcomings. First, managers struggle to understand and accept the uncommon weighting schemes of existing TCO-based DEA models because traditional TCO analyses require a common set of weights. Second, both the traditional TCO approach and TCO-based DEA models are designed to handle precise data, whereas TCO analyses often involve imprecise data from conflicting data sources and estimations.

To address the managerial and technical issues of handling weighting schemes and imprecise data, this paper proposes a novel TCO-based model: common set of weights imprecise DEA (CSW-IDEA). We validate the proposed methodology using real-life datasets from 175 suppliers that serve five key components to two multinational mechanical manufacturers. For both precise data and imprecise data, the proposed CSW-IDEA reliably approximates traditional TCO calculations significantly better than existing TCO-based DEA. The cost savings that can be theoretically generated by applying the CSW-IDEA approach are similar to the cost savings estimated by the traditional TCO approach.

1. Introduction

Modern approaches to supply management suggest that decision-making surpasses simple price-based considerations when evaluating a supplier's competitiveness [1,2]. Especially in the case of complex purchases, a lower initial price may conceal not only lower quality but also higher long-run sourcing costs [3]. To make sourcing decisions, the total cost of sourcing (e.g., procurement price, transportation costs, lead time, customs duties, packaging, inbound logistics, quality management, and accounting processes) should be considered [4,5].

Evaluation of a supplier's total cost of ownership (TCO) is a management accounting analysis that is aimed at obtaining the total cost of leading relationships with suppliers. Traditionally based on an activity-based costing approach, TCO considers both the direct cost and indirect cost of the operations that are needed for business relationships with suppliers [6]. Therefore, TCO is a powerful tool for comprehensively evaluating supplier performance and guiding sourcing decisions [7–9]. TCO is not commonly applied because it requires a significant amount of time and effort to attribute costs to different activities, which is an essential initial step of the activity-based costing procedure [10].

To increase the accessibility of TCO, researchers have proposed the use of data envelopment analysis (DEA) in TCO calculations. Mohammady Garfamy [11] identifies the cost drivers of a supply chain using the traditional TCO approach. The identified cost drivers are subsequently employed as DEA's factors. Ramanathan [12] argues that the power of the TCO technique when considering quantitative (objective) information and the power of the analytical hierarchy process (AHP) technique when considering qualitative (subjective) information can be combined in a DEA model to evaluate suppliers' performance. Visani et al. [13,14] explore the applicability of DEA as a proxy of TCO to reduce the time and effort required for TCO calculations. They employ the cost drivers of TCO as inputs of a DEA model and the amount purchased as the only output to obtain a "TCO-based DEA". Applied to a real-life case, the results of TCO-based DEA significantly correlate to the results of TCO for both the efficiency indexes and the rankings of suppliers. TCO-based DEA requires 90% less effort and time because it

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avoids extended interviews with employees to calculate the costs of activities.

Contrary to the traditional TCO approach, which assigns a common set of weights (CSW) to the cost drivers to evaluate all suppliers, existing TCO-based DEA models allocate supplier-specific uncommon sets of weights (USW) to the inputs and outputs of each supplier. Consequently, decision makers may struggle to understand and accept the results of a TCO approach that uses USW [15]. Moreover, the use of USW can cause TCO-based DEA to overestimate the performance of a supplier by allocating high weights to the factors for which a supplier has a satisfactory rating and disregarding the factors for which the supplier is not successful [13].

Scholars have proposed several methods to control the weighting system in DEA [16–20]. According to Saati et al. [15], CSW is a special case of weight restrictions when inter-supplier weight flexibility is not integrated in a DEA model; however, weights are endogenously determined from the observed data. CSW identifies only one weight for each input/output factor and guarantees the absence of weighting flexibility across suppliers. Studies of DEA discuss several developments for determining CSW [21–25] which can be applied to make the weighting scheme of a TCO-based DEA comparable to that of a traditional TCO.

Another shortcoming of the traditional TCO approach and existing TCO-based DEA is that they are unable to handle the possible imprecision of the cost drivers' data. Imprecise data may arise for multiple reasons in a TCO analysis, e.g., from the use of different and inconsistent data sources or the reliance on experts' subjective evaluations of costs that are imposed performing different activities. The issue of imprecise data in the TCO domain has remained unaddressed. In practice, once imprecision in data occurs, decision makers subjectively interpret the imprecise data to use them in the TCO calculations. An example of such an interpretation is the case where the value of a cost driver cannot be perfectly determined, but its range of variation can be assessed. For handling this type of imprecise data in TCO calculations, a common method is to use the lower bound, the upper bound or the average of the range. Therefore, decision makers may omit information, which causes inaccurate analyses. Although disregarding imprecise data in a TCO study is questionable, handling these data may be costly and time-consuming.

Existing studies describe several DEA models, which are referred to as imprecise DEA (IDEA) [26], to handle imprecise data, such as models proposed by Cooper et al. [27,28], Wang et al. [29], and Toloo et al. [30]. The use of the IDEA concept can enhance the TCO-based DEA model to address the issue of imprecise data. IDEA models can alleviate subjective and labor-intensive data gathering and processing required by the TCO approach. However, most IDEA models have one or several shortcomings, such as e.g. modeling complexity and computational burden [31,32], limitation in considering several imprecise factors for a problem [29], and generation of interval efficiency scores (i.e., lower bounds and upper bounds, which may be ambiguous in decision-making) due to the lack of exact value of imprecise data [32].

This paper addresses the managerial and technical issues of the TCO-based DEA approach in allocating weights and in handling imprecise data. A novel IDEA model that overcomes the shortcomings of existing IDEA formulations is presented. Because this model employs an uncommon set of weights to evaluate suppliers, we refer to this model as "Uncommon Sets of Weights Imprecise DEA" (USW-IDEA). We note that USW-IDEA is equivalent to existing TCO-based DEA model of Visani et al. [13] if the data are precise. This paper extends USW-IDEA to apply a common set of weights (CSW) to evaluate suppliers' performance. We refer to this model as "Common Set of Weights Imprecise DEA" (CSW-IDEA). This paper is the first study that develops a TCO-based DEA model that handles imprecise data and uses CSW to estimate TCO results.

To examine how effectively CSW-IDEA approximates TCO, we employ real-life datasets of 175 companies who supply five strategic components to two large multinational mechanical manufacturers. From five available datasets that contain supply specifications, three datasets are imprecise and two datasets are precise. First, the computational results indicate that supplier rankings based on both CSW-IDEA and USW-IDEA are significantly positively correlated to the supplier rankings of traditional supplier TCO calculations in the presence of both precise and imprecise data. Second, in approximating the TCO results, CSW-IDEA performs significantly better than USW-IDEA for both precise data and imprecise data. Third, an analysis of the suppliers' performance indicates that management cost savings estimated based on the results of CSW-IDEA are similar to the management cost savings of the traditional TCO approach. As such, this paper proposes an easily accessible (reliable and parsimonious) proxy for the TCO approach and extends the applicability of TCO to the realm of imprecise data.

We organized the remainder of this paper as follows: Section 2 reviews the research background, and Section 3 presents the proposed USW-IDEA and CSW-IDEA models. Section 4 describes the research methodology, and Section 5 reports our empirical findings. Sections 6 and 7 present the discussion and concluding remarks, respectively.

2. Research background

2.1. TCO-based DEA

The assessment of a supply relationship should consider both the purchasing price and the management costs to quantify the TCO of each supplier [33]. Applying TCO to evaluate suppliers' performance requires a significant amount of time and effort because a complex activity-based costing approach is needed to analyze all processes linked to the acquisition, ownership, and post-ownership of the purchased goods or services and their respective costs [6]. These costs are allocated to suppliers by several cost drivers that represent the effort required by each supplier to conduct each activity (e.g., the number of quality issues for the activities related to the quality management process or the number of order lines for the order management process).

In suppliers' TCO analysis, the Supplier Performance Index (SPI) expressed by Eq. (1) represents the relative business partnership cost of a supplier [34]. In Eq. (1), J is the set of all suppliers, I is the set of cost drivers, v_i is the cost (weight) associated with cost driver $i \in I$, x_{ij} is cost driver $i \in I$ of supplier $j \in J$, and y_j is the total amount purchased from supplier $j \in J$. SPI uses CSW to evaluate the suppliers because the cost driver weight vector (i.e., $v_i, \ \forall i \in I$) is unique across all suppliers. That is, v_i represents the cost of managing one unit of cost driver i (e.g., a quality issue or an order line) regardless of which supplier j is under evaluation [35].

$$SPI_j^{TCO} = \frac{\sum_{i \in I} v_i x_{ij}}{y_j}, \qquad \forall j \in J \tag{1}$$

Finding the weights of the cost drivers is the most challenging and time-consuming part of the suppliers' TCO evaluation, which has limited applicability of TCO. To enhance the usability of this approach, Visani et al. [13,14] suggest the use of DEA for the TCO calculations. DEA does not require prior weights of inputs and outputs because it endogenously determines the weights of the factors [36]. To propose a TCO-based DEA method, Visani et al. [13] apply the cost drivers of the TCO approach as the inputs and the total value of the purchased products/services as the single output of the DEA model. They obtain the weights of the TCO cost drivers by the well-known CCR model (see model 2 in the next section) that is proposed by Charnes et al. [37]. The decision variables of this model are, in fact, the set of weights for the cost drivers and the purchased amount related to the supplier under evaluation.

According to Visani et al. [13], TCO-based DEA adequately approximates the outcomes of TCO for both the efficiency indexes and the rankings of suppliers and requires 90% less time and effort to perform the TCO analysis by avoiding extended interviews with employees to obtain the weight of each cost driver.

Despite the practical potential of TCO-based DEA, its adoption remains limited due to several shortcomings. Since the CCR model is separately run for each supplier and generates a different set of weights in each run, it has an uncommon weighting scheme. The use of uncommon sets of weights (USW) in TCO-based DEA may prevent decision makers from accepting the results because traditional TCO employs a CSW. Moreover, the use of USW for a supplier evaluation may cause a TCO-based DEA to overestimate the performance of suppliers. This approach labels suppliers as "efficient" if they perform significantly strong (weak) on some (most) of the inputs by assigning very high (low) weights to the inputs [38].

Second, TCO-based DEA, similar to the basic DEA models, cannot handle imprecise data because it assumes that all input and output factors are accurately known. In the real-life applications, however, data may be missing, judgmental, forecasted or ordinal [30,39,40]. Supplier evaluation can be affected by unreliable, imprecise or vague data, because some supplier's characteristics may not be quantifiable in a precise and unambiguous manner [41].

The issue of imprecise data in the TCO domain has not received sufficient attention from scholars, while Ellram [42] admits the presence of imprecise data in a TCO analysis, which is triggered in different ways such as inaccurate interviews with employees, misinterpretation of the linguistic data, and inconsistent sources of data. The lack of systematic approaches to handle imprecise data for traditional TCO calculations urges decision makers to make subjective interpretations of imprecise data, which affects the effectiveness of the TCO analyses and any consequent decision accuracy.

2.2. Imprecise DEA models

To handle imprecise data in DEA, several imprecise DEA (IDEA) models have been proposed. Initial research on this topic was performed by Cooper et al. [27,28]. They developed an IDEA model to incorporate bounded data, ordinal data and ratio bounded data in the calculations. They transformed a nonlinear programming (NLP) problem into a linear programming (LP) problem via a series of scale transformations and variable alternations. Their IDEA model is extended by Lee et al. [43]. Despite allowing imprecise data, both IDEA models are very complicated due to high data/scale transformations and variable alternations, which cause a rapid increase in the computational burden. To decrease the computational burden of IDEA in applications, Zhu [31] provides a procedure to eliminate the scale transformation. Moreover, Zhu [26,31,32] propose the use of standard DEA method to deal with imprecise data by converting bounded and ordinal data into exact data. By doing so, decision makers can perform efficiency sensitivity analysis and obtain all possible multiple optimal solutions in the presence of imprecise data. The efficiency evaluations based on the approaches in [26,31,32] are optimistic because the best possible inputs/outputs of the supplier under examination is compared with the worst possible inputs/outputs of other suppliers. Despotis and Smirlis [44] and Entani et al. [45] propose different IDEA models to obtain interval efficiency scores. However, their model uses non-unique efficiency frontiers to calculate the efficiency intervals [29,30]. Entani et al.'s [45] model regards only one imprecise input factor and one imprecise output factor, with other precise factors, for the lower bound efficiency calculation. Motivated by a unique efficiency frontier and multiple imprecise input/output factors, Wang et al. [29] and Toloo et al. [30] extended a new pair of interval DEA models that characterize efficiency by an interval bound: the best lower bound and the best upper bound efficiency. Hatami-Marbini et al. [25] and Puri et al. [24] also combine the concept of interval efficiency and CSW for the situations where suppliers are structurally composed of several components and their resources need to be (re)allocated. These proposed interval efficiency approaches are innovative because they do not require extra variable alternations for considering imprecise data. The output of their model is an efficiency interval for each supplier, and in some cases, choosing the lower bound or the upper bound for decision-making can be confusing, e.g., when one supplier outperforms all suppliers according to its upper bound efficiency and underperforms other suppliers according to its lower bound efficiency.

Despite the shortcomings of the IDEA models, scholars have applied them to the supplier evaluation problem to address imprecise data, such as ordinal data, e.g., satisfaction, supplier reputation, and hygiene level of logistics facility, and bounded data, e.g., price, on-time shipments, error-free bills received from suppliers, and capacity of cold storage [46–49].

Robust DEA (RDEA) is another technique that enables DEA to handle imprecise data. RDEA has recently received increased attention from researchers (see, e.g., [50–52]). It is an optimization technique to achieve reliability in the DEA outcomes by considering data perturbation [53]. RDEA indeed immunizes efficiency scores against uncertainties in the data when the probability distribution is unknown or difficult to define [54,55]. Literature indicates that RDEA has mainly been applied to two cases. In the first case, data of the input and output factors contain some degrees of uncertainty and decision maker has no or little intuition on the lower and upper bounds of the uncertainty level [56,57]. In the second case, data falls between a lower bound and an upper bound but the decision maker has (no) intuition on the uncertainty level within these bounds [58,59]. Intuitively, the first case is more general than the second case. For both cases, RDEA explores the change of efficiency scores upon a change in the uncertainty level and, therefore, a range of efficiency scores is produced [60].

There are mainly two difficulties in implementing the RDEA approach. First, decision makers usually have insufficient insight about the uncertainty level in the data and, therefore, complex simulation techniques are often required to find the appropriate uncertainty level [59]. Second, similar to the interval efficiency approach in [29,30], RDEA produces a range of efficiency scores according to different uncertainty level for individual suppliers and, therefore, drawing a decision on their efficiency may be challenging.

This paper presents a novel IDEA model for handling imprecise data in suppliers' TCO evaluation processes. The objective is to overcome the shortcomings of existing IDEA models by avoiding formulation complexity, considering multiple imprecise input/output factors, and offering a single unambiguous efficiency score. This paper also equips the novel IDEA model with a common weighting system, which ensures that its weighting scheme is very similar to the weighing mechanism of a conventional TCO method and ensures high usability for supply managers.

3. Proposed model

To evaluate the relative efficiency of a set of decision making units (DMUs), Charnes et al. [37] propose the well-known Charnes, Cooper, and Rhodes (CCR) model (model 2). In model (2), J denotes the set of comparable suppliers (DMUs), which use the set I of inputs to generate the set R of outputs, and x_{ij} and y_{rj} represent the quantity of input $i \in I$ consumed by supplier $j \in J$ and the quantity of output $r \in R$ produced by the same supplier, respectively.

The decision variables in this model are v_i and u_r, which represent the weights of input $i \in I$ and output $r \in R$, respectively. Subscript o indicates the input and output quantities of the supplier under evaluation. If E_{jo} (i.e., efficiency of the supplier under evaluation), which is calculated by model (2), is (not) one, the supplier is considered to be (in)efficient. This model is an input-oriented formulation that determines the reduction in the inputs of a supplier (without changing outputs) to ensure the efficiency of the supplier.

$$
\begin{aligned}
& max\ E_{jo} = \sum_{r\in R} u_r y_{rjo}, \\
& s.t. \\
& \sum_{i\in I} v_i x_{ij0} = 1, \\
& \sum_{r\in R} u_r y_{rj} - \sum_{i\in I} v_i x_{ij} \le 0,\ \forall j \in J, \\
& u_r \ge 0\, \forall r \in R,\ v_i \ge 0\, \forall i \in I.
\end{aligned} \tag{2}
$$

An underlying assumption of model (2) is that data for inputs (x_{ij}) and outputs (y_{rj}) are accurately known. However, precisely obtaining all data is impossible in many applications because finding exact values for these data would be costly. Consistent with studies on IDEA, even if the quantities of inputs and outputs cannot be accurately measured, they are often known to lie within lower and upper bounds. We represent these lower and upper bounds by the interval $[\underline{x}_{ij},\ \bar{x}_{ij}]$ for the inputs and the interval $[\underline{y}_{rj},\ \bar{y}_{rj}]$ for the outputs, where $\underline{x}_{ij}$ and $\underline{y}_{rj}$ are both positive and $\underline{x}_{ij} \le x_{ij} \le \bar{x}_{ij}$ and $\underline{y}_{rj} \le y_{rj} \le\ \bar{y}_{rj}$. Compared with IDEA approaches proposed by Cooper et al. [28] and Lee et al. [43], which require scale transformation not only for the interval inputs $[\underline{x}_{ij},\ \bar{x}_{ij}]$ and interval outputs $[\underline{y}_{rj},\ \bar{y}_{rj}]$ but also for exact data (i.e., where $\underline{x}_{ij} =\ \bar{x}_{ij}$ and $\underline{y}_{rj} =\ \bar{y}_{rj}$), our proposed IDEA does not need data rescaling and directly employs both interval data and exact data in the calculations. Different from the approaches proposed by Zhu [26,31,32], which evaluate suppliers from an optimistic perspective by comparing the best inputs and outputs of a given supplier (i.e., $\underline{x}_{ij}$and $\bar{y}_{rj}$) with the worst inputs and outputs of other suppliers (i.e., $\bar{x}_{ij}$ and $\underline{y}_{rj}$), our approach combines both optimistic and pessimistic scenarios to evaluate suppliers. The IDEA of Entani et al. [45] regards only one imprecise input in set I and one imprecise output in set R for a problem, but our approach can handle entirely imprecise I and R sets. The proposed model of this paper, which differs from the models by Wang et al. [29] and Toloo et al. [30], considers the lower bounds (i.e., $\underline{x}_{ij}$ and $\underline{y}_{rj}$), the upper bounds ($\bar{x}_{ij}$, $\bar{y}_{rj}$) and all intermediate values between these extreme points when dealing with imprecise data. In this manner, all available information is utilized for efficiency evaluations.

The IDEA model of Despotis and Smirlis [44] is the most similar to ours. However, their model does not use a discretization method nor is it fully linearized to deal with imprecise data. Moreover, our approach compares a supplier with all other suppliers on the reference set under the same conditions. In particular, our approach uses the same level of each imprecise factor for all suppliers. On the contrary, the approach proposed by Despotis and Smirlis [44] may evaluate a supplier by considering the lower (upper) bound of an imprecise input (output) while considering the upper (lower) bound of the same input (output) for the reference suppliers. Compared to RDEA, the proposed approach does not require information on the uncertainty level when working with interval data, because it determines the best efficiency score for the suppliers. The proposed model also generates a single efficiency score which facilitates the decision-making process.

To assign a specific value to x_{ij} in the range between the lower bounds and the upper bounds, we apply Eq. (3), in which λ_i is a variable that is bounded between zero and one. In this equation, $x_{ij} = \underline{x}_{ij}$ if $\lambda_i = 0$ and $x_{ij} = \bar{x}_{ij}$ if $\lambda_i = 1$. Other values of λ_i determine the similarity between the quantity of x_{ij} and the lower bound or the upper bound. Similarly, to assign a specific value to y_{rj} in the range between the lower bound and the upper bound, we employ Eq. (4).

$$x_{ij} = \lambda_i \bar{x}_{ij} + (1-\lambda_i)\underline{x}_{ij}, \quad 0 \le \lambda_i \le 1\ , \quad \forall i \in I, \quad \forall\ j \in J \tag{3}$$

$$y_{rj} = \lambda_r \bar{y}_{rj} + (1-\lambda_r)\underline{y}_{rj}, \quad 0 \le \lambda_r \le 1, \quad \forall r \in R, \quad \forall j \in J \tag{4}$$

Replacing x_{ij} by $\lambda_i \bar{x}_{ij} + (1-\lambda_i)\underline{x}_{ij}$ and y_{rj} by $\lambda_r \bar{y}_{rj} + (1-\lambda_r)\underline{y}_{rj}$ in the objective function and constraints of model (2), we obtain model (5).

$$
\begin{aligned}
& max\ E_{jo} = \sum_{r\in R}\left(u_r\lambda_r\bar{y}_{rjo} - u_r\lambda_r\underline{y}_{rjo} + u_r\underline{y}_{rjo}\right), \\
& s.t. \\
& \sum_{i\in I}\left(v_i\lambda_i\bar{x}_{ijo} - v_i\lambda_i\underline{x}_{ijo} + v_i\underline{x}_{ijo}\right) = 1, \\
& \sum_{r\in R}\left(u_r\lambda_r\bar{y}_{rj} - u_r\lambda_r\underline{y}_{rj} + u_r\underline{y}_{rj}\right) - \sum_{i\in I}\left(v_i\lambda_i\bar{x}_{ij} - v_i\lambda_i\underline{x}_{ij} + v_i\underline{x}_{ij}\right) \le 0, \\
& \quad \forall j \in J, \\
& 0 \le \lambda_i \le 1\ , \quad \forall i \in I, \\
& 0 \le \lambda_r \le 1, \quad \forall r \in R, \\
& u_r \ge 0, \quad \forall r \in R; \qquad v_i \ge 0, \quad \forall i \in I.
\end{aligned} \tag{5}
$$

Model (5) is a nonlinear programing (NLP) problem, in which the maximum is well-defined because the feasible set for this model is bounded and defined by closed level sets of continuous functions, i.e., $u_r \le \frac{1}{\underline{y}_{rjo}}$ and $v_i \le \frac{1}{\underline{x}_{ijo}}$.

The NLP model (5) is computationally intractable because an efficient optimization method is not available. Therefore, it is reasonable to transform this NLP model into mixed integer programming (MIP) by the discretization method, which is a standard operational research technique to tackle the issue of continuous variables in the NLP problems. The discretized model will be tractable, and we can prove that the optimal objective value of the MIP model converges to the optimal objective value of the NLP model as the discretization level goes to infinity. Kotsiantis and Kanellopoulos [61] review several discretization methods, such as equidistant interval binning, chi-square based, entropy based, wrapper based, evolutionary based, and adaptive methods. In this paper, we apply the equidistant interval binning method and transform model (5) into an MIP program because it limits the formulation complexity and does not require an assumption about the distribution probability of the intervals $[\underline{x}_{ij},\ \bar{x}_{ij}]$ and $[\underline{y}_{rj},\ \bar{y}_{rj}]$.

Applying the Equidistant interval binning method, the intervals $[\underline{x}_{ij},\ \bar{x}_{ij}]$ and $[\underline{y}_{rj},\ \bar{y}_{rj}]$ are partitioned into K equal division points, where K is determined by the decision maker. We change the variables $p_i =\ v_i\lambda_i$ and set constraint (6) for each input i.

$$
\begin{cases}
\sum_{k=0}^{K}\gamma_{ki} = 1, \quad \gamma_{ki} \in \{0,\ 1\}, \quad k \in \mathbb{N}^0, \quad k = 0,\ldots,K, \quad \forall i \in I, \\
\frac{k}{K}v_i - (1-\gamma_{ki})M \le p_i \le \frac{k}{K}v_i + (1-\gamma_{ki})M, \quad k \in \mathbb{N}^0, \quad k = 0,\ldots,K, \quad \forall i \in I,
\end{cases} \tag{6}
$$

Similarly, we change the variables $p_r =\ u_r\lambda_r$ and set constraint (7) for each output r.

$$
\begin{cases}
\sum_{k=0}^{K}\gamma_{kr} = 1, \quad \gamma_{kr} \in \{0,\ 1\}, \quad k \in \mathbb{N}^0, \quad k = 0,\ldots,K, \quad \forall r \in R, \\
\frac{k}{K}u_r - (1-\gamma_{kr})M \le p_r \le \frac{k}{K}u_r + (1-\gamma_{kr})M, \quad k \in \mathbb{N}^0, \quad k = 0,\ldots,K, \quad \forall r \in R,
\end{cases} \tag{7}
$$

Therefore, we obtain MIP model (8), which we refer to as the "uncommon set of weight imprecise data envelopment analysis" (USW-IDEA) model.

$$
\begin{aligned}
&[\text{USW}-\text{IDEA}] \quad \max E_{jo} = \textstyle\sum_{r\in R} \left(p_r \bar{y}_{rjo} - p_r \underline{y}_{rjo} + u_r \underline{y}_{rjo} \right), \\
&s.t. \\
&\textstyle\sum_{i\in I} \left(p_i \bar{x}_{ijo} - p_i \underline{x}_{ijo} + v_i \underline{x}_{ijo} \right) = 1, \\
&\textstyle\sum_{r\in R} \left(p_r \bar{y}_{rj} - p_r \underline{y}_{rj} + u_r \underline{y}_{rj} \right) - \sum_{i\in I} \left(p_i \bar{x}_{ij} - p_i \underline{x}_{ij} + v_i \underline{x}_{ij} \right) \le 0, \quad \forall j \in J, \\
&\begin{cases} \sum_{k=0}^{K} \gamma_{ki} = 1, \quad \gamma_{ki} \in \{0,\ 1\}, \quad k \in \mathbb{N}^0, \quad k = 0, \dots, K, \quad \forall i \in I, \\ \frac{k}{K} v_i - (1-\gamma_{ki})M \le p_i \le \frac{k}{K} v_i + (1-\gamma_{ki})M, \quad k \in \mathbb{N}^0, \quad k = 0, \dots, K, \quad \forall i \in I, \end{cases} \\
&\begin{cases} \sum_{k=0}^{K} \gamma_{kr} = 1, \quad \gamma_{kr} \in \{0,\ 1\}, \quad k \in \mathbb{N}^0, \quad k = 0, \dots, K, \quad \forall r \in R, \\ \frac{k}{K} u_r - (1-\gamma_{kr})M \le p_r \le \frac{k}{K} u_r + (1-\gamma_{kr})M, \quad k \in \mathbb{N}^0, \quad k = 0, \dots, K, \quad \forall r \in R, \end{cases} \\
&u_r, p_r \ge 0, \quad \forall r \in R; \quad v_i, p_i \ge 0, \quad \forall i \in I.
\end{aligned} \tag{8}
$$

Model (8) is capable of determining the optimal (exact) levels of imprecise inputs and outputs and, accordingly, finds the exact and single efficiency score for supplier under evaluation. The optimal solution of model (8) converges to the optimal solution of model (5) as the discretization level (i.e., K) increases. Model (8) determines the specific value of x_{ij}, which falls within the range between the lower bound and upper bound based on the optimal value of A_{ki}. Since $k \in \mathbb{N}^0$ and $k = 0, \dots, K$, the specific value of x_{ij} is equal to the lower bound (i.e., $\underline{x}_{ij}$) if $\gamma_{0i} = 1$. The specific value of x_{ij} is equal to the upper bound (i.e., $\bar{x}_{ij}$) if $\gamma_{Ki} = 1$. The similarity between the quantity of x_{ij} and the lower bound or the upper bound is determined by $\gamma_{ki} = 1$ when $0 < k < K$. Likewise, the specific value of y_{rj}, which ranges from the lower bound to the upper bound, depends on the optimal value of γ_{kr} in model (8).

Note that a decision maker should determine the value for K (i.e., the number of equal division points). Different values of K may affect the optimum values of x_{ij} and y_{rj} and, accordingly, result in different optimal efficiency scores. For the cases where the decision maker has no intuition about the appropriate level of discretization, a practical way of determining an appropriate value of K consists of checking the stability of the efficiency scores. That is, if increasing the value of K affects the optimum levels of x_{ij} and y_{rj} to the extent that it alters the efficiency scores, then a larger value of K is required. The impact on the efficiency scores can consist of a change in the efficiency ranking of the suppliers and/or a change in the efficiency status of one of the suppliers (inefficient/efficient). If the ranking or efficiency status of the suppliers does not change, then the value of K is sufficiently high.

Model (8) is typically solved for each supplier because it generates supplier-specific weights of input and output factors. As previously discussed, this type of weighting scheme is questionable in some settings, such as TCO calculations. Therefore, we extended model (8) by modifying its objective function and first constraint to represent the quantity of the inputs and outputs of all suppliers, following Chen [22] and Shabani et al. [36]. In this manner, model (8) generates a CSW for input/output factors. As a result, we obtain model (9) and refer to it as "common set of weight imprecise data envelopment analysis" (CSW-IDEA).

We note that model (9) aims to acquire common weights for input/output factors to assign the best possible efficiency for the entire set of suppliers, contrary to model (8), which obtains the set of weights for the input and output factors that maximize the efficiency of an individual supplier.

$$
\begin{aligned}
&[\text{CSW}-\text{IDEA}] \quad \max E_{jo} = \textstyle\sum_{j\in J} \sum_{r\in R} \left(p_r \bar{y}_{rjo} - p_r \underline{y}_{rjo} + u_r \underline{y}_{rjo} \right), \\
&s.t. \\
&\textstyle\sum_{j\in J} \sum_{i\in I} \left(p_i \bar{x}_{ijo} - p_i \underline{x}_{ijo} + v_i \underline{x}_{ijo} \right) = 1, \\
&\textstyle\sum_{r\in R} \left(p_r \bar{y}_{rj} - p_r \underline{y}_{rj} + u_r \underline{y}_{rj} \right) - \sum_{i\in I} \left(p_i \bar{x}_{ij} - p_i \underline{x}_{ij} + v_i \underline{x}_{ij} \right) \le 0, \quad j \in J, \\
&\begin{cases} \sum_{k=0}^{K} \gamma_{ki} = 1, \quad \gamma_{ki} \in \{0,\ 1\}, \ k \in \mathbb{N}^0, \ k = 0, \dots, K, \ \forall i \in I, \\ \frac{k}{K} v_i - (1-\gamma_{ki})M \le p_i \le \frac{k}{K} v_i + (1-\gamma_{ki})M, \ k \in \mathbb{N}^0, \ k = 0, \dots, K, \ \forall i \in I, \end{cases} \\
&\begin{cases} \sum_{k=0}^{K} \gamma_{kr} = 1, \quad \gamma_{kr} \in \{0,\ 1\}, \ k \in \mathbb{N}^0, \ k = 0, \dots, K, \ \forall r \in R, \\ \frac{k}{K} u_r - (1-\gamma_{kr})M \le p_r \le \frac{k}{K} u_r + (1-\gamma_{kr})M, \ k \in \mathbb{N}^0, \ k = 0, \dots, K, \ \forall r \in R, \end{cases} \\
&u_r, p_r \ge 0, \quad \forall r \in R; \quad v_i, p_i \ge 0, \quad \forall i \in I.
\end{aligned} \tag{9}
$$

Let $u_r^*,\ v_i^*,\ p_r^*,\ p_i^*,\ \gamma_{ki}^*$ and γ_{kr}^* be the optimal solution of model (9). To compute E_j (i.e., the efficiency of supplier j), such that $0 < E_j \le 1$, we define Eq. (10). This equation is the efficiency ratio (i.e., the weighted sum of outputs over the weighted sum of inputs), which considers imprecise inputs and outputs. Supplier j is considered to be efficient if and only if $E_j = 1$; otherwise, it is considered to be inefficient.

$$
E_j = \frac{\sum_{r\in R} \left(p_r^* \bar{y}_{rj} - p_r^* \underline{y}_{rj} + u_r^* \underline{y}_{rj} \right)}{\sum_{i\in I} \left(p_i^* \bar{x}_{ij} - p_i^* \underline{x}_{ij} + v_i^* \underline{x}_{ij} \right)}, \quad j \in J \tag{10}
$$

4. Methodology

To verify the capability of the proposed CSW-IDEA and USW-IDEA models in approximating the results of the traditional TCO approach, we applied them to the real-life context of two multinational mechanical manufacturers from the same industry. To ensure confidentiality, we refer to these manufacturers as 'Alpha' and 'Beta'. The datasets from Alpha contain imprecise data, whereas the datasets of Beta are precise.

Both Alpha and Beta are among the leading companies in their industry worldwide. Alpha's annual turnover exceeds €300 million; the company employs nearly 1300 people. Intense use of outsourcing required more than €190 million of purchasing costs for components, spread over 1100 active suppliers. Beta employs approximately 2400 people, with an annual turnover of nearly €500 million and more than 1000 active suppliers. These two manufacturers are ideal contexts of study because effective supplier management is essential to their business success. They demonstrated significant dedication to the project by sharing information that was required for performing the analyses of this study and by conducting several meetings to discuss the findings.

Beta is the company that Visani et al. [13] considered in their study. We applied the same datasets in this paper because (i) Beta's datasets are precise which, in addition to Alpha's three imprecise datasets, offers the opportunity to apply the proposed models to both data types, and (ii) when data is precise, USW-IDEA (8) is equivalent to TCO-based DEA proposed by Visani et al. [13]. Thus, we can compare CSW-IDEA (9) with their TCO-based DEA approach.

Section 4.1 describes Alpha's supply categories, which are included in the analysis, and Section 4.2 explains how the data were collected and analyzed to calculate suppliers' SPIs according to the traditional TCO approach. Section 4.3 reports the way we applied CSW-IDEA and USW-IDEA on Alpha's datasets.

The summary of supply specifications and the SPIs of Beta's suppliers are reported in Section 5.3, where we present the findings based on precise datasets. Interested readers are referred to

Table 1
The main features of the three supply categories of Alpha.

Category	Number of suppliers	Value	Value of the procured product (€)
Foundry	25	Avg.*	801,020
		SD.**	926,676
Machining	46	Avg.	689,679
		SD.	1,308,206
Gears	30	Avg.	904,350
		SD.	1,605,477

* Average.
** Standard deviation.

Visani et al. [13] for a detailed description of the procedures employed to collect and analyze the data of the purchasing process in this company.

4.1. Alpha: Selection and description of supply categories

From more than 1100 Alpha's suppliers, we focused on 101 companies that deliver three main classes of components to this manufacturer. These three categories are the most relevant categories in terms of expenditures and the number of suppliers, which implies their highest strategic importance to Alpha. The three supply categories are Foundry (25 suppliers, total purchased amount exceeds €20 million), (46 suppliers, total purchased amount exceeds €31 million) and Gears (30 suppliers, total purchased amount exceeds €27 million).

We included several datasets in the analyses to determine the reliability of the proposed approach for outsourced components, which differ with regard to supply/demand features, supplier characteristics, engineering technicalities, and production processes. The "Foundry" components are iron items, which are usually heavy and bulky, designed by Alpha and manufactured in large plants by medium-sized companies that are primarily located in Northern Italy. The quality of the received products is a relevant issue for this supply category, even if Alpha is involved in several initiatives (co-design, specific projects with main suppliers, and analysis of the equipment of each supplier) that are aimed at increasing the average quality level. The "Machining" supply category includes suppliers for which Alpha provides materials and asks the suppliers to perform various machining operations (such as turning, drilling, and milling) according to their plans. The main source of the complexity in this category is the high number of orders to manage for moving materials between the company's warehouse and the suppliers. The "Gears" are more standardized components that are primarily constructed by small local manufacturers that exclusively work for Alpha. All activities needed to manage the projects in this category are perceived to be expensive. In addition to the financial relevance of the three considered categories for Alpha, we expected that activities required to manage the relationships with suppliers in each category have different impacts on the Alpha's purchasing process. Table 1 lists the main features of the three supply categories.

4.2. Data collection and SPI calculation

In this study, we evaluated suppliers' TCO using a classic activity-based costing approach suggested by previous studies, e.g., Wouters et al. [10]. We initially established a focus group that consisted of Alpha's Chief Executive Officer (CEO), the head of the Management Accounting Department and the directors of the Logistics, Operations, Purchasing, Quality Assurance, and Accounting Departments who are involved in the purchasing activities in Alpha. The outcome of this focus group was a list of the main activities performed in each department and the people to interview in each department. For the very costly and strategic activities, we selected all in-charge employees and managers. For each of the remaining (operational) activities, we selected at least one related employee. Of the 198 employees in the five departments, we selected 81 people.

We conducted semi-structured interviews with these 81 employees to obtain a final list of the performed activities, the time dedicated to each activity, and a list of resources needed to perform the activities. To measure the time absorbed by each activity, we timed the operators when they were performing standard activities and asked them to estimate the time required to perform non-standard activities. We multiplied the time spent on each activity by the hourly cost of each employee provided by the Management Accounting Department to compute the cost of the activities. We prepared a list of 66 activities for which Alpha incurred €14.7 million expenses.

In the next step, starting from the information collected during the interviews and by establishing a second focus group with the directors of the five departments, we identified five cost drivers for the activities: Delivery reminders (12 activities, €0.9 million), Order lines (19 activities, €1.9 million), Contract works order lines (9 activities, €1.1 million), Pallets received (14 activities, €6.9 million) and Quality issues (12 activities, €3.9 million). Alpha's Management Accounting department provided suppliers' data related to the cost drivers and the total value of the supplied products.

We calculated the SPI of each supplier according to Eq. (1) by dividing the cost of activities allocated to each supplier by the amount purchased. Table 2 lists the main phases of the TCO development in Alpha with the time and effort requested by each phase.

Table 3 reports the descriptive statistics of the cost drivers and SPIs for the three supply categories of Alpha. Note that the "Purchasing" and "Quality" departments in Alpha autonomously track the Quality issues, which caused the lack of a sole, uniform measure at the company level. For almost all suppliers, discrepancies among the two sources of data were identified, which raises the issue of imprecise data. As the quantity of the Quality issues of each supplier, we applied the data provided by the Purchasing and Quality departments to obtain interval data by the lower bound and the upper bound. Since data on Quality issues were imprecise (i.e., interval), we considered the average of the lower bound and the upper bound of Quality issues to calculate the SPIs.

4.3. Efficiency analysis

To calculate the suppliers' efficiency, we applied USW-IDEA (8) and CSW-IDEA (9) to the three supply categories of Alpha. We considered the five cost drivers as input factors and the value of the procured products from suppliers as the single output factor for the proposed models. Both models are formulated based on a discretization technique; therefore, we should set a suitable value for K as the discretization level. We examined two different levels for K and took the following steps to determine the effect of changes in K on the efficiency. For all supplied categories, we set $K = 10$ and then run models (8) and (9) to obtain the efficiency scores. We set $K = 20$ and run models (8) and (9) to obtain the efficiency scores. We noticed that the changes in the efficiencies of the suppliers were negligible by going from $K = 10$ to $K = 20$ in models (8) and (9) such that the ranking order of suppliers did not change and none of the suppliers' efficiency status shifted from efficient to inefficient and vice versa. Given the low computational effort, we applied $K = 10$ as the discretization level for all datasets in this paper. We obtained the efficiency of the suppliers by CSW-IDEA and USW-IDEA.

Setting the discretization level to $K = 10$, CSW-IDEA model determined $\lambda^*_{(i=5)} = 1, 0,$ and 0.8 for the imprecise input 'Quality Issue' in the categories Foundry, Machining, and Gears, respec-

Table 2
Process of developing the TCO analysis.

Step	Output	Employees		Researchers		Sum	
		People involved	Total hours	People involved	Total hours	People involved	Total hours
Establishing the first focus group (the CEO and the directors of the departments involved in purchasing process)	Initial list of activities performed and people to interview	7	21	4	12	11	33
Semi-structured interviews with 81 employees	Final list of activities, time required for each activity	81	312	4	380	85	692
Establishing the second focus group (the directors of the departments involved in the purchasing process)	Final list of the cost drivers	6	24	5	20	11	44
Measuring the cost of each activity and allocating them to the suppliers	Calculation of the SPIs	1	12	3	36	4	48
	Sum	**106**	**369**	**16**	**448**	**122**	**817**

Table 3
Descriptive statistics for the identified cost drivers and SPIs in Alpha.

Category		Inputs (cost drivers)						SPI
		Delivery reminders	Order lines	Contract works order lines	Pallets Received	Quality issues*		
						Lower bound	Upper bound	
Foundry	Avg.	40	5,533	0.2	1,583	48	65	0.10
	SD.	45	6,563	0.8	2,290	74	87	0.09
Machining	Avg.	74	11,515	21.8	1,446	14	22	0.09
	SD.	78	15,120	70.8	1,667	33	47	0.08
Gears	Avg.	41	7,153	28.9	2,126	5	11	0.11
	SD.	68	10,671	53.4	4,361	9	18	0.10

* The smallest the value, the higher the quality.

tively. Eq. (3) can now calculate the optimal level of Quality Issue in each supply category. Accordingly, between the lower and upper bounds of Quality Issue, CSW-IDEA assigned the upper bound $[x^*_{i=5} = 1\bar{x}_{i=5} + (1-1)\underline{x}_{i=5}]$ in category Foundry, the lower bound $[x^*_{i=5} = 0\bar{x}_{i=5} + (1-0)\underline{x}_{i=5}]$ in category Machining, and an intermediate value $[x^*_{i=5} = 0.8\bar{x}_{i=5} + (1-0.8)\underline{x}_{i=5}]$ in category Gears.

While CSW-IDEA finds a common $\lambda^*_{i=5}$ for evaluating the efficiency which is applicable across all suppliers, USW-IDEA finds a specific $\lambda^*_{i=5}$ for each supplier. For the category Foundry, USW-IDEA found $\lambda^*_{i=5} = 0,\ 0.2,\ 0.3,\ 0.5,\ 0.8$ and 0.97 for 19, 1, 1, 2, 1, 1 suppliers, respectively. These values indicate that for the evaluation of the efficiency of 19 (out of 25) suppliers, the lower bound of the imprecise inputs 'Quality Issue' was considered, and for the rest of the suppliers, intermediate values between the lower and upper bounds were effective. Likewise, this model found $\lambda^*_{i=5} = 0,\ 0.6,\ 0.8,\ 0.9,\ 1$ for respectively 36, 1, 4, 1, 4 suppliers in category Machining. In the category Gears, USW-IDEA found $\lambda^*_{i=5} = 0,\ 0.14,\ 0.2,\ 0.3,\ 0.4,\ 0.7,\ 0.8,\ 0.9,\ 1$ for 18, 2, 1, 1, 2, 1, 1, 1, 2, 1 suppliers, respectively.

It is worthwhile stating the difference in computational effort in formulating and solving the models. Although the CCR, IDEA model (proposed by Wang et al. [29]), USW-IDEA and CSW-IDEA models are linear and can be efficiently solved, they require a different number of models to be formulated. They require J, $2 \times J$, J and only a single model to be formulated, respectively. The proposed CSW-IDEA, therefore, offers formulation and computational benefits over competing models.

5. Empirical findings

To evaluate the reliability of the proposed CSW-IDEA approach compared with USW-IDEA in approximating the TCO results, we analyzed the efficiency values and rankings generated by the three approaches for the three supply categories of Alpha (imprecise data) and the two supply categories of Beta (precise data). Section 5.1 presents the findings based on the analyses of Alpha's imprecise datasets, and Section 5.2 extends these analyses by comparing the results of the proposed models with the results of the TCO for the most efficient and least efficient suppliers. Section 5.3 illustrates the results of the analyses for the Beta's precise datasets.

5.1. TCO approximation in Alpha (imprecise data)

We started the analysis by comparing the efficiency values that are provided by USW-IDEA (8) and USW-IDEA (9) and listed in Table 4. First, the efficiency averages generated by USW-IDEA are substantially higher than the efficiency scores of CSW-IDEA for

Table 4
Summary of efficiency scores based on the proposed IDEA models.

Item	CSW-IDEA (9)			USW-IDEA (8)		
	Foundry	Gears	Machining	Foundry	Gears	Machining
Efficiency (average)	0.269	0.327	0.196	0.627	0.596	0.390
Efficiency [min, max] (across all suppliers)	[0.031, 1]	[0.033, 1]	[0.014, 1]	[0.037, 1]	[0.066, 1]	[0.020, 1]
Efficient suppliers (no.)	1/25	2/30	1/46	9/25	9/30	7/46

Table 5
Accuracy comparison of USW-IDEA (8) and CSW-IDEA (9) in approximating TCO.

Category	Spearman's rank correlation coefficient	
	TCO and CSW-IDEA	TCO and USW-IDEA
Foundry	0.959*	0.704*
Machining	0.913*	0.829*
Gears	0.863*	0.639*

* Correlation is significant at the 0.01 level (2-tailed).

the three categories: Foundry (0.627 vs. 0.269), Gears (0.596 vs. 0.327) and Machining (0.390 vs. 0.196). Second, the minimal efficiency values obtained by USW-IDEA are higher than the minimal efficiency values obtained by CSW-IDEA (i.e., 0.037 vs. 0.031 for Foundry; 0.066 vs. 0.033 for Gears and 0.02 vs. 0.014 for Machining). Third, as confirmed by the previous observations, the discriminatory power of CSW-IDEA is considerably higher than the discriminatory power of USW-IDEA. USW-IDEA identified nine efficient suppliers, nine efficient suppliers and seven efficient suppliers for Foundry, Gears, and Machining, respectively, whereas CSW-IDEA identified only one efficient supplier, two efficient suppliers and one efficient supplier for the same categories.

The variable discriminatory power of USW-IDEA vs. CSW-IDEA stems from the different weighting schemes of these two models. USW-IDEA provides input/output weights with utmost flexibility to maximize the efficiency of a supplier. In this manner, the input/output factors on which a supplier performs well receive higher importance, and therefore, the model evaluates the supplier's efficiency based on these factors, thereby leading to overrated efficiency [13]. CSW-IDEA obtains the best weights such that the efficiency of the entire set of suppliers is maximized. As a result, the suppliers with poor performance on the most input and output factors are considered to be inefficient, which causes better discrimination of suppliers' efficiencies by CSW-IDEA compared with USW-IDEA. That is why (*i*) the minimum efficiency scores, (*ii*) the average of efficiency scores, and (*iii*) the number of efficient suppliers are smaller for CSW-IDEA (9) than USW-IDEA (8).

To evaluate the capability of the proposed model to approximate the results of the TCO approach, we ranked suppliers according to their CSW-IDEA efficiency scores and SPIs. We applied the nonparametric Spearman's rank correlation coefficient, which is a measure of rank correlation that evaluates the relationship between two sets of orders. The results reported by the second column of Table 5 indicate that the correlation was positive, very high and significant at the 0.01 level in the three supply categories. Specifically, the correlation coefficients were 0.959 for "Foundry", 0.913 for "Machining" and 0.853 for "Gears".

To compare the results of CSW-IDEA with the results of USW-IDEA in approximating the TCO results, we ranked the suppliers of the three categories according to their USW-IDEA efficiency scores. We calculated the correlation among this new set of rankings and the correlation among the SPIs. The results listed in the third column of Table 5 indicate a positive, moderate-to-strong effect. The correlation coefficients were 0.704, 0.829 and 0.639 for the categories Foundry, Machining, and Gears, respectively. The observed relationship between the outcome of USW-IDEA and the outcome of TCO is consistent with the findings of Visani et al. [13].

By comparing the second columns with the third columns of Table 5, the accuracy of CSW-IDEA in approximating the results of a TCO approach is higher than USW-IDEA because the correlation coefficients are consistently high. In Fig. 1, we display the scatterplots that represent the rankings generated by SPIs (based on the traditional TCO calculations) compared with the scatterplots of the rankings generated by CSW-IDEA (on the left) and USW-IDEA (on the right). The scatterplots reveal that the correlation between TCO and CSW-IDEA is stronger than the correlation between TCO and USW-IDEA. This difference is visible in the right-hand scatterplots, where USW-IDEA ranked one among a number of suppliers, whereas TCO ranked them differently. In the category Foundry, e.g., supplier #17 was ranked one by USW-IDEA and 17 by both TCO and CSW-IDEA.

We employed a statistical test to investigate whether the approximation of the TCO calculation by CSW-IDEA is significantly better than the approximation of the TCO calculation by USW-IDEA. We conducted a one-tailed *t*-test to examine the null hypothesis that the distance between the CSW-IDEA-based rankings and TCO-based rankings is equal to the distance between the USW-IDEA-based rankings and the TCO-based rankings (the alternative hypothesis is that the distance between the CSW-IDEA-based rankings and the TCO-based rankings is lower than the distance between the USW-IDEA-based rankings and the TCO-based rankings).

The results of the *t*-test reveal that the approximations of the traditional TCO results by CSW-IDEA and USW-IDEA are significantly different at the 0.01 level and that approximations by CSW-IDEA are better than approximations by USW-IDEA for the individual supply categories (i.e., Foundry, Machining and Gears with the p-values $\leq$ 0, 0.005, and 0.006, respectively) and the entire set (with p-value $=$ 0).

5.2. TCO approximation in Alpha (the upper and lower tails)

Manufacturers often focus on purchasing from the best-performing suppliers and eliminating the least efficient suppliers. Consequently, detecting suppliers that belong to the upper and lower tails of the efficiency distribution is important for the manufactures. We claim that a suitable proxy for TCO should accurately identify the best-performing suppliers and the worst-performing suppliers (i.e., accurate estimation of the rankings in the upper and lower tails).

Starting from the SPI-based ranking of suppliers, we selected the suppliers that belong to the upper and lower quartiles of each category. In each quartile, we selected seven, eight and 12 suppliers for Foundry, Gears, and Machining categories, respectively. For these suppliers, we used the rankings obtained by applying CSW-IDEA and USW-IDEA. To compare the capability of CSW-IDEA and USW-IDEA in detecting suppliers from the first quartile and the last quartile with traditional TCO analysis, we defined the following measures:

i. $\Delta_{Q_1}^{CSW-SPI}$ and $\Delta_{Q_4}^{CSW-SPI}$ as the number of suppliers that are correctly detected by CSW-IDEA from the first quartile and the last quartile, respectively.

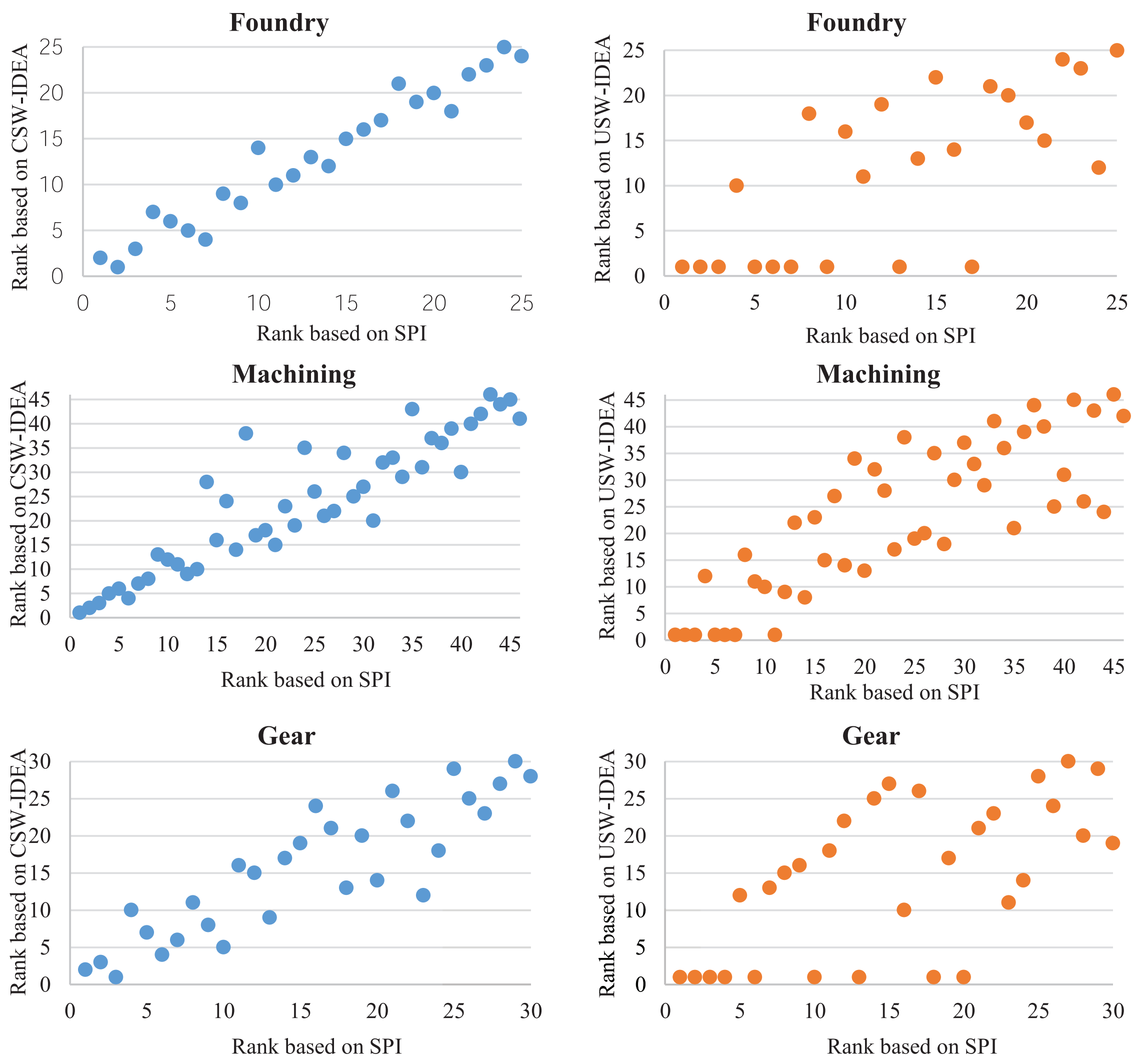

Fig. 1. The scatterplots of the rankings by the TCO approach vs. CSW-IDEA and USW-IDEA for Alpha.

Table 6
Analysis of the least and most efficient suppliers regarding the supplier TCO method.

Category	The first quartile (25% most efficient suppliers)				The last quartile (25% less efficient suppliers)			
	$\Delta_{Q_1}^{CSW-SPI}$	$\Delta_{Q_1}^{USW-SPI}$	$\Delta^{CSW-SPI}$	$\Delta^{USW-SPI}$	$\Delta_{Q_4}^{CSW-SPI}$	$\Delta_{Q_4}^{USW-SPI}$	$\Delta^{CSW-SPI}$	$\Delta^{USW-SPI}$
Foundry	7/7 (100%)	6/7 (86%)	1.67	3.43	6/7 (86%)	4/7 (57%)	0.71	3.43
Gears	6/8 (75%)	5/8 (63%)	2.25	3.88	7/8 (88%)	4/8 (50%)	3.75	6.13
Machining	11/12 (92%)	11/12 (92%)	1.08	4.08	10/12 (83%)	7/12 (58%)	2.83	7.83
Total	24/27 (89%)	22/27 (82%)	1.52	3.85	23/27 (85%)	15/27 (56%)	2.56	6.19

ii. $\Delta_{Q_1}^{USW-SPI}$ and $\Delta_{Q_4}^{USW-SPI}$ as the number of suppliers that are correctly detected by USW-IDEA from the first quartile and the last quartile, respectively.
iii. $\Delta^{CSW-SPI}$ as the average distance between the SPI-based rankings and the rankings provided by CSW-IDEA for the suppliers in the first quartile and the last quartile, respectively.
iv. $\Delta^{USW-SPI}$ as the average distance between the SPI-based rankings and the rankings provided by USW-IDEA for the suppliers in the first quartile and the last quartile, respectively.

Table 6 presents the results for the three supply categories. For the entire sample, both CSW-IDEA and USW-IDEA by an average success rate more than 82% detect the most efficient suppliers consistent with TCO. The average error in the rankings based on USW-IDEA ($\Delta^{USW-SPI} = 3.85$) is significantly higher than the average error in the rankings of CSW-IDEA ($\Delta^{CSW-SPI} = 1.52$).

Among the least efficient suppliers, CSW-IDEA outperforms USW-IDEA with regard to the capability of detecting suppliers from the last quartile similar to TCO (85% vs. 56%) and the average error (2.56 vs. 6.19 positions in the ranking). All results are consistent among the three supply categories, which indicates that CSW-IDEA is preferred for approximating the supplier's TCO when data are imprecise.

5.3. TCO approximation in Beta (precise data)

Beta's datasets contain supply specifications of 74 companies that deliver two strategic components: Turning (50 suppliers, total purchased amount exceeds €52 million) and Gearwheels (24 suppliers, total purchased amount exceeds €35 million). A total of 57 activities that account for a total cost of €13.9 million were

Table 7
Descriptive statistics of the datasets (Beta).

Category	No. of suppliers	Value	Output	Inputs (cost drivers)					
			Total value of the procured product €	Delivered pallets	Received pallets	Order lines	Late deliveries	Samplings	Quality issues
Turning	50	Avg.	1,041,997	36,761	5005	6103	3393	1090	23,336
		SD.	1,233,581	39,193	5322	7034	3905	1065	31,387
Gearwheels	24	Avg.	1,483,852	10	642	1887	700	35	1750
		SD.	2,935,131	41	1134	2803	1307	85	2851

Table 8
Summary of the TCO and efficiency calculations using Beta's datasets.

Category	SPI			Efficiency by USW-IDEA (8)			Efficiency by CSW-IDEA (9)		
	Avg.	[min, max] (across all suppliers)	SD.	Avg.	[min, max] (across all suppliers)	Number of efficient suppliers	Avg.	[min, max] (across all suppliers)	Number of efficient suppliers
Turning	0.094	[0.009, 0.257]	0.058	0,388	[0.118, 1.000]	9/50 (18%)	0.280	[0.055, 1.000]	2/50 (4%)
Gearwheels	0.010	[0.003, 0.079]	0.016	0.520	[0.035, 1.000]	5/24 (21%)	0.334	[0.007, 1.000]	1/24 (4%)

identified. Six cost drivers were selected and analyzed: Pallets delivered to suppliers (four activities, operating costs of €4.8 million), Pallets received from suppliers (six activities, €2.7 million), Contract work order lines (20 activities, €1.2 million), Late deliveries (5 activities, €693,000), Samplings (two activities, €253,000), and Quality issues (21 activities, €4.2 million). Table 7 provides a summary of data related to the six cost drivers.

We computed Eq. (1) to obtain a supplier's SPI based on the weights obtained via the traditional TCO technique and ranked suppliers. Then, we implemented USW-IDEA (8) and CSW-IDEA (9) to calculate the efficiency scores of suppliers in each supply category and ranked suppliers. Table 8 provides a summary of suppliers' SPIs and efficiency scores. The findings indicate that CSW-IDEA exhibits higher discriminatory power in selecting the efficient suppliers (2 vs. 9 for the Turning category and 1 vs. 5 for the Gearwheels) in the presence of the two precise datasets of Beta and yields significantly lower efficiency scores than USW-IDEA (efficiency average of 0.280 vs. 0.388 for the Turning category and 0.334 vs. 0.520 for the Gearwheels category).

To compare the performance of USW-IDEA and CSW-IDEA as proxies for TCO, we applied the non-parametric Spearman's rho coefficient. In the presence of precise data, the correlation between TCO-based and CSW-IDEA-based rankings was statistically significant, high, and higher than the correlation between TCO-based and USW-IDEA-based rankings (i.e., 0.834 vs. 0.727 for the Turning category and 0.819 vs. 0.787 for the Gearwheels category). The scatterplots depicted in Fig. 2 compare the suppliers' ranks generated by TCO, CSW-IDEA, and USW-IDEA: the correlation between TCO and CSW-IDEA is stronger than the correlation between TCO and USW-IDEA for both supply categories.

We applied a statistical t-test to determine if a significant difference exists between the results of CSW-IDEA and the results of USW-IDEA in approximating the TCO results in the presence of precise data. The results of the one-tailed t-test confirm that CSW-IDEA statistically outperforms USW-IDEA for the individual supply categories (i.e., Turning and Gearwheel with p-values $\leq$ 0.024 and 0.015, respectively) and the entire set of Beta's suppliers (p-value $\leq$ 0.006).

6. Discussion

TCO is widely recognized as a powerful yet difficult method for supplier evaluation and selection problems [6]. By developing, testing, and comparing the CSW-IDEA and USW-IDEA models for the evaluation of TCO, this study provides additional evidence that appropriately tailored DEA models can provide reasonable approximations of traditional TCO calculations with significantly lower implementation effort. Empirical tests developed on five supply categories from two mechanical manufacturers indicate that both CSW-IDEA and USW-IDEA can be excellent proxies for the TCO approach for imprecise and precise data. CSW-IDEA approximates the traditional TCO calculation statistically better than USW-IDEA. All Spearman correlations coefficients between suppliers' rankings by CSW-IDEA and suppliers' rankings by TCO exceed 83% (to 96%), which implies significant similarity among the results of the two approaches. The proposed CSW-IDEA and USW-IDEA models expand the domain of applicability of DEA in the study of TCO in the context of imprecise data.

Visani et al. [13] discussed the conditions under which TCO and TCO-based DEA (as an USW-DEA model) scores could diverge due to the different weighting schemes. Findings from this paper support the idea that once the weighting schemes of TCO and DEA become similar, the ranking divergence considerably decreases, which yields a high approximation accuracy of CSW-IDEA.

In addition to the lower accuracy in approximating traditional TCO results, the uncommon weighting system of classic DEA models may be unsettling compared with the clear and stable common weighting system of the TCO calculations. According to Raffoni et al. [62], the different and sometimes limited managerial perceptions of the mathematical and technical performance measurement approaches represent a source of failure in the adoption of analytical tools in practice. Due to the consistent weighting scheme of the TCO approach, the proposed CSW-IDEA model is likely to be better accepted by managers.

Empirical tests indicate that CSW-IDEA is more successful than USW-IDEA for identifying the suppliers that TCO positions in the first and the last performance quartiles. This capability of CSW-IDEA is relevant because suppliers on the upper (lower) tails are the main candidates with whom a company extends (limits) collaboration [7]. For the upper tail, both CSW-IDEA and USW-IDEA correctly identify the best performers. Due to its lower average error in ranking the suppliers compared with the TCO results, CSW-IDEA is more accurate than USW-IDEA. For the lower tail, CSW-IDEA outperforms USW-IDEA for detecting the TCO-inefficient suppliers and their ranks.

CSW-IDEA revealed a substantially higher discriminatory power (measured by the number of efficient suppliers) than USW-IDEA. The lack of discriminatory power is a relevant issue for USW-IDEA. As reported by Visani et al. [13], TCO-based DEA (an USW approach) tends to generally overestimate the efficiency of

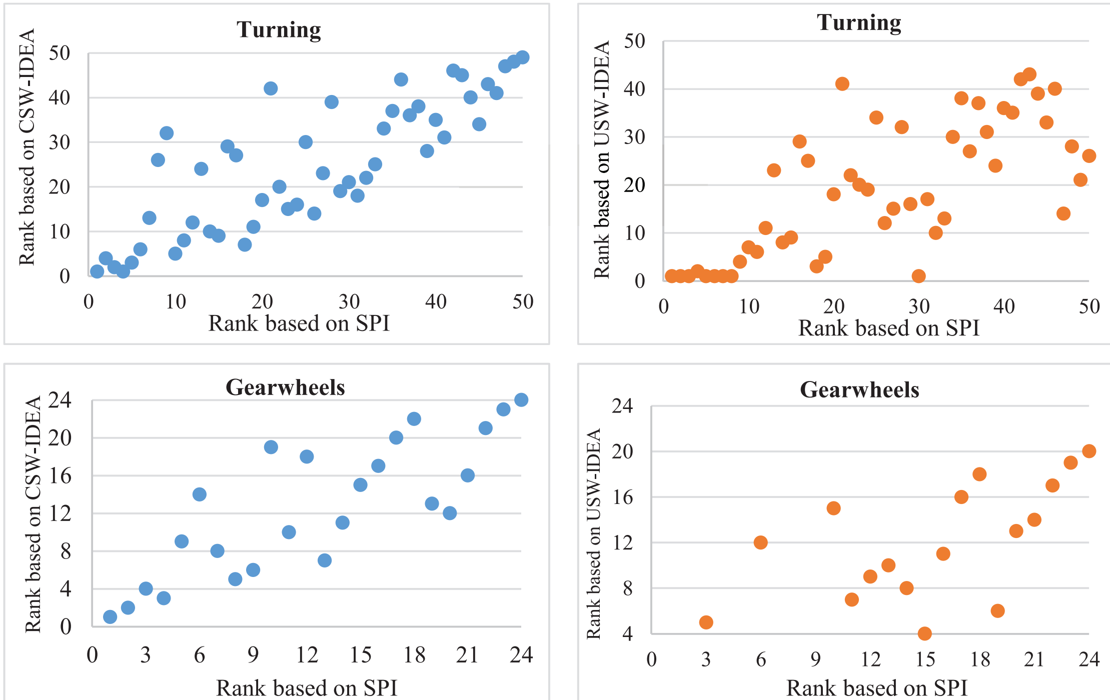

Fig. 2. The scatterplots of the rankings by the TCO approach vs. CSW-IDEA and USW-IDEA for Beta.

suppliers by placing high weights on the input/output factors on which suppliers performed well. The efficiency overestimation distorts the rankings when suppliers variably perform with different factors. Our analysis confirms this claim. Considering the specific input/output data of each supplier, the suppliers with high partial efficiency for one or few inputs—measured by the ratio between the output and each input—are generally overvalued by USW-IDEA compared with TCO. These suppliers are often highlighted as efficient even if the performance measured by TCO is substantially low. When CSW-IDEA is applied, a substantial reduction in the number of these efficient suppliers is observed, and the rankings assigned by CSW-IDEA to these "deviant" cases are similar to the TCO's rankings. Similar to the TCO approach, CSW-IDEA detects the performance differences better than USW-IDEA. Therefore, CSW-IDEA mitigates the risk of presenting an inefficient supplier as suitable or a suitable supplier as a high-performing supplier.

The experiments that employ precise data reveal that CSW-IDEA performs better than USW-IDEA to approximate the TCO results. This finding suggests that the results of our study are attributable to the conditions of both imprecise data and precise data.

From a managerial point of view, CSW-IDEA shows several interesting implications. The increasing reliability of the TCO proxy can support real supplier-selection-based cost-saving initiatives. To illustrate this point, we run a simulation of the management cost if the entire amount of purchases in each supply category was split among the most efficient suppliers, i.e., suppliers in the first quartile. In this simulation, first, we selected the 25% most efficient suppliers of each supply category according to TCO, USW-IDEA, and CSW-DEA. Second, we calculated the average SPI of each supply category for the three groups. Third, we estimated the expected supplier management cost by multiplying the average SPI (given that the SPI quantifies the cost of managing the relationship with suppliers for one monetary unit of purchased product) times the total purchased amount for each supply category. As shown in Table 9, the sum of the total costs of managing the purchasing process of all supply categories increases from €1.53 million to €2.24 million when selecting the suppliers proposed by USW-IDEA instead of TCO, i.e., a deviation of more than 46%. Applying CSW-IDEA, the operating cost would be only €1.68 million, i.e., less than 10% deviation, with a total savings of €560,000 compared with USW-IDEA. This simulation implicitly assumes that the suppliers of the first quartile have sufficient capacity to take on the production share of suppliers in the second, third and fourth quartiles.

Consistent with supplier relationship management, analyzing the performance for the quartiles may establish benchmarks for suppliers. A supplier in the Foundry category, e.g., may gauge its performance against the average SPI of the first quartile (i.e., 2.373%). This performance standard can inspire suppliers to improve their performance. CSW-IDEA can accelerate the supplier TCO evaluation on a daily basis because it estimates the supplier's TCO with reasonable accuracy yet requires less time and effort than the traditional TCO approach.

The TCO approach is a data-sensitive method, which indicates that any change in the original data set may demand effort for updating the results of the traditional TCO results. A case for this data alternation is, e.g., when a (new) supplier (joins) leaves the supply network. Although CSW-IDEA has the same data sensitive feature, it does not require as much time/cost as the TCO approach to regenerate weights for the cost drivers. Once any change in the dataset occurs, CSW-IDEA can be run to obtain a reliable estimation of the total supplier relationship management cost.

CSW-IDEA can be effectively employed to estimate the potential performance of a candidate supplier in joining a supply network. In this situation, the absence of past transactions precludes the buying company from having access to well-established supplier performance data. Yet, it might be possible to achieve at least a rough estimate of the supplier performance (e.g., by interval data considering the best-case scenario vs. the-worst case scenario) through supplier audits, informal discussions with supplier's clients, and inquiries from professional networks and industry associations. CSW-IDEA can use these data to obtain TCO-based performance projections for potential suppliers with limited effort. Likewise, when a

Table 9
Supplier selection based on different methods and its impact on the management cost.

Supply Category	Total purchased amount (i)	Average SPI of the suppliers on the first quartile detected by			Expected supplier management costs based on		
		TCO (ii)	USW-IDEA (iii)	CSW-IDEA (iv)	TCO $(v)=(i)\times(ii)$	USW-IDEA $(vi)=(i)\times(iii)$	CSW-IDEA $(vii)=(i)\times(iv)$
Foundry	€ 20,025,514	2.373%	3.567%	2.373%	€ 475,177	€ 714,368	€ 475,177
Gears	€ 27,130,512	1.445%	3.046%	1.893%	€ 392,036	€ 826,318	€ 513,637
Machining	€ 31,725,243	2.104%	2.218%	2.195%	€ 667,552	€ 703,809	€ 696,375
				Total	€ 1,534,765	€2,244,495	€ 1,685,188
				Deviation from TCO	–	€ 709,731	€ 150,423

company terminates its procurement contract with a supplier(s), the new supplier management cost and any change in the cost structure can be easily estimated.

Since CSW-IDEA can manage imprecise data, subjective and labor-intensive data gathering and processing, which are required by traditional TCO calculations and existing TCO-based DEA models, may be alleviated.

Classic DEA models should be separately built for each supplier. Therefore, they can be computationally intensive in settings with a high number of suppliers. CSW-IDEA needs to be created and solved only one time for all suppliers, which implies fewer computations than classic USW DEA models, including the TCO-based DEA approach.

To evaluate the managerial effect of adopting a CSW-IDEA approach on managing business relationships with suppliers, we shared the findings of this study with the chief purchasing officers (CPOs) of Alpha and Beta. Both companies introduced the existing TCO-based approach as a decision-making tool to support their sourcing strategies, which are aimed at reducing the complexity and the total cost of managing the supply chain relationship. Both CPOs had concerns about the complexity and cost of implementing the traditional TCO approach. Their concerns primarily involved the initial execution of the TCO approach and the subsequent activities required for updating the system. As an alternative to traditional TCO calculations, CPOs experienced difficulty understanding the concept of an USW-DEA approach because its weighting system differed from the TCO approach. Both CPOs believe that the USW-IDEA can provide interesting insights, however, justifying the applicability of the USW-IDEA approach for other divisions in their companies would be difficult. Both CPOs highly appreciated the CSW-IDEA approach as a significantly more consistent method of evaluating TCO. At the end of the analysis, Alpha started a pilot program for including CSW-IDEA in its performance management system.

7. Concluding remarks

The evaluation of supplier performance requires a compromise between the desire to obtain high-quality information and the cost of its collection and analysis [63]. The total cost of ownership (TCO) is a comprehensive economic analysis of business partnerships with suppliers which extends the focus from the purchase price to all involved costs. Due to its intense data collection effort requirements, TCO adoption remains limited among practitioners [10]. To increase the applicability of TCO in practice, data envelopment analysis (DEA) has shown to be a reliable and parsimonious proxy for traditional TCO calculations [13]. Although the TCO-based DEA model was a major step toward the extensive adoption of TCO in supplier performance evaluations, this model has numerous drawbacks. First, TCO-based DEA employs an uncommon set of weights to evaluate suppliers. Managers often doubt this weighting scheme [64] because they prefer the common set of weights employed by a traditional TCO. They are accordingly reluctant to accept the evaluation results [13]. Second, TCO analyses often involve inaccurate data from conflicting data sources, estimations, and interviews, whereas the imprecise data are disregarded by the traditional TCO calculations and the TCO-based DEA model. The resultant decision may be inaccurate.

This paper develops a novel common set of weights imprecise DEA (CSW-IDEA) approach to overcome the drawbacks of existing TCO and TCO-based DEA models. Compared with previous attempts to find a proxy for TCO via DEA, the model we propose provides substantial benefits for practitioners. First, it demonstrates higher accuracy in the estimation of TCO, which increases a user's confidence that it will facilitate right decision-making. Second, it can handle precise and imprecise data in practice. Last, similar to traditional TCO, the proposed model uses a common weighting, which facilitates comparison of the two methods, which supports the adoption of CSW-IDEA model outcomes in practice. Thus, we believe that this research contributes to the promotion of a "TCO-oriented" approach to supplier evaluation, which can improve the effectiveness of this key managerial task.

In performing this study, we faced a few limitations that open up directions for future research. Although we illustrated the applicability of the proposed model by assessing TCO of 175 suppliers who deliver five strategic components to two mechanical manufacturers, the generalizability continues to be bound by this sample. Therefore, we encourage scholars to evaluate the effectiveness of the models proposed in this study by applying them to new contexts and industries. Future studies can assess the proposed model's average precision in reproducing the results of TCO. In this study, we have encountered only one type of imprecise data, i.e., interval data, for a single variable. The capability of the proposed model to estimate TCO should be tested when imprecision affects a larger number of variables; it also assumes different forms, e.g., ordinal data. Scholars can also identify conditions under which the model becomes less effective.

In dealing with imprecise data, Robust DEA (RDEA) can offer interesting research avenues. One could examine the vulnerability of a DEA estimation of TCO by applying RDEA to show at which level of uncertainty the DEA estimations deviate from the TCO calculations. In Section 3, we suggested a decision-maker friendly approach to determine the discretization level K. Future studies could examine whether RDEA can facilitate the estimation of appropriate discretization levels, e.g. following the approaches proposed by Shokouhi et al. [58,59]. The level of uncertainty in RDEA is currently decided by a decision maker or through complex simulation techniques [59]. Future research could examine if the proposed model can help finding a suitable uncertainty level for RDEA.

Consistent with existing TCO literature, we have applied suppliers' operational performance as an input for our TCO analysis. Future research, however, can include modeling suppliers' internal operations by performing audits of suppliers' production capacity, working procedures, quality measures, and labor skills to determine whether suppliers' (in)efficient processes or manufacturer's (in)ability to handle procurement activities create a high (low)

TCO. This insight can help manufacturers build stronger, more collaborative business partnerships with suppliers to mitigate supply chain disruptions.

TCO should consider three cost components: acquisition costs, ownership costs, and post-ownership costs [6]. Although costs associated with acquisition and ownership are often identifiable in the short run after procurement, a considerable amount of time is required for the manufacturer to identify the post-ownership costs, such as environmental, warranty, product liability, and customer dissatisfaction costs. A business relationship with suppliers has carry-over consequences that affect the TCO of future. Future studies can involve the development of dynamic TCO models and a corresponding dynamic TCO-based DEA proxy to better measure a supplier's performance over time and determine how the performance in a given term affects the TCO of future time periods.

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