International Journal of Production Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

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To cite this article: Chong Wu, Jing Gao & David Barnes (2022): Sustainable partner selection and order allocation for strategic items: an integrated multi-stage decision-making model, International Journal of Production Research, DOI: 10.1080/00207543.2022.2025945

To link to this article: https://doi.org/10.1080/00207543.2022.2025945

INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
https://doi.org/10.1080/00207543.2022.2025945

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Sustainable partner selection and order allocation for strategic items: an integrated multi-stage decision-making model

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ABSTRACT
Current environmental issues and government requirements, together with pressure from the market and other stakeholders, emphasise the importance of partner selection in constructing and operating sustainable supply chains. Strategic items, which carry both high supply risk and high importance of purchase, are particularly important in sustainable supply chains. This paper presents an integrated decision-making model, which aims to solve the partner selection and order allocation problem for strategic items in sustainable supply chains. In the proposed model, weightings of different decision-makers are first calculated using Trapezoidal Fuzzy Numbers. Then, Taguchi loss function is used to evaluate the relative importance of potential partners, with the weighting results of criteria by Best-Worst Method. Finally, considering the weights of different potential partners, Particle Swarm Optimisation (PSO) is used to solve the multi-objective programming problem, and Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) is applied to identify the most appropriate Pareto solution for sustainable partner selection and order allocation of strategic items. An illustrative application of the proposed model is undertaken in a leading Chinese LED lighting manufacturer to show its effectiveness and applicability.

ARTICLE HISTORY
Received 25 May 2021
Accepted 27 December 2021

KEYWORDS
Strategic item; sustainable partner selection; order allocation; trapezoidal fuzzy numbers; Taguchi loss function; particle swarm optimisation

1. Introduction

An increasing focus on the Triple Bottom Line (Elkington 1997) has seen an explosive growth in research on sustainable supply chain management (SSCM) over the last few decades (Villena and Gioia 2018). Supply chain managers must now be concerned not only with economic performance, but also with the environmental and social impact of business activities (Mohammed, Harris, and Govindan 2019). SSCM is now seen as a prerequisite for the success of the whole supply chain (Wu et al. 2020a). This requires a focus not just on the performance of the focal company, but also on the different partners along the whole supply chains (Hollos, Blome, and Foerstl 2012; Kusi-Sarpong, Gupta, and Sarkis 2019). It is thus vital to select approporiate partners that share the same vision and meet required standards in economic, environmental and social aspects of performance (Wu and Barnes 2012; Zimmer, Froehling, and Schultmann 2016).

In the generic partner selection literature, Kraljic (1983) has pointed to the need to distinguish between different categories of purchased items, arguing that each category requires a different approach to procurement. Accordingly, the well-known Kraljic Portfolio Matrix (KPM) identifies four categories of purchased items according to the supply risk and the importance of purchase, namely strategic items, bottleneck items, leverage items and non-critical items. Among them, strategic items carry both high supply risk and high importance of purchase, which makes partner selection for such items particularly important as these partners not only have a significant impact on the profitability and innovation capability of a purchasing company, but also influence the reliability and flexibility of the focal company (Lechler, Canzaniello, and Hartmann 2019). For instance, production on Boeing's 787 Dreamliner was delayed by an insufficient supply of fasteners; Hyundai shut down its assembly plant in South Korea due to a lack of key components made in China, whilst Renault Samsung halted production in South Korea due to strategic semiconductor chip shortage, and the world's leading ventilator manufacturer, Hamilton, was unable to obtain the core accessory of ventilators, humidifiers, due to export restrictions of medical products in Romania, resulting in unexpected disruption of manufacturing (Aspan and Elegant 2020).

Therefore, considering both the requirements of SSCM and the distinguish features of strategic items in

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the KPM, decision-making about the choice of partners for strategic items in SSCs and the corresponding optimal order allocation has now become more significant (Alikhani, Torabi, and Altay 2019). The right decisions can not only help focal companies avoid the serious consequences of shortages or even disruption of strategic items, but also help them construct excellent SSCs which can achieve required Triple Bottom Line (TBL) goals. However, this decision-making is different from that of the traditional sustainable partner selection problem which only considers the challenges from the perspective of the TBL. Sustainable partner selection and order allocation for strategic items needs to carefully consider and balance extended impact factors, including supply risk and importance of purchase, as well as supply partners' performance in social responsibility and environmental protection.

Existing partner selection models are inadequate to solve the strategic items partner selection and order allocation problem in the case of SSCs. There are five main research gaps that need to be addressed: (1) The KPM, which takes the characteristics of different items into account, has not been applied to partner selection in SSCs yet. It is particularly important for strategic items, which have both high supply risk and high importance of purchase. Thus, they result in the highest interdependence between the purchaser and partner. (2) Group decision-making is one of the features considered in multi-criteria decision-making (MCDM) problems. Yet, there has been insufficient research on how to evaluate and weight different decision-makers reasonably, according to their specific characteristics. (3) Whilst Taguchi loss function (TLF) has been used by some researchers to solve the partner selection problem, there are few examples of its application in the SSCs context, especially its use to solve the partner selection and order allocation problem, simultaneously. (4) Whilst research on order allocation is rich and plentiful, the existing research can be further extended by considering the investment profitability in long-term partnerships. (5) Partner selection in SSCs is inherently a complex MCDM problem (Mohammed, Harris, and Govindan 2019). Yet, the issue of how to identify the most appropriate solution from the Pareto solution set has not been researched in-depth.

This research aims to address the above research gaps and proposes an integrated model for strategic items partner selection and order allocation in SSCs. The model draws on several appropriate decision-making techniques, making full use of their distinguished characteristics and advantages to solve the respective subproblems in turn. Firstly, the KPM is applied to distinguish the strategic items. Then, trapezoidal fuzzy numbers (TrFN) are applied to weight the relative importance of the decision-makers, as this can provide more detailed information. It uses best-worst method (BWM) to weight evaluation criteria. At the same time, an improved TLF is proposed to weight potential partners and their social influence. The integration of BWM and TLF combines both subjective and objective analysis, thereby improving feasibility and validity of decision-making. Particle swarm optimisation (PSO), one of effective heuristic algorithms for multiple objective programming problems (Wu and Barnes 2016), is used to obtain Pareto solutions of optimal order quantity. Finally, Technique of Order Preference Similarity to the Ideal Solution (TOPSIS), a simple but effective approach to identify the most appropriate solution (Memari et al. 2019), is used to determine the optimal solution.

The contributions of this research can be summaried as follows: First, the proposed model is able to consider both the characteristics of strategic items in the classic KPM framework and the requirements of the TBL in the sustainable partner selection and order allocation decision-making process, simultaneously and effectively. To date, literature has not addressed this problem in this context, thereby ignoring the different characteristics of different types of products. Second, the proposed model is able to consider weights of decision-makers, evaluation criteria and potential partners systematically, an issue which, to date, has attracted little research attention in partner selection and order allocation in SSCs. Third, the proposed model combines BWM with TLF to obtain the weights of potential partners which takes advantages of both objective and subjective methods together and enriches the application of TLF in SSCs. Fourth, the proposed model considers the investment profitability from where long-term partnerships have been established, thereby enabling not only the consideration of sourcing and purchasing on a short-term bid-by-bid basis, but also by focusing attention on the sustainable sourcing of strategic items. Last, but not least, the proposed integrated model not only solves the multi-objective programming problem and obtains Pareto solution set by PSO, but also applies TOPSIS flexibly to further analyse and identify the most appropriate solution considering different combinations of multiple objectives in accordance with different and changing decision-making requirements and situations. Furthermore, a pair of concepts, namely homogeneous and heterogeneous objectives, have been proposed in the process of Pareto solutions in-depth analysis. These two concepts can be used to classify and identify the key objectives to focus on for further partner improvement actions.

The rest of this paper is constructed as follows. Firstly, a comprehensive literature review of partner selection and order allocation for strategic items is presented in

Section 2. In Section 3, an integrated model is constructed. Section 4 then presents an empirical illustration of its application in a leading Chinese LED lighting manufacturer. Sensitivity analysis is considered in Section 5 followed by corresponding managerial implications in Section 6. Section 7 concludes this paper and offers guidelines for future research.

2. Literature review

This section provides a comprehensive review of relevant literature on the KPM and strategic items, existing methods for sustainable partner selection and order allocation, and existing models which apply TLF and PSO methodologies, respectively.

2.1. Kraljic portfolio matrix and strategic items

The Kraljic Portfolio Matrix (KPM) (Appendix A) aims to minimise supply vulnerability and maximise purchasing power whilst simultaneously matching external resources with internal demands (Padhi, Wagner, and Aggarwal 2012). It has been widely used to classify partners (Caniëls and Gelderman 2007). For example, Wu and Barnes (2014) and Wu et al. (2020b) used it within an information processing model to classify potential partners by using artificial neural networks or ensemble learning model. In addition, Montgomery, Ogden, and Boehmke (2018) improved the qualitative classification KPM model by quantifying the items by single-attribute value function and sorting them using multi-attribute value function. The above three research papers overcome one of the primary weaknesses of the KPM, which is a subjective qualitative model, by proposing objective quantitative approaches to enable partners to be positioned within the KPM.

Strategic items are one of the categories in KPM, having the characteristics of both high supply risk and high importance of purchase (Padhi, Wagner, and Aggarwal 2012). The interdependence between partners and buyers of strategic items is not an expected equilibrium state, but a highly interdependent one (Caniëls and Gelderman 2007). Therefore, the establishment of a cooperative relationship between partners and buyers of strategic items will have a significant impact on their future operations and the whole supply chain's performance (Padhi, Wagner, and Aggarwal 2012). In other words, the selection of partners for strategic items in SSCM should involve taking a more holistic view (Saputro, Figueira, and Almada-Lobo 2021), with both buyers and suppliers needing to take a more comprehensive consideration in their decision-making for partner selection and lot-sizing for strategic items.

2.2. Methods for sustainable partner selection and order allocation

Research on partner selection in SSCs has built on previous research on agile/lean supply chains (Wu and Barnes 2011), while Geyi et al. (2020) argue that agile capabilities are a necessary condition for maximising sustainability. Dai and Blackhurst (2012) integrated TBL into supplier selection which enriches the research of SSCs. Later, various approaches have been proposed to optimise environmental goals (e.g. Kannan et al. 2013; Banaeian et al. 2018). In recent years, there has also been a concern to emphasise social aspects of performance in decision-making on partner selection in SSCs (e.g. Yawar and Seuring 2015; Feng, Zhu, and Lai 2017; Khan et al. 2021). As to the methods for sustainable partner selection, many MCDM techniques have been proposed. For instance, Cui, Wu, and Dai (2021) developed a hybrid model which integrates fuzzy set theory and Bayesian network for sustainable supplier selection. One of the main contributions is that it considers three multi-tier supply chain structures. Among the MCDM techniques, *analytic hierarchy process* (*AHP*) remains the most widely applied method (Feng, Hu, and Orji 2021). However, work by Zarte, Pechmann, and Nunes (2019) has questioned whether AHP is the most appropriate method for sustainable partner selection. Therefore, further research in the field of sustainable partner selection is still required.

In order allocation, decision-makers typically face the question of whether to implement single or multiple sourcing (Deng and Elmaghraby 2005). Single sourcing can decrease purchasing costs by long-term cooperation and economic of scale from bigger lot-sizing, but it tends to also increase the dependence of the buyer on the seller (Swift 1995). Consequently, many supply chain managers opt for multiple sourcing to reduce the risk of supply disruption associated with over-reliance on a single partner. Furthermore, multiple sourcing can also achieve the advantage of single sourcing through building strategic partnerships with key partners (Costantino and Pellegrino 2010). In multiple sourcing decision-making, the key question is order allocation, that is how to assign the optimal order quantities for each selected partner whilst achieving multiple objectives. Previous research tended to focus on issues of cost and purchasing value when solving the order allocation problem (e.g. Ghadimi, Ghassemi Toosi, and Heavey 2018; Jia, Liu, and Bai 2020). Yet, Azadnia, Saman, and Wong (2015) has shown that sustainable purchasing has a higher value than a single-objective cost-based model.

Some approaches to solving the order allocation problem have incorporated a consideration of decision-makers' preferences, which makes decision-making more accurate. For example, Kannan et al. (2013) utilised fuzzy set theory to show decision-makers' preferences for criteria in their integrated model for partner selection and order allocation. The main limitation is that the proposed maxi-min method may not be Pareto-efficient. Zarte, Pechmann, and Nunes (2019) also point out that the preferences of decision-makers for objective measures will influence the evaluation of sustainable partners. Meanwhile, some literature has paid attention to reducing supply risk whilst solving the order allocation problem (e.g. Gören 2018; Kellner, Lienland, and Utz 2019; Saputro, Figueira, and Almada-Lobo 2021). For instance, to integrate risk factors into the supplier selection, Kellner, Lienland, and Utz (2019) proposed a multi-objective optimisation model based on investment portfolio theory. One of the advantages of the proposed model is that it provides graphical decision support through a visualisation of the Pareto front.

2.3. Taguchi loss function and particle swarm optimisation models

The TLF has been widely used in different problem solving fields (e.g. Wu, Shamsuzzaman, and Pan 2004; Chang, Liu, and Hung 2009). It is especially useful when undertaking optimisation (e.g. Chuang and Wu 2018). Some researchers have shown the benefits of using TLF in combination with other techniques. For example, Sivakumar, Kannan, and Murugesan (2015) used TLF with AHP, and Gören (2018) integrated fuzzy DEMATEL with TLF to weight partners. Alizadeh and Yousefi (2019) applied the fuzzy cognitive map with TLF to select the optimal partner. Importantly, Ordoobadi (2009) quantified the intangible criteria in the partner selection process by using TLF. This is especially important for SSCs, where most TBL criteria are hard to quantify. TLF has the capability to solve these challenges. Therefore, this research will adopt this approach to calculate the relative loss of partners, and then identify the relative importance of potential partners and their social influence.

There are two basic methodologies to solve order allocation multi-objective problems. One is to combine and transform the multi-objective problem into a single objective problem (Babbar and Amin 2018). However, this methodology changes the structure of the programming model and loses feasible optimal solutions. The other is to apply heuristic algorithms. Heuristic methods can solve multi-objective problems effectively and obtain a set of Pareto solutions (Kao and Jacobson 2008). PSO is one of the effective heuristic algorithms for the partner selection problem (Wu and Barnes 2016). Based on random optimisation strategies, PSO is inspired by the behaviour of birds and other animals. The particle follows the current optimal particle in space, where it is different to the genetic algorithm. The basic concept is that at each moment, the velocity of each particle varies between its best personal and its best global position. PSO has already been effectively used in the field of partner selection (e.g. Kannan, Haq, and Devika 2009; Wu and Barnes 2016). However, PSO can only solve the multi-objective problems and collect Pareto solutions. It cannot tell decision-makers which Pareto solution to apply in real business practices.

Table 1 provides a summary of recent representative research on decision-making methods of sustainable partner selection and order allocation discussed above.

3. The proposed multi-stage decision-making model in SSCs

The objective of this research is to help decision-makers in SSCs to select sustainable partners of strategic items and allocate order quantities efficiently and effectively. The proposed model is shown in Figure 1.

There are three stages in the proposed model. In the first stage, fuzzy set theory is utilised to capture the relative importance of decision-makers who take part in the decision-making team. The subjective evaluation methodology BWM is used to calculate the weighting of criteria. In the second stage, an improved TLF is proposed to evaluate the weights of potential partners and their social influence. In the third stage, the order allocation programming model is constructed by using the weights from the previous stage. With the help of PSO, Pareto solutions of optimal order quantity will be obtained. Finally, TOPSIS will be used to identify the most appropriate optimal solution by considering different combinations of multiple objectives in accordance with specific decision-making requirements and situations. More details of these three stages are presented in the three subsections below.

The reasons for integrating the above methodologies are threefold. First, fuzzy set theory is acknowledged to be a useful and effective tool to overcome the vagueness of decision-makers' opinions (Banaeian et al. 2018). Specifically, TrFN which have four parameters can provide more detailed information when determining the relative importance of decision-makers (Babbar and Amin 2018), and can form most generic classes of fuzzy numbers. In addition, when weighting the criteria, BWM only needs to simply compare criteria with each other, rather than needing to precisely measure their quantitative values (Kusi-Sarpong, Gupta, and Sarkis 2019). Therefore, applying TrFN and BWM appropriately can help

Table 1. The comparison of recent representative research on decision-making methods of sustainable partner selection and order allocation.

Author(s)	Partner selection	Order allocation	Strategic item	Preferences of decision-makers	Key methods/ approaches	Application	Main contributions
Dai and Blackhurst (2012)	√	/	/	/	AHP + QFD	Retail company	The proposed four-phase model can obtain the weightings of customer requirements. It extends the understanding of the performance effects of purchasing.
Azadnia, Saman, and Wong (2015)	√	√	/	/	FAHP + mathematic programming	Packaging films company	The proposed model can deal with severe uncertainty and evaluate qualitative and quantitative data simultaneously
Ghadimi, Ghassemi Toosi, and Heavey (2018)	√	√	/	/	Multi-Agent Systems	Medical device company	Addresses the communication and information exchange challenges in suppliers-buyers relationship by Multi-Agent Systems approach.
Babbar and Amin (2018)	√	√	/	/	QFD + linear programming	Beverage company	Considers both quantitative and qualitative criteria, while special attention has been made to environmental factors; Considers ambiguity in human behaviour.
Alizadeh and Yousefi (2019)	√	/	/	√	TLF + goal programming	Paint and coating company	Allows decision-makers to set their preferences in form of utility function.
Jia, Liu, and Bai (2020)	√	√	/	/	Ambiguity set + goal programming	Steel company	Derives a new tractable robust approximation model by proposing robust counter-part forms of the expected constraints and safe approxi-mation systems of the chance constraints.
Wu et al. (2020b)	√	/	/	/	Ensemble learn-ing + fuzzy set theory	Electronic equipment & instrument company	Overcomes the weakness of the existing ensemble learning model, which can typically only handle numerical quantitative data, and offering a simple classification and a stable prediction performance.
Cui, Wu, and Dai (2021)	√	/	/	/	Fuzzy set the-ory + Bayesian network	Robot automation equipment company	Considers three multitier supply chain structures. Fuzzy set theory and SWARA are applied to overcome the limitations of Bayesian network
Wu, Lin, and Barnes (2021)	√	/	/	/	FGRA + FMEA+ DEMATEL	Petrochemical company	Analyses and integrates the eco-nomic, social and environmental dimensions based on the specific features of the chemical industry.
The proposed model	√	√	√	√	TLF + PSO	LED lamp company	(1) Considers both strategic items in KPM framework and the requirements of TBL, simultaneously& effectively; (2) Considers weights of decision-makers, evaluation criteria and potential partners, reasonably & systematically; (3) Considers the investment profitability from where long-term partnerships have been established; (4) Considers different combina-tions of multi-objectives according to the changing decision-making requirements and situations.

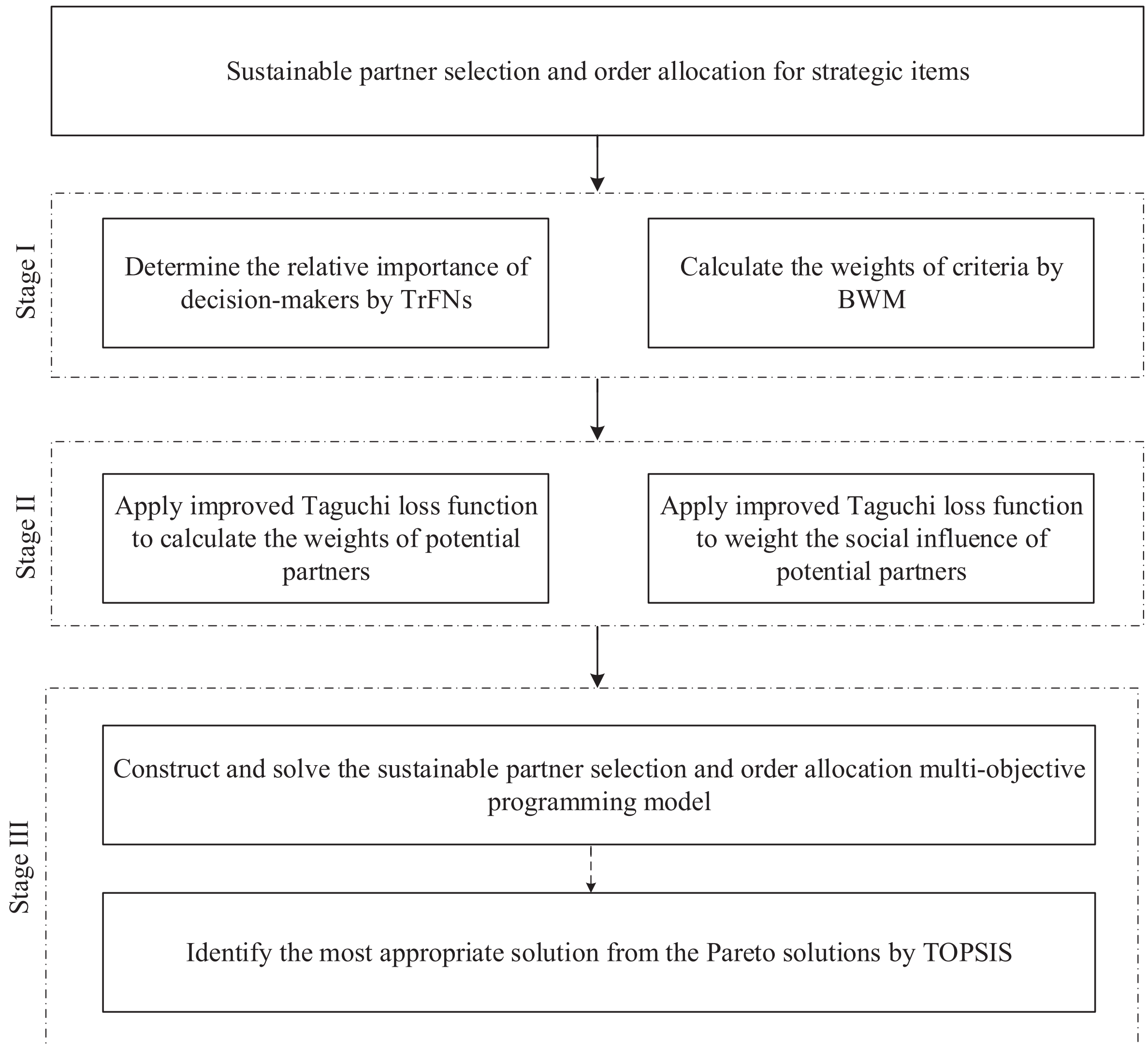

Figure 1. The proposed model of sustainable partner selection and order allocation for strategic items.

decision-makers obtain the weights of both decision-makers and criteria, effectively and efficiently. Second, TLF has the capability to solve the challenges that most of TBL criteria are hard to quantify (Ordoobadi 2009). The improved TLF can better express preferences irrespective of whether criteria are tangible or intangible, and thereby ensure more effective decision-making. In addition, the integration of BWM and TLF combines subjective and objective analysis, thereby improving both feasibility and validity. Third, PSO can deal with the multi-objective problem effectively (Wu and Barnes 2016). However, as the common characteristics of the heuristic algorithm, PSO cannot tell decision-makers which Pareto solution for strategic items sustainable partner selection and order allocation to apply in real business practices. In other words, when PSO solves one hard problem for managers, it creates another one. The combination of PSO and TOPSIS is a wise approach for this dilemma, while TOPSIS is a feasible and effective method to determine the most appropriate solution.

3.1. Calculating relative importance of decision-makers and weights of criteria

3.1.1. The relative importance of decision-makers

This sub-section outlines how TrFN is used to calculate decision-makers' relative importance by evaluating four key attributes, namely their total working experience, length of service experience in the company, their position and education background. The decision-makers' characteristics are quantified by TrFN, and then, the fuzzy toolbox of MATLAB 2019a is used to run the rules of TrFN to obtain the relative importance of each decision-maker. The rules of TrFN are shown in Appendix B. The four attributes describe the different characteristics of each decision-maker.

The corresponding TrFN for each decision-maker can be identified from the cumulative sum of the evaluation values of the four attributes. Finally, the relative importance of decision-makers is determined by normalising the defuzzified value. The general steps of TrFN method are: a TrFN M can be defined by (a_k, b_k, c_k, d_k), where $a_k < b_k < c_k < d_k$ and k is the number of decision-makers, meanwhile the linear membership function of M is presented by $\mu_{\tilde{\propto}(x)}$.

3.1.2. Criteria weighting

It is important to check the importance and applicability of any criteria used for partner selection (Zimmer, Froehling, and Schultmann 2016). This study does this by following Wu and Barnes (2016) and Wu et al. (2020a) in using a semi-structural questionnaire based on the literature. Although comparing environmental and social criteria is difficult, BWM offers an ideal way of solving this issue as it simply compares criteria with each other, rather than needing to precisely measure their quantitative values (Kusi-Sarpong, Gupta, and Sarkis 2019). Accordingly, BWM is applied in obtaining the weights of sustainability criteria. The basic concept is illustrated in Appendix C. The value of the consistency w_i is desired to be close to zero (Rezaei 2016).

3.2. Weighting partners and their social influence

In the second stage, an improved TLF is used to calculate the weights of partners and their social influence, simultaneously. The proposed model improves the application of TLF in two ways. Firstly, by combing the strengths of BWM with TLF, it integrates the interactions between tangible and intangible criteria into the evaluation and ranking process. Specifically, the weights of criteria collected by BWM will be one of the inputs to calculate the total loss. Secondly, it also integrates decision-makers' relative importance into the TLF calculations. Specifically, the decision-making matrices of potential partners are obtained in accordance with each decision-maker's own individual judgement. The decision-makers' relative importance are then multiplied by the respective decision-making matrix. Ultimately, a comprehensive evaluation matrix is obtained by considering both the weights of the criteria and the decision-makers' relative importance, simltaneously. In this way, the improved TLF can better express preferences irrespective of whether criteria are tangible or intangible, and thereby ensure more effective decision-making.

TLF can be classified into three types, namely one-sided of lower, one-sided of higher and two-sided functions (Pi and Low 2006). These three functions can be respectively termed 'nominal is the best' (Equation 1), 'lower is better' (Equation 2) and 'higher is better' (Equation 3). Function figures are illustrated in Appendix D.

$$L(y) = k(y - m)^2 \tag{1}$$

$$L(y) = k * (y)^2 \tag{2}$$

$$L(y) = \frac{k}{y^2} \tag{3}$$

In this sub-section, the improved TLF is used to measure every partner's performance in terms of risk and benefit categories. The categories are analysed and divided by decision-makers. The specification limit values of indicators are also determined by decision-makers. Therefore, the lower and higher functions are adopted to calculate the loss coefficient (k) of risk and benefit criteria, respectively. Then, the individual Taguchi loss score of each partner is also calculated by Equations (2) and (3). In order to obtain the total Taguchi loss value of every partner, the individual Taguchi loss values of each criterion are multiplied by the criterion weight obtained through BWM. The Taguchi loss scores of the social influence of every partner is then calculated in the same way. Following the above methodology, both the weights of partners and the relative value of their social influence are determined through inverse normalisation of the total Taguchi loss scores.

3.3. Construction of multi-objective programming model

The third stage will determine the optimal partners and their order allocation quantities. It does this through the use of a multi-objective mathematical programing model designed to calculate the lot-sizing of each partner by considering the profitability from investment in long-term partnership.

3.3.1. Construction of sustainable partner selection and order allocation model

The following notations are used:

3.3.1.1. Indices.

i: Index of potential partners of strategic item, for all $i = 1, 2, \ldots, I$.

3.3.1.2. Decision variables.

X_i: Quantity to be ordered from partner i.

Y_i: A binary variable for partner i that is equal to 1 if the partner is selected and 0 otherwise.

Z_i : A binary variable for partner i that is equal to 1 if the partner is selected as long-term partner and 0 otherwise.

There are three decision variables. The binary variable Y_i represents whether to select the partner i. The binary variable Z_i represents whether partner i been selected as a long-term partner which deserves investment. Not all partners are worth investment unless they are long-term strategic partners (Qi, Ahn, and Sinha 2015; Jin et al. 2019). In addition, in business practice, if a long-term relationship has been built, mutual investment is the normal way to stabilise a cooperative relationship between buyers and partners. Thus, in the proposed model, if Y_i is equal to 0, Z_i must be 0, while Z_i may not be 1 when Y_i is equal to 1. Selecting the right strategic partner(s) and building a long-term relationship is a key decision for managers in SSCs.

3.3.1.3. *Parameters.*

I : Total numbers of potential partners.
D : Total demand of strategic product.
W_i: Weights of partner i. (obtained through the improved TLF)
W_i^s : Social influence of partner i (obtained through the improved TLF)
C_i: Maximum capacity of partner i.
P_i: Unit purchasing price of the ith partner.
O_i: Fixed ordering cost of the ith partner.
OC_i: Variable ordering cost of the ith partner.
T_i: Unit transportation cost from the ith partner.
TD_i: Transportation distance from the ith partner.
V_i: Unit return profits rate from the ith partner which has long-term relationship.
q_i: Average defect rate of the ith partner.
d_i: Average delay delivery rate of the ith partner.
G_i: Unit carbon emission while manufacturing process in the ith partner.
Q: Maximum acceptable defect ratio.
R : Maximum acceptable delivery delay ratio.
TG_i: Carbon emissions per unit distance per unit weight during transportation in the ith partner.
m: Unit product weight.
B : Total budget for procurement.
EC : Carbon emission cap.
N : The limited number of partners who are selected as long-term partners.

In short, parameters include the order cost, carbon emission related indicators, shortage rate and delivery delay rate. Combined with the partner weights (W_i) and social influence (W_i^s) discussed in Section 3.2, the proposed multi-objective functions are constructed as below.

3.3.1.4. *Multi-objectives functions.*

We propose six multi-objective functions, which can be divided into two categories. The first three objective functions, Equations (4), (5) and (6), focus on the requirements of the TBL. The last three objective functions Equations (7), (8) and (9), focus on the two dimensions of KPM. In more detail:

Equation (4) aims to minimise the total cost of purchasing, ordering and transportation, and maximise subtracting the profit feedback. Specifically, the first part $P_i{*}X_i$ represents the total purchasing cost of the ith partner. The second part $(O_i{+}OC_i){*}Y_i$ indicates the sum of total fixed ordering cost and variable ordering cost of the ith partner. The third part $T_i{*}X_i$ represents the total transportation cost of the ith partner. The fourth part $V_i{*}X_i{*}Z_i$ expresses the total return profits of the partners which has built the long-term partnership.

$$\text{Min } OB_1(\text{Total Cost}) = \sum_{i=1}^{I}(P_i * X_i + (O_i + OC_i) * Y_i + T_i * X_i - V_i * X_i * Z_i) \tag{4}$$

Equation (5) aims to minimise the carbon emission. More specifically, the first part $G_i{*}X_i$ represents the total carbon emission occurring while manufacturing process in the ith partner. The second part $X_i{*}m{*}TD_i{*}TG_i$ indicates total carbon emission occurring during transportation process from the ith partner.

$$\text{Min}OB_2(\text{Total Carbon emission}) = \sum_{i=1}^{I}(G_i * X_i) + \sum_{i=1}^{I}(X_i * m * TD_i * TG_i) \tag{5}$$

Equation (6) aims to maximise the value of the social influence of partners. In terms of KPM, one direction is the risk of supply and the other is partner value.

$$\text{Max}OB_3(\text{Total Social Value}) = \sum_{i=1}^{I} W_i^s * X_i \tag{6}$$

Equations (7) and (8) are constructed to minimise the risk of supply disruption from defects and delivery delay respectively.

$$\text{Min}OB_4(\text{Total Defect rate}) = \sum_{i=1}^{I} q_i * X_i \tag{7}$$

$$\text{Min}OB_5(\text{Total Delivery delay rate}) = \sum_{i=1}^{I} d_i * X_i \tag{8}$$

Equation (9) tries to maximise the value of the selected partners.

$$\mathrm{Max}OB_6(\text{Total Supplier Value}) = \sum_{i=1}^{I} W_i * X_i \tag{9}$$

3.3.1.5. Operational constraints. Through a comprehensive literature review and analysis of current practices in SSCM, this paper adopts nine operational constraints in the proposed sustainable partner selection and order allocation model. In more detail:

Constraint (10) ensures that the total supply meets the total demand (D).

$$\sum_{i=1}^{I} X_i = D \tag{10}$$

Constraint (11) ensures that total expenditure is under total budget (B).

$$\sum_{i=1}^{I} (P_i * X_i + (O_i + OC_i) * Y_i + T_i * X_i - V_i * X_i * Z_i) \leq B \tag{11}$$

Constraints (12) restricts partner shortage ($Q*D$).

$$\sum_{i=1}^{I} q_i * X_i \leq Q * D \tag{12}$$

Constraint (13) restricts late delivery ($R*D$).

$$\sum_{i=1}^{I} d_i * X_i \leq R * D \tag{13}$$

Constraint (14) ensures that the purchased amount for each partner (X_i) does not exceed its supply capacity (C_i).

$$X_i \leq C_i \forall i \tag{14}$$

Constraint (15) controls the total carbon emissions during the manufacturing and transportation process under the carbon emission cap (EC).

$$\sum_{i=1}^{I} (G_i * X_i) + \sum_{i=1}^{I} (X_i * m * TD_i * TG_i) \leq EC \tag{15}$$

Constraint (16) is the constraint on the total numbers of long-term relationship partners.

$$\sum_{i=1}^{I} Z_i \leq N \tag{16}$$

Constraint (17) ensures that the order quantity is an integer and non-negative.

$X_i \geq 0$ and integer, $\forall i$ (17)

Constraint (18) ensures that decision variables Y_i and Z_i are binary.

$$Y_i,\ Z_i = 0 \mathrm{or} 1, \forall i \tag{18}$$

3.3.1.6. The PSO and its Pareto solutions. In this subsection, the heuristic algorithm, PSO, has been adopted to solve the above multi-objective programming model to obtain the Pareto solutions. There are two main reasons for choosing heuristic algorithms: on the one hand, there are six objective functions and nine constraints in the proposed programing sub-model. It is a NP-hard problem. Therefore, the heuristic algorithm is one of the most appropriate methodologies to solve it. On the other hand, any single solution will not fit for all different decision-making situations and environments. However, a Pareto solution set obtained by the heuristic algorithm combined with an appropriate ranking methodology will give decision-makers more flexibility to identify the most suitable solution from the Pareto solution set according to the different and changing decision-making requirements. The Pareto solutions, as the corollary of the heuristic algorithm, are the presentation of the optimal order quantities. The Pareto solution can also be termed the non-inferior or effective solution. Let x_k^i and v_k^i be respectively the position and velocity of the ith particle in the search field at the kth iteration. The relevant calculation formulae are:

$$v_{k+1}^i = \underbrace{w \cdot v_k^i}_{\text{inertia}} + \underbrace{c_1 \cdot r_1 \cdot (p_k^i - x_k^i)}_{\text{personal influence}} + \underbrace{c_2 \cdot r_2 \cdot (p_k^g - x_k^i)}_{\text{social influence}} \tag{19}$$

$$x_{k+1}^i = x_k^i + v_{k+1}^i \tag{20}$$

where r_1 and r_2 are random numbers from 0 to 1, c_1 and c_2 are constants, p_k^i corresponds to the best location of the ith particle, and p_k^g is the global best location of the kth iteration.

3.3.2. The in-depth analysis of the Pareto solutions

Although the Pareto solutions are all feasible solutions, it is still necessary to identify the most appropriate solution for real business practice. Otherwise, managers would be confused. According to the concept and characteristics of Pareto solution, no set of solution goals can all be the best. TOPSIS is a feasible and effective approach to identify the most appropriate solution (Mohammed, Harris, and Govindan 2019). Accordingly, in this research, the six objectives of each Pareto solution are used as the evaluation criteria of TOPSIS. The key steps are shown as below.

The positive ideal solution A^+ will be sorted by comparing the value of the same indicator for each alternative Equation (21). Similarly, the negative ideal solution A^- is picked out by Equation (22). In the proposed model, A^+ and A^- are the collection of the two maximum objectives (OB_3, OB_6) and the four minimise objectives (OB_1, OB_2, OB_4, OB_5), respectively. $\tilde{v}_n^+$ and $\tilde{v}_n^-$ represent the numerical value of the objectives of each case, respectively.

$$\tilde{A}^+ = \{\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\} \tag{21}$$

$$\tilde{A}^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\} \tag{22}$$

Then, the positive ideal solution d^+ and the negative ideal solution d^- are calculated, where d^+ indicates the distance of each alternatives from the positive ideal solution. On the contrary, d^- indicates the distance from the negative ideal solution.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - v_j^+)^2} \tag{23}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - v_j^-)^2} \tag{24}$$

Using these values, the closeness index C_i for alternatives are obtained by Equation (25). Specifically, C_i means the synthetic distance between the positive ideal solution and the negative ideal solution. The greater the closeness index value, the better the alternative solution of partner selection and optimal order allocation.

$$C_i = \frac{(d_i^-)}{(d_i^+) + (d_i^-)} \tag{25}$$

4. Empirical illustration

As one of the leading LED lamps manufacturers in China, Company Q designs, manufactures and sells high-end LED lamps and solar cells. Gallium arsenide substrate (GAS) is one of the key raw materials for LED lamps. The production of LED lamps is completely dependent on a sustainable supply of GAS, which has a very limited number of partners around China. At the same time, the LED lamp industry has significant potential environmental pollution problems due to the involvement of highly risky chemical materials (e.g. arsenide). Thus, how to achieve sustainable development is a prominent issue for the industry. Moreover, it is very difficult to check the quality of GAS raw material in the initial production phase of LED products manufacturing. The investigation of the quality of LED lamps, for instance for brightness and colour, can only be checked after the manufacturing process. If raw materials have a quality problem, this will result in a great loss of economic value, time, and reputation for Company Q. Therefore, it is vital to select the right partners and build a long-term partnership with excellent partners. With these goals in mind, Company Q requires an effective and efficient decision-making process and procurement solution.

According to the above decision-making requirements, the decision-making group identify six potential GAS partners (S_1, S_2, S_3, S_4, S_5 and S_6). They are all large domestic core producers of GAS. Specifically, in terms of market share, S_2 and S_3 have largest share, with an average of 33%, while S_4 and S_6 have smallest market share. From the technical level, S_2 and S_3 are two partners with similar technologies and are in the leading position. In terms of transportation distance, S_3 and S_5 are geographically closer to Company Q, which gives advantages in transportation costs and time. In terms of capacity, S_2 and S_5 can supply large quantities of GAS in a short time period. The step by step application process of the proposed model is shown as below.

4.1. Calculation of relative importance of decision-makers and weight of criteria

4.1.1. The relative importance of decision-makers

Company Q assembled a decision-making team of five senior executives, which is in accordance with the findings of Rezaei (2016), who point to the need for between 4 and 10 experts to obtain reliable data for MCDM analysis. In order to ensure high quality decision-making, the five members of the decision-making team were drawn from different levels and different functional departments and had different experience, education background, and professional expertise. They were DM_1 the Vice-General Manager, who has a comprehensive understanding of the Company, DM_2 the Director of Purchasing Department, who is familiar with the potential partners, DM_3 one of Managers in the Purchasing Department, who is responsible for the GAS raw material sourcing, DM_4 is Director of the Production Department, who has a deep understanding of the LED lamp production process, and DM_5 a Quality Supervisor, who has expertise in quality management.

The different characteristics of heterogeneous group decision-making have a great influence on results (Govindan and Sivakumar 2016). Thus, it is important and necessary to evaluate the different decision-makers first and give them correspondingly different weights in the decision-making process. The linguistic evaluation scale (showed in Appendix E) was applied to measure their total working experience, working experience in Company Q, their position in the company, and their educational background. A five-point Likert scale

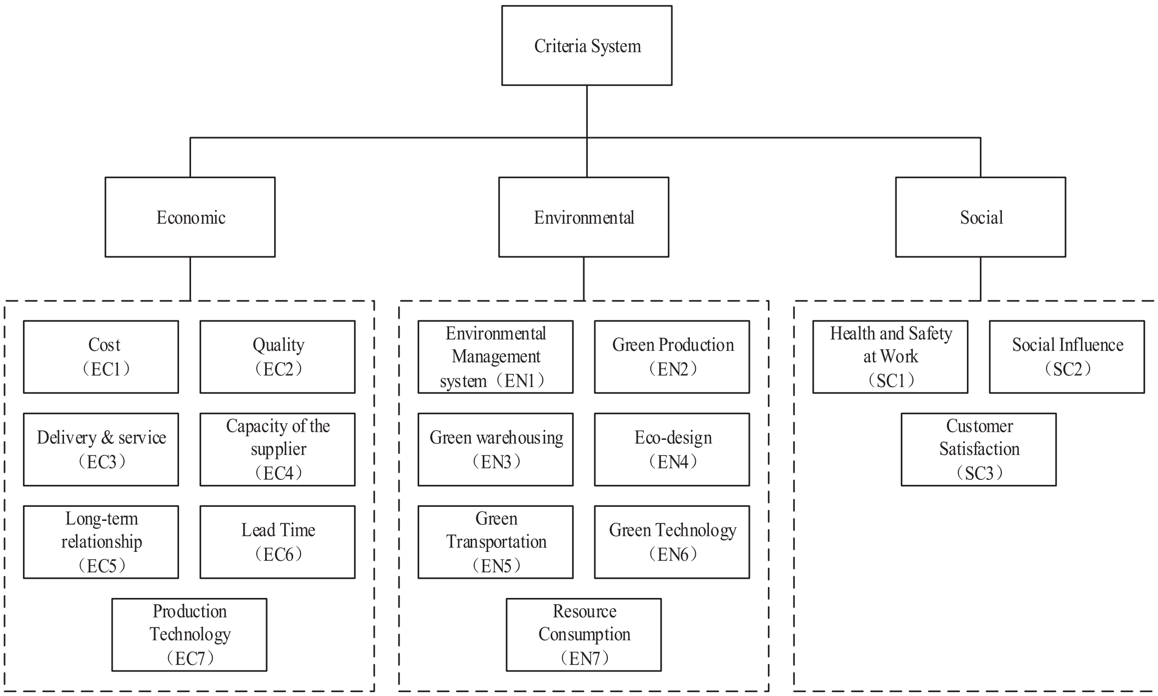

Figure 2. The sustainable criteria system for GAS partner selection of Company Q.

Table 2. The different chararcteristics and relative importance of decision-makers.

	DM_1	DM_2	DM_3	DM_4	DM_5
Total working experience	VH	H	H	H	H
Experience in this company	VH	H	H	M	H
Position	VH	H	M	M	L
Education background	H	M	M	M	M
Defuzzified weight	0.75	0.6	0.6	0.45	0.45
Normalised weight	0.26	0.21	0.21	0.16	0.16

was used to quantify the different characteristics of the decision-makers. Following the methodology proposed in Section 3.1.1, TrFN method was used to calculate the relative importance of the different decision-makers. Both inputs and results are showed in Table 2.

4.1.2. The weights of criteria

A list of 20 criteria (Appendix F) were identified from the literature on sustainable partner selection, for further consideration. Then, the Delphi method was used to determine the applicability of these criteria for GAS raw material partner selection in Company Q. Finally, 17 criteria were validated for use (Figure 2).

BWM was then used to calculate the weights of each criteria according to the process described in Section 3.1.2. Lingo 11 was used as the platform for the BWM calculation process. The score of the best master criterion relative to the other master criterion for Company Q and the score of the other master criterion relative to the worst criterion are presented in Appendix G. In the same way, the ratings of sub-criteria for economic, environmental and social factors are shown in Appendix H to J. Finally, the weights of each criteria (shown in Table 3) are calculated based on Appendix G to J.

Table 3. Weights of main and sub-criteria.

Main criteria	Local Weights Main criteria	Sub-Criteria	Local Weights Sub-Weight	Global weights
Economic (EC)	0.62	EC_1	0.28	0.17
		EC_2	0.23	0.14
		EC_3	0.03	0.02
		EC_4	0.20	0.12
		EC_5	0.07	0.04
		EC_6	0.09	0.06
		EC_7	0.10	0.06
Environment (EN)	0.29	EN_1	0.25	0.07
		EN_2	0.19	0.06
		EN_3	0.08	0.02
		EN_4	0.11	0.03
		EN_5	0.03	0.01
		EN_6	0.14	0.04
		EN_7	0.20	0.06
Society (SC)	0.09	SC_1	0.07	0.01
		SC_2	0.30	0.03
		SC_3	0.63	0.06

4.2. Decision on weight of potential partners and their social influence

In order to apply TLF to calculate the weights of potential partners, a decision-making matrix first needs to be constructed. The decision-making matrix is generated by

Table 4. The comprehensive decision matrix.

Partner	EC_1 min	EC_2 max	EC_3 max	EC_4 max	EC_5 max	EC_6 min	EC_7 max	EN_1 max	EN_2 max	EN_3 max	EN_4 max	EN_5 max	EN_6 max	EN_7 min	SC_1 max	SC_2 max	SC_3 max
S_1	3	79	80	79	79	3	80	82	81	76	79	80	79	2	80	79	77
S_2	3	88	90	90	93	2	89	84	84	83	83	85	86	2	84	86	90
S_3	3	81	84	81	85	2	83	82	84	82	83	81	82	3	83	82	82
S_4	2	79	84	79	83	2	79	83	83	79	81	82	79	3	82	84	81
S_5	4	90	87	86	88	2	87	88	86	83	82	82	86	3	86	85	83
S_6	5	83	79	77	80	4	84	89	87	84	84	80	84	2	87	89	79

Table 5a. Specification limits and range values for benefit criteria.

Criteria	Weights of criteria	Desired value (%)	Range (%)	Specification limit (%)	Loss coefficient (k)
EC_2	0.14	100	95–100	95	90.25[a]
EC_3	0.02	100	85–100	85	72.25
EC_4	0.12	100	90–100	90	81.00
EC_5	0.04	100	90–100	90	81.00
EC_7	0.06	100	95–100	95	90.25
EN_1	0.07	100	95–100	95	90.25
EN_2	0.06	100	90–100	90	81.00
EN_3	0.02	100	80–100	80	64.00
EN_4	0.03	100	85–100	85	72.25
EN_5	0.01	100	70–100	70	49.00
EN_6	0.04	100	85–100	85	72.25
SC_1	0.01	100	80–100	80	64.00
SC_2	0.03	100	90–100	90	81.00
SC_3	0.06	100	95–100	95	90.25

Note: $^{a}L(X_1) = k_1 * X_1^2$; where L = 100 (Taguchi loss at the lower specification limit) and $X_1 = 0.65$ (Lower specification limit set by decision-makers). Thus, k_1 =100∗(0.95^2) = 90.25.

Table 5b. Specification limits and range values for risk criteria.

Criteria	Weights of criteria	Desired value (%)	Range (%)	Specification limit (%)	Loss coefficient (k)
EC_1	0.17	0	0–90	90	123.46[a]
EC_6	0.06	0	0–70	70	204.08
EN_7	0.06	0	0–80	80	156.25

Note: $^{a}L(X_1) = k_1/Y_1^2$; where L = 100 (Taguchi loss at the upper specification limit) and $Y_1 = 0.90$ (Upper specification limit set by decision-makers). Thus, k_1 =100 / (0.95^2) = 123.46.

the individual evaluation of each decision-maker in the decision-making team. Then, the individual evaluations are integrated with the decision-makers' weights (shown in Table 2). The final decision-making matrix is presented in Table 4.

The next step is to categorise each criterion as either a benefit or a risk, and to obtain the specification constraints and range of each criterion. According to the concepts of TLF, the higher the score, the better the quality. The higher the score, the smaller the loss. Therefore, all the higher scoring criteria belong to the benefit category, and vice versa. The normative specification constraints are shown in Tables 5a and 5b according to the discussions of the decision-making team. The unilateral loss functions with minimum specification constraints are used to assess the loss of the benefit criteria and unilateral loss functions with maximum specification constraints are used to assess the loss of the risk criteria. In more details, the Loss coefficient (k) of each benefit criterion is calculated by Equation (2), whereas, the Loss coefficient (k) of each risk criterion is calculated by Equation (3). Finally, in order to obtain the total value of each partner's loss, the value of each partner's loss is multiplied by the criteria weights obtained by BWM in Section 4.1. The total loss value of each partner is shown in Table 6.

To obtain the weights of the six potential partners and the weights of the social influence of each, the total loss scores need first to be normalised and then the rating value of the partner with the minimum Taguchi loss score to be maximised. The calculation process and results are both shown in Tables 7a and 7b .

4.3. Solutions of the multi-objective order allocation programming model

In the third stage, the optimal solution is determined by using the multi-objective order allocation programming model with the weights of partners and their social influence. Relevant parameters are shown in Appendix K. In addition, according to the market competition and requirements of Company Q, the number of long-term partners is taken to be no more than two.

MATLAB 2019a is used as the platform to programme the proposed model (Equations 4–18). The heuristic algorithm PSO is applied to solve the proposed model. The programming results are summarised in Table 8. Each case in Table 8 represents a Pareto solution, which contains rich decision-making support information for Company Q. (Two comparative analyses between PSO and traditional genetic algorithm are shown in Appendix L and M to compare their relative effectiveness and efficiency.)

The final step is to undertake an in-depth analysis of the Pareto solutions and find the most appropriate solution for Company Q. As discussed in Section 3.3.2, the six goals of each Pareto solutions were seen as the TOPSIS evaluation criteria. Then, decision-makers can find the most appropriate solution which is closest to the ideal solution. The result is shown in Table 9. The in-depth

Table 6. Overall calculation results of TLF.

Partner	Individual loss score of criteria																	Total loss score
	EC_1	EC_2	EC_3	EC_4	EC_5	EC_6	EC_7	EN_1	EN_2	EN_3	EN_4	EN_5	EN_6	EN_7	SC_1	SC_2	SC_3	
S_1	12.31148	0.00015	0.00011	0.00013	0.00013	14.70405	0.00014	0.00013	0.00012	0.00011	0.00012	0.00008	0.00012	9.56111	0.00010	0.000130	0.00015	3.51240
S_2	8.89504	0.00012	0.00009	0.00010	0.00009	11.96224	0.00011	0.00013	0.00011	0.00009	0.00011	0.00007	0.00010	8.76472	0.00009	0.000108	0.00011	2.72010
S_3	8.21107	0.00014	0.00010	0.00012	0.00011	10.94465	0.00013	0.00013	0.00011	0.00010	0.00011	0.00007	0.00011	10.39214	0.00009	0.000119	0.00013	2.63899
S_4	6.32331	0.00014	0.00010	0.00013	0.00012	8.59856	0.00014	0.00013	0.00012	0.00010	0.00011	0.00007	0.00012	15.06666	0.00009	0.000116	0.00014	2.45148
S_5	20.27632	0.00011	0.00010	0.00011	0.00011	9.04517	0.00012	0.00012	0.00011	0.00009	0.00011	0.00007	0.00010	13.09297	0.00009	0.000112	0.00013	4.78416
S_6	32.17742	0.00013	0.00011	0.00014	0.00013	32.65306	0.00013	0.00011	0.00011	0.00009	0.00010	0.00008	0.00010	5.30211	0.00008	0.000102	0.00015	7.71565
Weights	0.17	0.14	0.02	0.12	0.04	0.06	0.06	0.07	0.06	0.02	0.03	0.01	0.04	0.06	0.01	0.03	0.06	

Table 7a. The potential partner's weights.

Partner	Total loss score	Inverse value	Partners' weights (W_i)
S_1	3.51239820	0.28471	0.160
S_2	2.72010329	0.36763	0.207
S_3	2.63898616	0.37893	0.213
S_4	2.45148425	0.40792	0.229
S_5	4.78416163	0.20902	0.118
S_6	7.71565104	0.12961	0.073
Total inverse		1.77782	

Table 7b. The potential partner's social influence.

Partner	Total loss score	Inverse value	Social influence (W_i^s)
S_1	0.000130	7694.675285	0.146
S_2	0.000108	9220.491775	0.175
S_3	0.000119	8386.703601	0.159
S_4	0.000116	8624.000547	0.164
S_5	0.000112	8952.922267	0.170
S_6	0.000102	9813.740980	0.186
Total inverse		52692.53446	

analysis shows that case #1 is the most appropriate Pareto solution. In other words, Company Q should purchase GAS from S_2, S_3 and S_5, with optimal order quantities 800k, 600k and 800k, respectively. Company Q should build long-term partnership with partner S_3 and S_5.

5. Sensitivity analysis

This section undertakes three sensitivity analyses from different perspectives to verify the effectiveness of the proposed model and to reveal interesting findings.

5.1. Sensitivity analysis of the weights of decision-makers

The first sensitivity analysis compares the weights of different potential partners in two different scenarios. Scenario #1 (in Figure 3) considers the weight given by the experts, whereas scenario #2 does not. As shown in Figure 3, there are significant differences between these two scenarios. In more detail, the weights of S_1, S_3 and S_4 in Scenario #1 are higher than their weights in Scenario #2, and the weights of other three partners are just the reverse. In the real business practice of Company Q, especially in the order allocation phase, these differences will directly affect the results of partner selection and optimal order allocation. Figure 4 shows the illustrative results of partner selection and optimal order quantities in accordance with the different weights shown in Figure 3. We can see not only that the optimal order quantities are impacted, but also the partner selection decision-making is changed. Furthermore, considering the rankings of potential partners by the five decision-makers individually, the results of each decision-maker are totally different from each other (shown in Figure 5).

Table 8. The Pareto solutions of the programming model.

	Order quantity (unit: 100k)						Long-term investment						Objective values					
	x1	x2	x3	x4	x5	x6	z1	z2	z3	z4	z5	z6	OB_1	OB_2	OB_3	OB_4	OB_5	OB_6
Case1	0	8	6	0	8	0	0	0	1	0	1	0	3794.9	2.89	4.20	0.42	1.28	4.40
Case2	0	8	0	4	8	2	0	1	0	0	0	1	4187.9	3.31	3.48	0.42	1.58	4.50
Case3	4	10	8	0	0	0	0	1	1	0	0	0	3795.8	3.01	4.3	0.54	1.54	3.86
Case4	3	7	5	0	7	0	0	1	1	0	0	0	3961.9	2.86	4.00	0.435	1.40	4.27
Case5	4	9	8	0	0	1	0	1	1	0	0	0	4012.9	2.95	4.27	0.54	1.64	3.76
Case6	4	0	0	5	10	3	0	0	0	0	1	1	4275.8	2.65	3.24	0.435	1.95	3.99

Table 9. The selection of most appropriate Pareto solutions.

	d+	d_	c	
Case1	0.040000801	0.238130844	0.856180333	Best
Case2	0.415203806	0.146073527	0.260251962	
Case3	0.424474569	0.151896654	0.263539622	
Case4	0.448452793	0.188554033	0.296000019	
Case5	0.402483929	0.132710615	0.247967056	
Case6	0.345271417	0.124856721	0.265580192	

As illustrated in the three figures, we can conclude that: (1) The assignment of weights amongst the different decision-makers is one of the key decision-making steps in partner selection and order allocation. (2) It is necessary to undertake group decision-making, as the proposed model, to avoid the bias of any single decision-maker.

5.2. Sensitivity analysis of the quantity and combination of objectives

The second sensitivity analysis varies the number and combination of preferable objectives in the final Pareto solution analysis process to observe the potential impact of different goal orientations on the final decision. As Table 10 shows, the rankings of most appropriate Pareto solutions varies when different objectives (OB_1 through OB_6) are considered. According to Table 10, OB_1, OB_4 and OB_5 all point to C_1 as the most approporiate solution, whilst OB_2, OB_3 and OB_6 point to different cases, respectively. Accordingly, based on the above results, this paper introduces the concept of homogeneity and heterogeneity in objectives. Specifically, OB_1, OB_4 and OB_5 are defined as homogeneous objectives, whilst OB_2, OB_3 and OB_6 are defined as heterogeneous objectives. The mutual influence relationships between these two types of objectives is now further discussed.

Firstly, the influence of a single heterogeneous objective on homogeneous objectives can be analysed to identify relatively weak heterogeneous objectives. From Table 11a we can see that OB_1 cannot affect the optimal direction of OB_3 (scenario #2). However, when OB_1 is combined with other homogenous objectives (scenario #11, #17 and #20), the combination result is same as that of the single OB_1. These results show that the influence of OB_3 is weakened by combinations of multiple homogenous objectives. In addition, from Table 11a, it can also be seen that OB_6 has no influence on homogenous objectives (scenario #3, #6, #9, #12, #15, #18 and #21). In other words, OB_6 is not only a heterogeneous objective but also the weakest influence amongst the six objectives. In general, from Table 11a we can see that homogeneous objectives have a relatively stronger influence than heterogeneous objectives.

Secondly, the influence of a single homogeneous objective on heterogeneous objectives is analysed to identify which key objective is worthy of more attention. From Table 11b, we can see that the most appropriate solution is C_6 when combined with OB_2 and OB_4 (scenario #2). However, when OB_2 is combined with OB_3 and OB_6, the most appropriate solution is C_1 in different scenarios (scenario #11, #17 and #20). Similar phenomena are also shown in OB_3 and OB_6. In other words, when multiple heterogeneous objectives and any single homogeneous objective are combined, the analysis results have increased robustness. In addition, from Table 9b, we can also see that no matter what combination is used, OB_5 will not be dominated by the heterogeneous objectives.

Table 10. Ranking orders of cases with only one objective.

	Different quantity of objectives						
Scenario	OB_1	OB_2	OB_3	OB_4	OB_5	OB_6	Rankings of cases
1	*						$C_1 > C_3 > C_4 > C_5 > C_2 > C_6$
2		*					$C_6 > C_4 > C_1 > C_5 > C_3 > C_2$
3			*				$C_3 > C_5 > C_1 > C_4 > C_2 > C_6$
4				*			$C_1 = C_2 > C_4 = C_6 > C_3 = C_5$
5					*		$C_1 > C_3 > C_4 > C_5 > C_2 > C_6$
6						*	$C_2 > C_1 > C_4 > C_5 > C_3 > C_5$

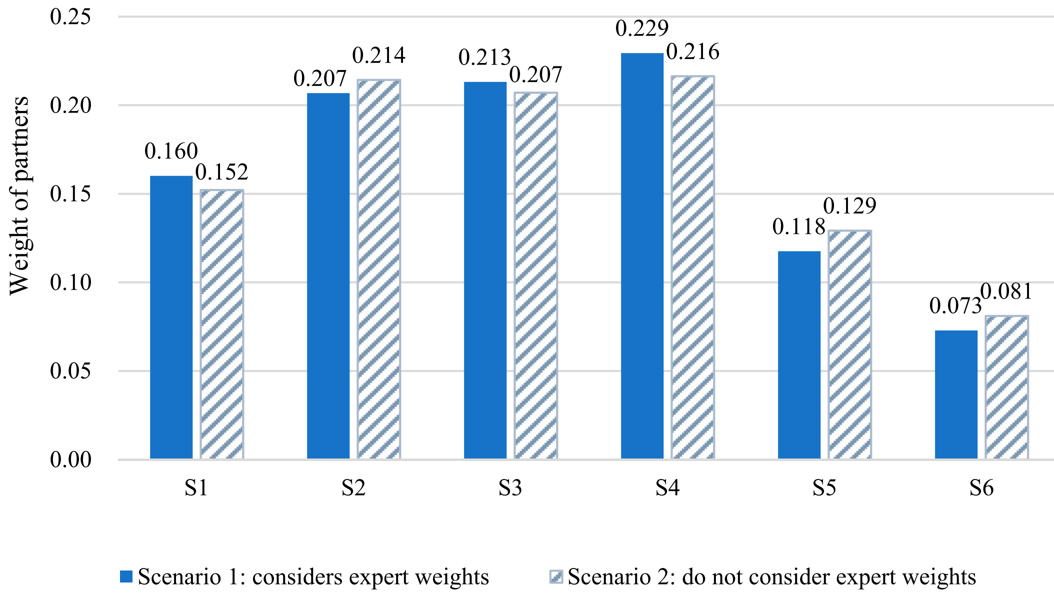

Figure 3. The weights of potential partners in different scenarios.

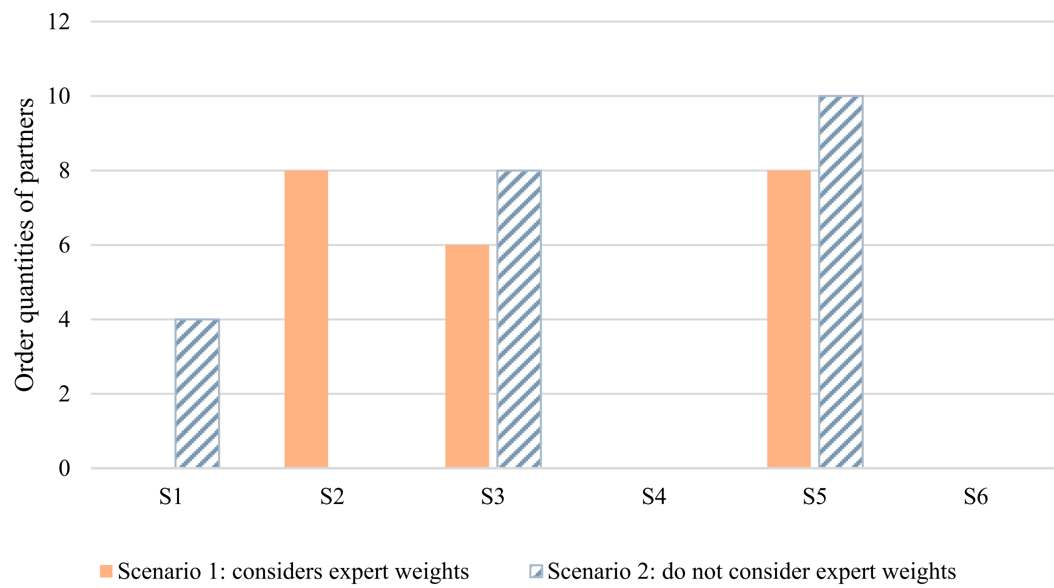

Figure 4. The order quantities of selected partners in different scenarios.

Based on the above analysis we can conclude that: (1) Homogeneous objectives have stronger influence than heterogeneous objectives. Homogeneous objectives will directly affect the final analysis results. (2) Different multi-objective preferences lead to different analysis results. Considering a single target preference alone will seriously affect the accuracy of decision-making. (3) The robustness of decision-making can be improved, not only by considering heterogeneous and homogeneous goals, but also by considering sustainability and strategic items objectives together.

5.3. Sensitivity analysis of the numbers of long-term partners

The third part of the sensitivity analysis conducts in-depth analysis on the numbers of long-term partners chosen for a SSC to observe the potential impact on the different objectives. As Figure 6 shows, the six objectives vary when different numbers of long-term partners are involved. Specifically, from Figure 6(a) and (b) we can see that, there are two opposite trends. As the number of long-term partners increases, the total cost (OB_1)

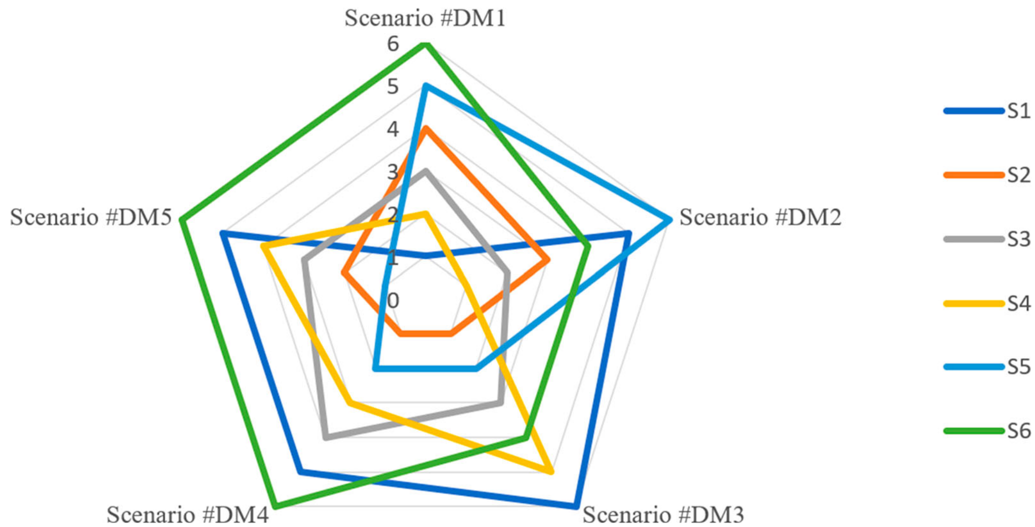

Figure 5. The rankings of potential partners in different scenarios.

Table 11a. The influence of a single heterogeneous goal on homogeneous goals.

Scenario	Different quantity of objectives						The most appropriate solution
	OB_1	OB_4	OB_5	OB_2	OB_3	OB_6	
1	◎			▲			C_1
2	◎				▲		C_3
3	◎					▲	C_1
4		◎		▲			C_6
5		◎			▲		C_1
6		◎				▲	C_2
7			◎	▲			C_1
8			◎		▲		C_1
9			◎			▲	C_1
10	◎	◎		▲			C_1
11	◎	◎			▲		C_1
12	◎	◎				▲	C_1
13		◎	◎	▲			C_1
14		◎	◎		▲		C_1
15		◎	◎			▲	C_1
16	◎		◎	▲			C_1
17	◎		◎		▲		C_1
18	◎		◎			▲	C_1
19	◎	◎	◎	▲			C_1
20	◎	◎	◎		▲		C_1
21	◎	◎	◎			▲	C_1

Note: ◎ represent homogeneous objectives; ▲ represent heterogeneous objectives.

Table 11b. The influence of a single homogeneous goal on heterogeneous goals.

Scenario	Different quantity of objectives						The most appropriate solution
	OB_2	OB_3	OB_6	OB_1	OB_4	OB_5	
1	▲			◎			C_1
2	▲				◎		C_6
3	▲					◎	C_1
4		▲		◎			C_3
5		▲			◎		C_1
6		▲				◎	C_1
7			▲	◎			C_1
8			▲		◎		C_2
9			▲			◎	C_1
10	▲	▲		◎			C_1
11	▲	▲			◎		C_1
12	▲	▲				◎	C_1
13		▲	▲	◎			C_1
14		▲	▲		◎		C_1
15		▲	▲			◎	C_1
16	▲		▲	◎			C_1
17	▲		▲		◎		C_1
18	▲		▲			◎	C_1
19	▲	▲	▲	◎			C_1
20	▲	▲	▲		◎		C_1
21	▲	▲	▲			◎	C_1

Note: ◎ represent homogeneous objectives; ▲ represent heterogeneous objectives.

tends to rise. On the country, the total defect rate (OB_4) and the total delay rate (OB_5) gradually decreases as the number of long-term partners increases. Furthermore, from Figure 6(c) we can see that, unlike the above three objectives which have relatively clear vary trends, the rest of three objectives have four different levels of combinations.

As illustrated in Figure 6, we can conclude that: (1) As the numbers of long-term partners increase, more investments are required. In addition, the bargain power and economic of scale from bigger lot-sizing will decrease when purchasing and allocating orders to a larger number of partners. Therefore, considering the above two factors, the total cost will increase. (2) As the number of long-term partners increases, there are more choices for purchasers when purchasing and allocating orders. Thus, the total defect rate and delay rate may decrease. (3) Similar to other multi-objective programming situations, the Pareto solution cannot be superior in every dimension. Decision-makers have to make trade-offs among

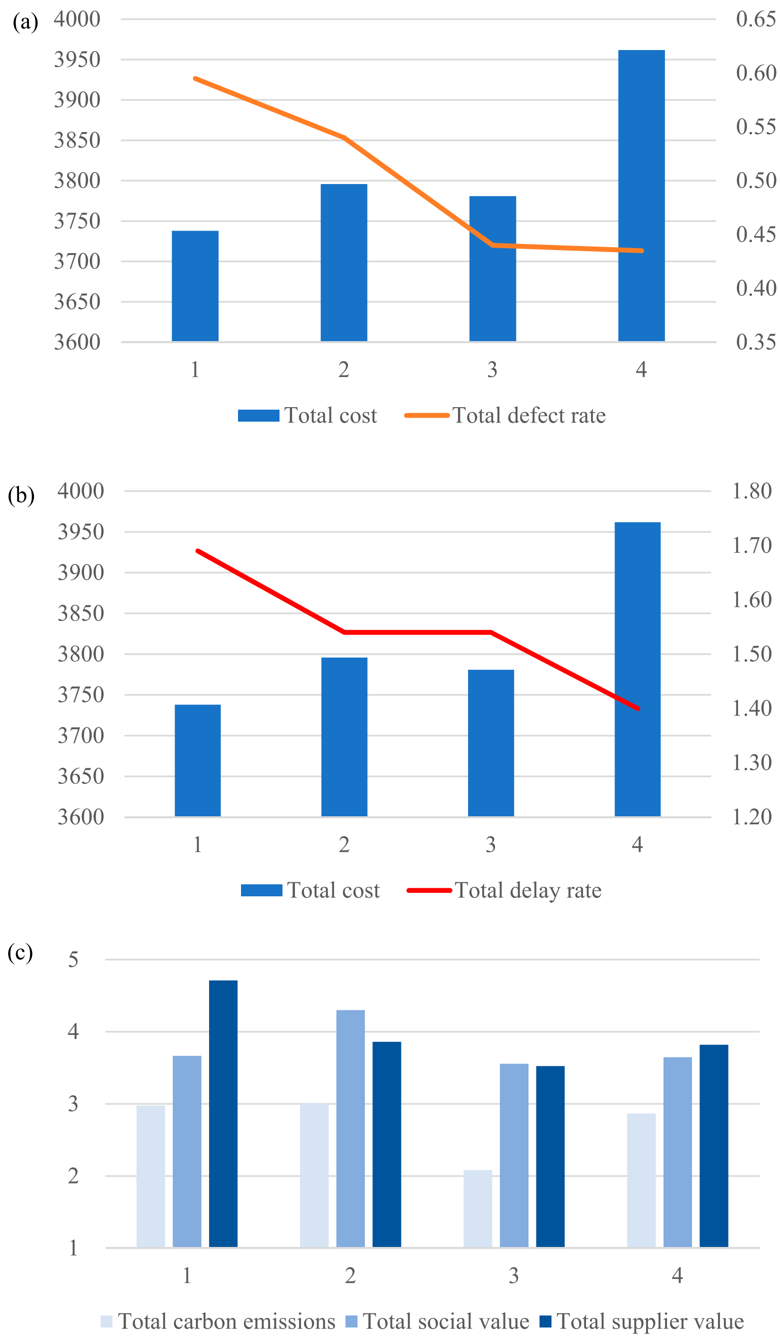

Figure 6. Sensitivity analysis in terms of the numbers of long term partners.

different objectives (e.g. OB_2, OB_3 and OB_6) according to changing market requirements and decision-making environments.

6. Managerial implications

First, from the sensitivity analysis in Section 5.1, it can be seen that group decision-making is more reliable and effective than that of any individual. Every individual decision-maker has their own limitations in information collection, processing and analysis, whereas the diversity of views provided by group decision-making can result in a more effective decision-making. Relying on any single decision-maker will cause large deviation (see Figure 5), resulting in a reduction in validity. Furthermore, without assigning reasonable weights to decision-makers in accordance with their different features, the obtained partner weights will change significantly (e.g. Figure 3), which will then impact the decision-making directly (e.g. Figure 4). Therefore, as for the managers of SSCs, there are two important jobs they have to do. The one is to build an appropriate decision-making team, which constitutes appropriate decision-makers from different levels and different functional departments, as Company Q did (shown in Section 4). The other is to assign appropriate weights to these decision-makers during the decsion-making process, reasonably.

Second, from the sensitivity analysis in Section 5.2, it can be concluded that focusing on different single objective results in different decisions (e.g. Table 10) and selection of the most appropriate Pareto solution is relatively stable when considering multiple objectives (e.g. Table 9). Therefore, managers of SSCs should avoid a single objective preference when selecting the most appropriate Pareto solution. In detail, C_1 is always the most appropriate solution when the homogeneous objective OB_5 combines with other heterogeneous objectives (see Table 11a). Yet, other homogeneous objectives cannot remain stable under the same conditions. Thus, OB_5 is deemed to have great influence in the decision-making system. In contrast, the heterogeneous goal OB_6 does not influence decision-making when combined with other objectives (see Table 11b). Therefore, in practice, the SSC managers in Company Q should pay more attention to the objective of delayed delivery rate (OB_5) as opposed to the objective of partner value (OB_6). When other companies adopt the proposed model, they should also identify the right targets to focus on for their future action plans.

Third, from the sensitivity analysis in Section 5.3, it can be seen that the classic single/multiple sourcing question faced by managers of SSCs is still a big issue, especially during the COVID-19 pandemic era. Sustainable practices have been affected substantially during the pandemic era (Chowdhury et al. 2021) and so managers of SSCs should be proactive in addressing these challenges. Specifically, before the pandemic, managers of SSCs should be prepared for the challenges of interruptions and high delay rate, by, for instance, building multiple long-term partnerships, even though it might mean higher total costs (see Figure 6(b)). During the pandemic, social issues, for instance, issues in health and safety, should receive the highest priority (e.g. scenario #2 in Figure 6(c)). The proposed model has the capability and flexibility to help the managers of SSCs make the right decisions and trade-offs on sustainable partner selection and order allocation for strategic items according to the changing decision-making requirements and situations.

Last but not least, existing literature already points to the need for decision-makers in supply chain management to pay attention to both sustainability and strategic items (e.g. Kusi-Sarpong, Gupta, and Sarkis 2019; Saputro, Figueira, and Almada-Lobo 2021). However, to date, there has been little attention given to them simultaneously. As the empirical illustration and the sensitivity analysis above shows, these two vital decisions can be made effectively and efficiently at the same time. Considering the two decisions together can enhance both the efficiency and effectiveness of decision-making. Making the two decisions stepwise, wastes valuable managerial time and increases management cost. Specifically, considering them simultaneously, enables a global optimal solution (e.g. Tables 8 and 9) to be found rather than a sequence of local optimal solutions.

7. Conclusion

The focus on sustainability and operations is moved from local optimisation to the entire supply chain (Linton, Klassen, and Jayaraman 2007). Partners play a vital role in implementing SSCM and in achieving social, environmental and economic goals (Wu, Lin, and Barnes 2021). This research proposes an integrated multi-stage decision-making model for partner selection and order allocation for strategic items in SSCs, taking both the characteristics of strategic items and the requirements of the TBL into account. The model comprises three stages. In stage I, the relative importance of decision-makers is calculated using TrFN, and the subjective method BWM is then used to calculate the weights of the evaluation criteria. In stage II, the objective approach TLF is used to obtain the weight of partners and their social influence. Thus, a combination of subjective and objective approaches is achieved to make decision-making more reasonable and comprehensive. In stage III, PSO is used to solve the multi-objective programming model and the most appropriate solution is identified from the Pareto solutions by TOPSIS. The effectiveness and applicability of the proposed model was verified in a Chinese leading LED lamps manufacturer.

There are also two main limitations. Firstly, the multi-objective programming sub-model proposed in this research is deterministic without uncertain parameters. Stochastic programming for sustainable partner selection and order allocation for strategic items is also an interesting direction for future research. Secondly, the proposed model focuses solely on strategic items as identified using KPM. It thereby ignores the other three categories of purchased items. Addressing the sourcing and order allocation problem for these items in SSCs requires further research as each different item has different characteristics.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by National Natural Science Foundation of China: [Grant Number 71872155].

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its appendix.

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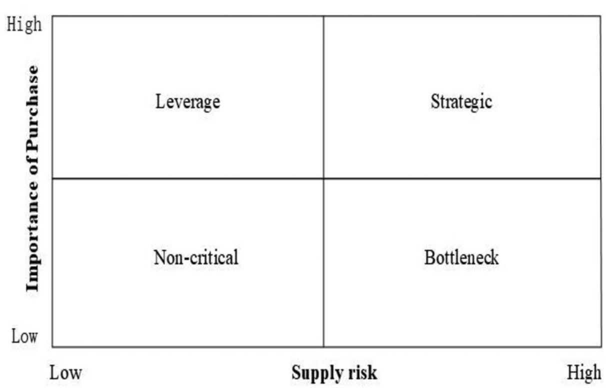
Appendices

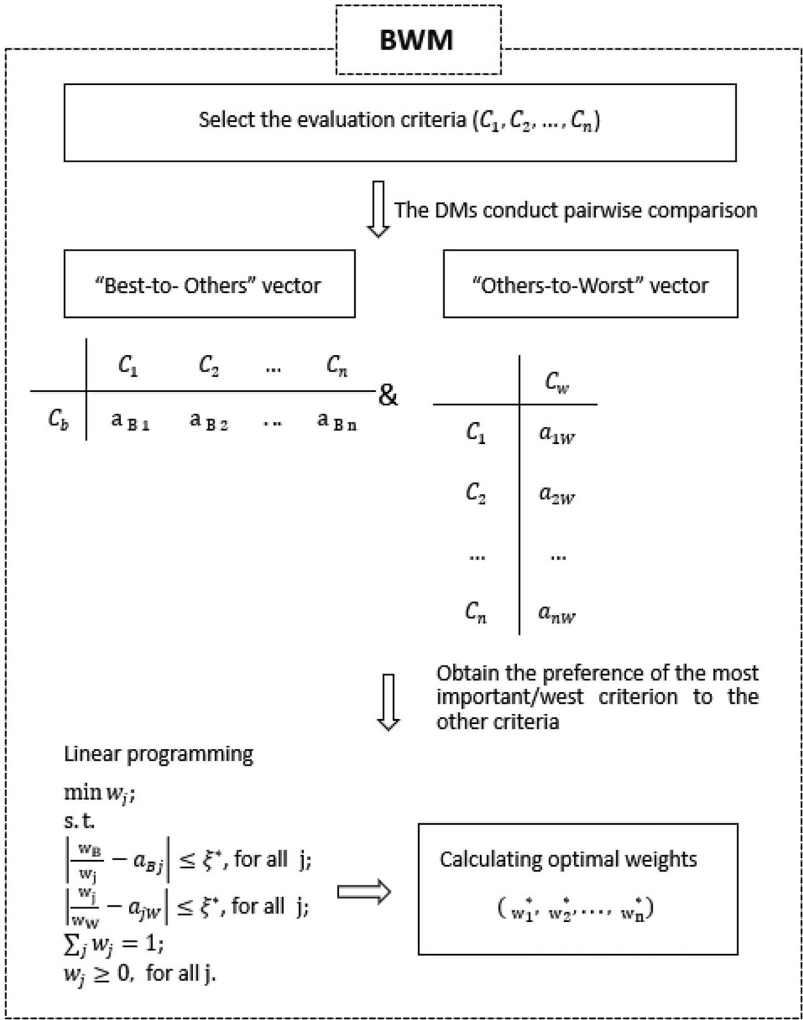
Appendix A. Kraljic Portfolio Matrix (Montgomery, Ogden, and Boehmke 2018).



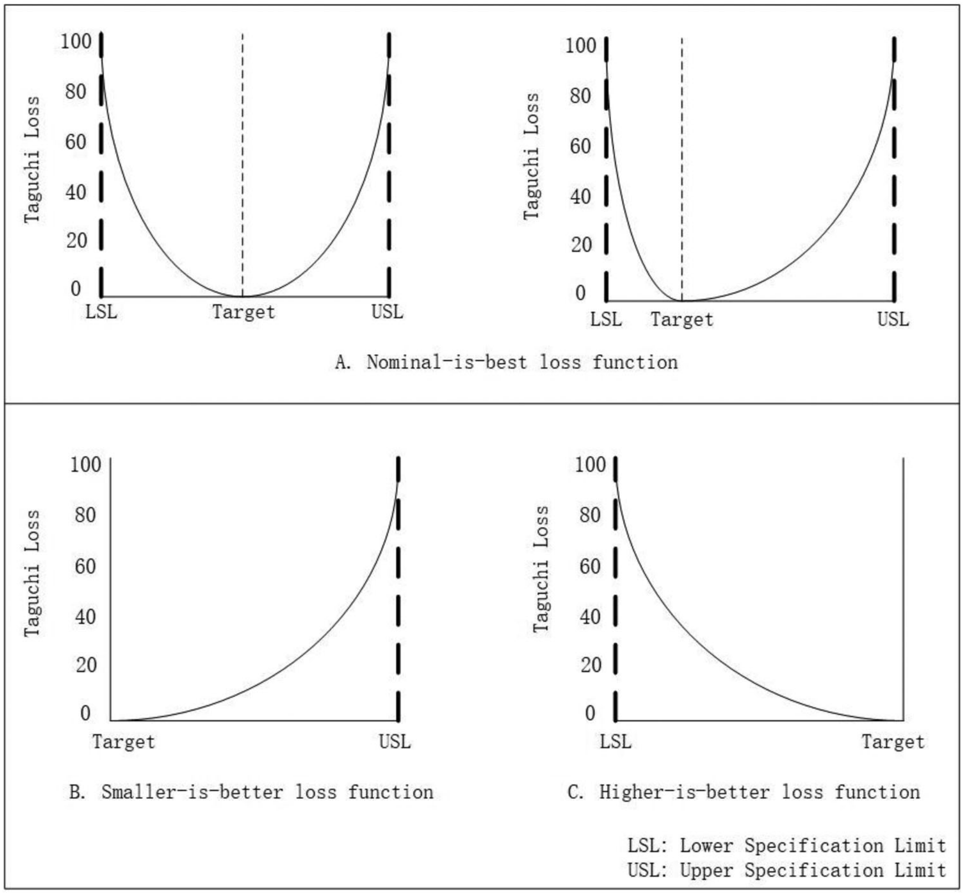
Appendix B. The rules of TrFN.

The evaluations of each attribute	The range of cumulative sum of evaluation values	The corresponding TrFN
X_1, X_2, X_3, X_4	4 ∼ 7	Very Low
X_1, X_2, X_3, X_4	8 ∼ 10	Low
X_1, X_2, X_3, X_4	11 ∼ 13	Medium
X_1, X_2, X_3, X_4	14 ∼ 16	High
X_1, X_2, X_3, X_4	17 ∼ 20	Very High

Appendix C. Overview of BWM methodology (Based on Lo et al., 2018).



Appendix D. Different types of TLF (Based on Gören 2018).



Appendix E. Linguistic variables and TrFN for criteria evaluation.

Variables	Fuzzy numbers
Very high	(0.8, 0.9, 0.9, 1.0)
High	(0.6, 0.7, 0.7, 0.8)
Medium	(0.4, 0.5, 0.5, 0.6)
Low	(0.2, 0.3, 0.3, 0.4)
Very low	(0.0, 0.1, 0.1, 0.2)

Appendix F. The sustainable criteria system for further validation.

TBL	Sub-criteria	References
EC	Cost	Azadnia, Saman, and Wong (2015), Memari et al. (2019)
	Quality	Lo et al. (2018), Memari et al. (2019)
	Delivery & service	Azadnia, Saman, and Wong (2015), Memari et al. (2019)
	Flexibility	Lo et al. (2018), Wu et al. (2020a)
	Capacity of the partner	Azadnia, Saman, and Wong (2015), Gören (2018)
	Long-term relationship	Gören (2018), Wu et al. (2020a)
	Lead time	Gören (2018), Saputro, Figueira, and Almada-Lobo (2021)
	Production technology	Gören (2018), Wu et al. (2020a)
EN	Environmental management system	Kannan et al. (2013), Gören (2018)
	Green production	Lo et al. (2018), Wu et al. (2020a)
	Green warehousing	Wu et al. (2020a)
	Eco-design	Kannan et al. (2013), Wu et al. (2020b)
	Green transportation	Lo et al. (2018), Wu et al. (2020a)
	Green technology	Dai and Blackhurst (2012), Wu et al. (2020b)
	Resource consumption	Gören (2018), Wu et al. (2020b)
SC	Human rights	Yawar and Seuring (2015)
	Health and Safety at Work	Yawar and Seuring (2015), Wu et al. (2020b)
	Supportive activities	Dai and Blackhurst (2012), Memari et al. (2019)
	Social influence	Wu et al. (2020a)
	Customer satisfaction	Dai and Blackhurst (2012), Wu et al. (2020a)

Appendix G. TBL criteria pairwise comparisons.

BO	Economic (EC)	Environmental (EN)	Social (SC)
Best criterion: Economic (EC)	1	3	6
OW	Worst criterion: Social (SC)		
Economic (EC)	6		
Environmental (EN)	4		
Social (SC)	1		

Appendix H. Pairwise comparisons for Economic sub-criteria.

BO	EC_1	EC_2	EC_3	EC_4	EC_5	EC_6	EC_7
Best criterion: EC_1	1	3	8	4	7	3	6
OW	Worst criterion: EC_3						
EC_1	8						
EC_2	6						
EC_3	1						
EC_4	5						
EC_5	6						
EC_6	5						
EC_7	7						

Appendix I. Pairwise comparisons for Environmental sub-criteria.

BO	EN_1	EN_2	EN_3	EN_4	EN_5	EN_6	EN_7
Best criterion: EN_1 EN_2	1	1	3	3	8	3	2
OW	Worst criterion: EN_5						
EN_1	8						
EN_2	6						
EN_3	4						
EN_4	5						
EN_5	1						
EN_6	6						
EN_7	7						

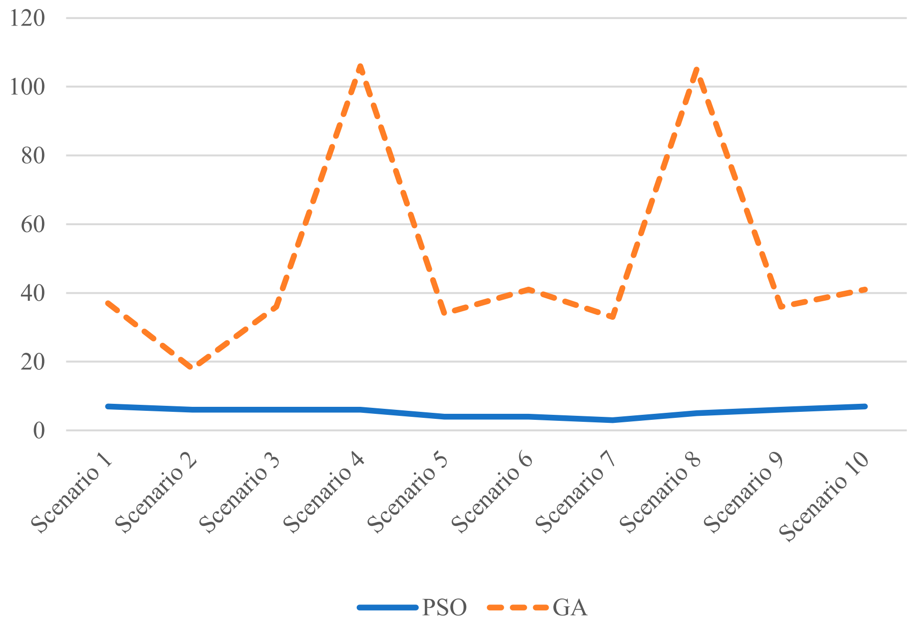
Appendix J. Pairwise comparisons for Social sub-criteria.

BO	SC_1	SC_2	SC_3
Best criterion: SC_3	8	3	1
OW	Worst criterion: SC_1		
SC_1	1		
SC_2	5		
SC_3	8		

Appendix K. The data of relevant parameters of Company Q.

Parameters	Parameters data
D	22
B	5000
Q	0.035
R	0.2
EC	4
D	22
m	11.9
P_i	116, 118, 116, 114, 123, 155
O_i	114, 116, 114, 109, 118, 135
OC_i	2, 2, 2, 5, 5, 20
T_i	56, 45, 25, 45, 38, 70
G_i	0.0038, 0.0054, 0.0041, 0.004, 0.0065, 0.0067
TG_i	0.00017, 0.00037, 0.0002, 0.00023, 0.00023, 0.00017
TD_i	56, 45, 25, 45, 38, 70
q_i	0.025, 0.02, 0.03, 0.035, 0.01, 0.02
d_i	0.1, 0.05, 0.08, 0.12, 0.05, 0.15
C_i	4, 10, 8, 5, 10, 13
W_i	0.160, 0.207, 0.213, 0.229, 0.118, 0.073
W_i^s	0.146, 0.175, 0.159, 0.164, 0.170, 0.186
V_i	0.003, 0.007, 0.004, 0.013, 0.009, 0.014

Appendix L. Comparative analysis of the numbers of Partro solutions.



Appendix M. Comparative analysis of the CPU Time.