Fostering supply chain resilience for omni-channel retailers: A two-phase approach for supplier selection and demand allocation under disruption risks

Shaohua Song[a,b], Elena Tappia[c], Guang Song[d*], Xianliang Shi[b], T.C.E. Cheng[e]

[a] Department of Decision Sciences, School of Business, Macau University of Science and Technology, Macau, China

Address: Avenida Wai Long Taipa Macau, China

[b] School of Economics and Management, Beijing Jiaotong University, Beijing, China

Address: No.3 Shangyuancun, Haidian District, Beijing, China

[c] Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Milan, Italy

Address: Via Raffaele Lambruschini 4/b, Milano, Italy

[d] National Academy of Economic Security, Beijing Jiaotong University, Beijing, China

Address: No.3 Shangyuancun, Haidian District, Beijing, China

[e] PolyU Business School, The Hong Kong Polytechnic University, Hong Kong, China

Address: 11 Yuk Choi Rd, Hung Hom, Hong Kong, China

Email addresses: songshaohua826@gmail.com (Shaohua Song), elena.tappia@polimi.it (Elena Tappia), songguang@bjtu.edu.cn (Guang Song), xlshi@bjtu.edu.cn (Xianliang Shi), edwin.cheng@polyu.edu.hk (T.C.E. Cheng)

Corresponding author: Guang Song (songguang@bjtu.edu.cn, +86 13811470052)

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Abstract

This study aims to optimize supplier selection and demand allocation decisions for omni-channel (OC) retailers to achieve supply chain resilience under the potential disruption risks. A two-phase approach with resilience factors that covers three main sourcing issues (i.e., supplier evaluation, supplier selection, and demand allocation) is proposed to support the decision-making. In the first phase, we construct a five-dimensional evaluation framework for OC retailers to identify supplier preferences and a hybrid model that combines the best–worst method to determine the weights of the evaluation criteria and evidential reasoning to evaluate potential suppliers. In the second phase, the preferences obtained from multiple suppliers are integrated into a multi-objective mixed-integer linear programming model aiming to minimize expected cost and maximize total purchasing value and geographical segregation based on three key resilience strategies of multiple sourcing, geographic diversification, and local sourcing. The efficiency of the aforementioned resilience strategies as well as the solvability of the proposed model are then validated numerically using a real-world case study and various MOEAs. The outcomes could be used as a decision-making tool to assist OC retailers in the performance assessment and optimal demand allocation among the alternative suppliers by considering costs, purchase value, and resilience simultaneously.

Keywords: supply chain resilience; supplier selection and demand allocation; disruption risks; omni-channel retailing

1. Introduction

In contemporary omni-channel retailing (OCR) businesses, retailers continuously strive to improve efficiency and resilience across channels (Caro et al., 2020). In particular, retailers seek strategic alliances within supply chains to manage the diversified daily demand and foster supply chain resilience (SCR) when navigating increasing supply chain complexity and various sources of inherent supply chain disruption risks caused by the multitude of channels (Alikhani et al., 2021). Some researchers have claimed that the ability to ensure product availability and mitigate disruption risks is dependent on efficient and effective relationships between omnichannel (OC) retailers and suppliers (Deloitte, 2021). Therefore, supplier selection to meet the company's strategic goals has a significant role in ensuring that retailers are more competitive (Hosseini et al., 2022).

As a traditional topic of supply chain management, supplier selection is primarily based on cost (Hosseini et al., 2022); however, in the era of economic globalization, modern supply chains now have an increased probability of disruption risks and resilience to ensure continuous operations must also be considered simultaneously (e.g., Namdar et al., 2018). The retail sector has a key role in communities' sustainability and livability, and retailers must take responsibility for responding to disruptions in their entire supply chain (Solomon et al., 2021). Thus, OC retailers are required to fully embed the concept of resilience in supplier management to survive and grow under such circumstances.

Although the importance of managing supply chain disruptions and selecting suitable suppliers for OC retailers has been recognized and examined in previous research, the problem has not yet been fully addressed. Most of the research on OCR consider the front-end of the supply chain, e.g., promotion and pricing, whereas there are very few studies on the back-end SCM (e.g., Kembro and Norrman, 2019). Existing studies have focused on supplier evaluation and selection for traditional retailers (e.g., Solomon et al. al., 2021) or pure online retailers (e.g., Kaushik et al., 2022) without simultaneously considering the characteristics of the OC business and various potential disruption risks. For example, to realize the vision of "buy anywhere, ship from anywhere" in the OC system, suppliers face various demands from different delivery channels (e.g., delivery from a warehouse, delivery from a physical store, and drop-shipping) and are located in diversified geographical regions to connect with consumers (Cai and Lo, 2020, Melacini et al., 2018). Therefore, in the OCR context, when managing suppliers, retailers must consider the demand from different channels and the impact of geographical locations as there are considerable geographically induced differences in consumer behavior, supply cost, and risk events (Agrawal et al., 2022). Although previous studies on supplier selection have considered disruption risks (e.g., PrasannaVenkatesan and Goh, 2016) and resilience factors (e.g., Namdar et al., 2018), the relevant mathematical models still lack comprehensive investigation of OC retailers' business process and main resilient supply strategies when selecting suppliers (i.e., multiple sourcing, geographical diversification and local sourcing).

Given the research gap, our research objective is to propose a two-phase approach to examine the supplier selection and demand allocation (SS&DA) problem considering OC retailers in a context of disruption risks. Specifically, the first phase develops a supplier evaluation model for the OC retailer to identify supplier preference by combining the best–worst method and evidential reasoning (BWM-ER). The evaluation consists of five dimensions, including product and service quality, cost, resilience capability, human capital, and digitalization. In the second phase, since purchasing under disruption risks is a challenging task as it involves tradeoffs among cost, purchase value, and geographical segregation (GS) to reduce geographically induced disruption risks, we construct a multi-objective mixed-integer linear programming (MILP) model to determine the optimal solution for SS&DA, where multiple sourcing, geographic diversification, and local sourcing are the primary resilient supply strategies.

Differently from existing SS&DA approaches, ours (i) incorporates the resilience factor, by considering the resilience capability in the supplier evaluation stage, and using GS as one of the objective functions in the optimization modeling, (ii) distinguishes disruption risks, suppliers, and costs according to geographical locations, (iii) captures the characteristics of the OC supply process (i.e., providing homogeneous products for multiple channels and allowing cross-channel delivery under disruption risks), and (iv) jointly models the main resilience strategies when selecting suppliers (i.e., multiple sourcing, geographic diversification, and local sourcing).

The main research contributions of our study are as follows:

- A two-phase approach is proposed to solve the SS&DA problem in OCR under disruption risks focusing on the front-end of the supply chain. In the first phase, we develop a supplier evaluation model comprising five dimensions for the OC retailer to evaluate suppliers. In the second phase, we formulate the SS&DA problem as a multi-objective MILP model for solution, which captures different types of delivery modes according to the OC paradigm, and different potential disruption risks and risk mitigation strategies that the OC retailers may adopt.
- Geographical locations are taken into consideration, distinguishing geographically-related suppliers, types of disruption risks, and objectives. Specifically, we divide suppliers into local and regional suppliers that are located outside the retailer's region, and model disruption risks at the super, regional, and local levels. Meanwhile, we include suppliers' geographical segregation in the multi-objective function of the optimization model.

- Applying the proposed two-phase approach to solve the SS&DA problem of an OC retailer in China, we illustrate the application process of the proposed approach in real practice and provide some interesting observations.

We organize the remainder of this paper as follows. Section 2 reviews the related literature on the SS&DA problem and identifies the research gap. Section 3 introduces the proposed two-phase approach for solving the SS&DA problem. Section 4 details the results of applying the approach to solve the SS&DA problem of an OC retailer in China, and Section 5 performs several test problems to validate the proposed model and algorithms. Finally, Section 6 concludes the paper, suggesting topics for future research.

2. Literature review

Our paper is primarily related to the quantitative research literature on SS&DA under the multiple sourcing strategy. The model developed in our paper is also related to the literature on resilience strategies applied by buyers when purchasing. Therefore, we review these issues, specifically those papers which are essential in building up our model.

In the context of supply chain disruption management, improving SCR from the perspective of sourcing is critical because stable upstream supply is the key to maintaining supply chain continuity (e.g., Namdar et al., 2018). Diversification, in which a buyer simultaneously orders from multiple suppliers, is an important sourcing strategy for managing yield risk and improving resilience, and it has been widely studied in the literature. For example, Whitney et al. (2014) showed that supplier diversification was the preferred way to reduce supply chain disruption risks. Solomon et al. (2021) claimed that retailers can insulate themselves from deeper struggles when a risk event strikes by choosing multiple suppliers from different geographical areas.

In multiple-sourcing models, the main decisions are two-fold, i.e., select the best suppliers and allocate the quantity of orders from each supplier (Alfares and Turnadi, 2018; Kamalahmadi and Parast, 2017). As the first step of SS&DA, supplier evaluation is considered as a multi-criteria decision-making (MCDM) problem in the literature that involves both tangible and intangible criteria (Ho et al., 2010). Literature studies have proposed several supplier selection criteria such as supply ability (e.g., response rate, lead time, and production capacity), product quality (e.g., failure rate), cost (e.g., procurement and logistics cost), firm development (e.g., sustainability and social responsibility), and resiliency criteria as a crucial capability for firms to resist disruption risks. For different strategic goals, decision makers have formulated corresponding evaluation criteria, and use suitable MCDM method to make evaluation decisions. These MCDM models involve Analytic Hierarchy Process (AHP) (e.g., Hamdan et al., 2017), Data Envelopment Analysis (DEA) (e.g., Pratap et al., 2021), Analytical Network Process (ANP) (e.g., Giannakis et al., 2020), TOPSIS and Fuzzy-TOPSIS (Gupta and Barua, 2017), and evidential reasoning (ER) (e.g., Hosseini et al., 2022).

Next, the decision maker assigns the demands to the best suppliers to optimize different objectives subject to pertinent constraints. An extensive literature prone to consider multiple objectives simultaneously when finding the optimal demand allocation strategy. For example, Almasi et al. (2019) combined sustainable the mentioned problem with inflation, risk and ambiguous uncertainty and set six objective functions in the model, including total cost, economic score, environmental score, social score, inflation rate, and risk level. Jia et al. (2020) developed a robust optimization goal programming model for a steel company and optimized it considering the total cost, CO_2 emission, and environmental objectives. Since the selection problems are recognized as an assignment problem, those have the nature of integer. Also, the allocated quantity of order has a continuous nature, the mixed integer programming (MILP) becomes the mainstream technique. For example, considering supply chain systems face a variety of disruptive events, Hosseini et al. (2019) proposed a stochastic bi-objective MILP model to achieve both the economic and resilience objectives. Sontake et al. (2021) developed a MILP for SS&DA, focusing on the selection of transportation alternatives while delivering items.

To solve mentioned multi-objective programming models, there are two primary approaches generally used to solve multi-objective programming models. The first category is based on aggregation, in which each objective in the original multi-objective problem is aggregated into one objective in a linear or nonlinear manner, such as the weighted sum approach (WSA), ε-constraint (Deb, 2014). The second category is optimization algorithms that employ evolutionary computation techniques to solve multi-objective optimization problems, such as multi-objective evolutionary algorithms (MOEAs). MOEA is a popular and effective approach for solving retailers' SS&DA challenges because MOEAs are designed to identify multiple solutions that optimize multiple conflicting objectives simultaneously. By determining Pareto optimal solutions, retailers can make tradeoffs between different objectives and choose the best possible solutions for their specific needs. Therefore, to determine the supply portfolio in such an OC supply chain, this study uses the widely-proposed MOEAs.

As mentioned, SS&DA is essentially a multi-stage problem involving supplier evaluation, selection, and demand allocation. Therefore, an extensive literature tends to develop multi-phase methodology to address the involved issues separately. For example, PrasannaVenkatesan and Goh (2016) evaluated suppliers using a hybrid fuzzy AHP-fuzzy PROMETHEE and formulated a multi-objective MILP model to find the optimal choice of suppliers and their order quantity allocation under disruption risk. Park et al. (2018) proposed a two-phase approach for SS&DA in which first the sustainable supplier regions are identified, and next the optimal DA strategy is obtained. Nasr et al. (2020) presented a novel two-stage fuzzy SS&DA model in a closed-loop supply chain, where they used fuzzy BWM for selecting the most suitable suppliers and fuzzy goal programming approach for solving the model. Kaur and Singh (2021) proposed a multi-stage hybrid model for integrated supplier segmentation, selection and order allocation considering risks and disruptions, where they evaluated suppliers based on DEA.

As the question of how we can manage and control the potential supply risks to improve SCR is the main objective of this study, in addition to reviewing SS&DA-related technical approaches, the research on SS&DA under disruption risks is also our main concerns. For example, PrasannaVenkatesan and Goh (2016) considered three types of risk events when solving the SS&DA problem, including unique event, semi-super event and super event. Esmaeili-Najafabadi et al. (2021) considered two types of disruption risk: local disruption risks and regional disruption risks. Hosseini et al. (2019) assumed that suppliers are subject to a variety of random disruption risks such as floods, earthquakes, hurricanes, and labor strikes. Similar to the most of the previous literature, based on the number of supply chain members involved in a disruption, this paper classifies disruption risks into local, s regional, and super disruption. A super disruption event disrupts all the suppliers regardless of their locations, rendering them unable to deliver their committed quantities; a regional disruption event occurs in a specific region and causes all the suppliers in the region to fail, while a local disruption event occurs in the buyer's region.

A major difference of our work compared with the previous SS&DA literature is that we perform the research in the context of OCR. The extant studies mostly focus on the manufacturing sector, and only little research on SS&DA is in the context of retailing. For example, Kaushik et al. (2022) developed seven main criteria for supplier selection for online fashion retailers, which are Operational Competency, Product Attribute, Logistic Warehousing, Ethics, Status, Business Competencies, and Versatility. In fact, SS&DA is an important purchasing issue because the purchasing cost often takes up a large portion of retail spending (Yoon et al., 2018). Moreover, the OC strategy increases the complexity of the supply process owing to the high requirement of integration (Adivar et al., 2019). Thus, the OC retailer's SS&DA problem is critical, yet it remains unsolved in the existing studies. This paper considers the demand from different channels, captures the characteristics of the supply process in the OCR system, that is, integrated supply across channels, and then constructs a two-phase approach to solve the SS&DA problem of OC retailers, finally uses a real case to verify the value of the proposed models.

In terms of model development, our work mainly differs from existing research in the following three aspects. First, this paper comprehensively considers the following three objective functions, the expected total cost (ETC), the total purchasing value (TPV), and geographic segregation (GS), which are considered as the main objectives from the economic and resilience perspective (see Table 1). Second, three key resilience strategies adopted by OC retailers are modeled, namely multiple sourcing, geographic diversification, and local sourcing (see Table 1). Particularly, although local suppliers are considered in the multiple sourcing context, e.g., Choi et al. (2013) considered a local supplier that offers a buyback contract for a fashion retail buyer, the extant literature lacks extensive discussion and consideration of the importance of local suppliers. Last, given the geographic differences in the main parameters (e.g., disruption probability, transportation cost), geographic location must be included in decision-making. Our consideration of geographic location is captured in definitions of disruption risks (i.e., local disruption, regional disruption, and super disruption) and suppliers' location (i.e., local suppliers, external regional suppliers).

Table 1. Recent studies related to multi-objective models for addressing the SS&DA problem.

	Involved resilience strategies			Multiple objectives			Solution		
	Multiple sourcing	Geographic diversification	Local sourcing	ETC	TPV	GS	WSA	ε-constraint	MOEAs
Kabadayi and Dehghanimohammadabadi (2022)	√			√					√
Rahman et al. (2022)	√								√
Wu et al. (2022)	√				√				√
Islam et al. (2021)	√			√			√	√	
Khoshsirat et al. (2021)	√			√				√	
Kaviani et al. (2020)	√			√			√		
Sobhanallahi et al. (2020)	√			√	√				√
Almasi et al. (2019)	√			√			√	√	
Kellner and Utz (2019)	√	√		√				√	
Moheb-Alizadeh and Handfield (2019)	√			√				√	

Salehi and Rezaei (2019)	√			√				√
Hosseini et al. (2019)	√	√		√		√	√	
Mohammed et al. (2018)	√			√	√		√	
Che (2017)	√			√				√
PrasannaVenkatesan and Goh (2016)	√	√		√	√			√
This study	√	√	√	√	√	√		√

3. The two-phase approach for supplier selection and demand allocation for OC retailers

Figure 1 illustrates the proposed two-phase approach to solve the SS&DA problem for OC retailers. The first phase concerns the evaluation of the OC retailer's suppliers, involving three steps. First, we determine the supplier evaluation criteria based on a comprehensive review of the OC and SCM literature. Then, we apply a hybrid BWM-ER method for evaluating and ranking suppliers according to Hosseini et al. (2022), who pointed out that BWM as an effective multi-criteria-decision-making method is used to determine the weight of the criteria and sub-criteria, and the ER method is employed to solve the potential uncertainty and the incompleteness of information about some of the sub-criteria. We then use BWM to determine the weights of the criteria and sub-criteria. In the final step, we derive supplier preferences by applying the ER method. In the second phase, we solve the OC retailer's SS&DA problem by constructing a multi-objective MILP model that includes the preferences derived in the first phase.

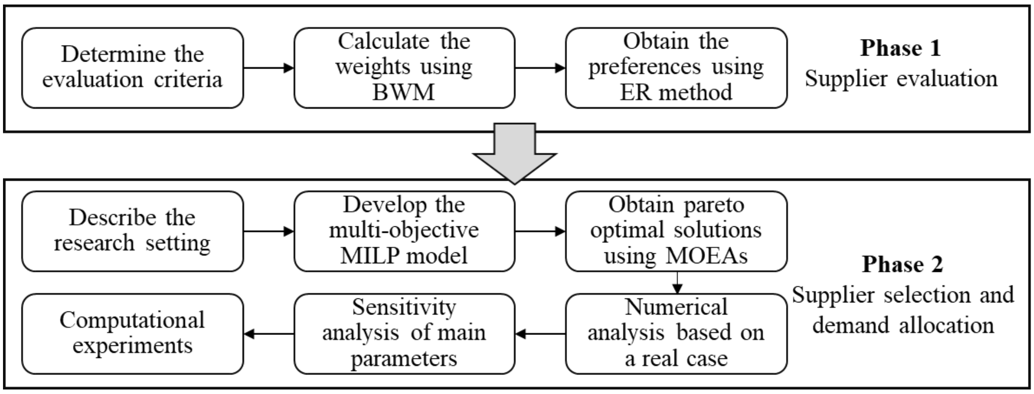


Figure 1. The two-phase approach.

3.1 Phase 1: OC retailer's supplier evaluation

Supplier evaluation is a typical MCDM problem that includes various qualitative and quantitative factors. During the evaluation process, the decision maker must endeavor to reduce errors caused by subjective judgment and unavoidable information incompleteness. Therefore, evaluation methods should be flexible and versatile, with reliable and reasonable results to conduct supplier evaluations economically and efficiently. In this study, we combine BWM and ER methods to evaluate the criteria developed in the OC context based on the advantages of BWM for capturing experts' opinions (Rezaei, 2015) and the effectiveness of the ER method in information aggregation and managing incompleteness and uncertainty.

To identify the most suitable set of criteria for OC retailers, we first examine the literature regarding supplier evaluation, combined with the OC supply chain's high requirements of timeliness, flexibility, and reliability, and propose an evaluation framework that spans five dimensions of supplier quality, cost, resilience capability, human capital, and digitalization. These criteria were studied and confirmed by case company experts (Section 4). The quantitative criteria are then assessed using real data, and the qualitative criteria are assessed by referencing opinions expressed on a five-point Likert scale. The chosen criteria and brief descriptions are presented in Table 2.

Table 2. Related information on the main criteria and sub-criteria.

Main criteria	Reference	Weight	Sub-criteria	Brief description	Weight
Product and service quality (PS)	Hosseini et al. (2016); Shi et al. (2017); Liu et al. (2018)	0.297	Annual revenue (PS1)	Average annual revenue in the past five years	0.077
			Response rate (PS2)	Proportion of timely order fulfillment after accepting the order	0.313
			Lead time (PS3)	Order fulfillment cycle time from order placement to delivery	0.233
			Product quality (PS4)	Product qualified rate	0.206
			Number of SKUs (PS5)	Product variety that suppliers can provide	0.069
			After-sale service (PS6)	After-sales service activities by suppliers that increase product value and enhance effective buyer–seller cooperation	0.102
Cost (CO)	Hosseini et al. (2016); Hu et al. (2020); Kaushik et al. (2022)	0.168	Unit ordering cost (CO1)	Cost related to supplier order preparation, including order processing, acceptance, and paperwork costs	0.083
			Unit purchasing cost (CO2)	Cost incurred by purchasing products	0.657
			Unit transportation cost (CO3)	In the complicated OC distribution network, transport cost is a crucial consideration due to various demand and delivery modes	0.260
Resilience capability (RC)	Hosseini et al. (2016); Kurniawan et al. (2017); Hosseini et al. (2019)	0.332	Diversified logistics network (RC1)	Diversified logistics networks mitigate disruption risks and reduce the likelihood of supply failure during risk events	0.277
			Back-up suppliers (RC2)	OC retailers' tier-one suppliers that have backup supply sources to absorb disruptive events and maintain continuous operations	0.124
			Redundancy stock (RC3)	Excess inventory of key products, which allows suppliers to mitigate disruption risks	0.262
			Multiple transportation modes (RC4)	Use of various transportation modes to fulfill product delivery	0.180
			Back-up funds (RC5)	Dedicated funds to resist disruption risks	0.079
			Risk management culture (RC6)	Formally embedding the consideration of risk management within the decision-making processes at every level	0.080
Human capital (HC)	Flöthmann et al. (2018); Zhang et al. (2020); Song et al. (2020)	0.082	Professional skills (HC1)	The depth and breadth of existing professional competence, knowledge, and experience	0.338
			Teamwork (HC2)	This capability is important since procurement practices occur at the inter-firm level	0.164
			Attitude (HC3)	Employees' positive attitude motivates a supplier to quickly restore damaged equipment and logistics facilities	0.085
			OC-related experience (HC4)	Suppliers with rich experience are expected to provide more quality, timely, and efficient products to different demand points	0.413
Digitalization (DG)	Burnson (2018); Büyüközkan and Göçer (2018); Song et al. (2021)	0.121	Visualization (DG1)	The ability to achieve real-time visualization of the entire supply chain	0.402
			Information sharing (DG2)	The ability to collaborate and communicate more efficiently with supply chain partners and share operational information	0.060
			Digital decision-making (DG3)	The ability to use advanced tools to improve decision-making processes and subsequent product quality	0.538

Introduced by Rezaei (2015), the BWM compares the best (most important) and worst (least important) criteria with other criteria. BWM allows designers to obtain weights with high reliability and consistency while inputting less information. We apply BWM to obtain the weights of the evaluation criteria. Referencing Kaushik et al. (2022), BWM proceeds in four steps as follows:

(i) Identifying the best and worst criterion among the selected and finalized criteria;

(ii) Pairwise comparisons between the best criterion and all other criteria;

(iii) Pairwise comparisons between the other criteria and the worst criterion (scale of 1–9 here);

(iv) Calculating the optimized weights for different criteria and sub-criteria at a reliable consistency level (normally, a consistency ratio < 0.1 is acceptable).

The ER method is effective and reasonable for solving MCDM problems with uncertain information. Because of its powerful evidence aggregation rules, this approach is suitable for managing mixed criteria and incomplete information. In this study, supplier evaluation for OC retailers is a typical MCDM problem that includes qualitative criteria (e.g., professional skills and attitude) and quantitative criteria (e.g., annual revenue and response rate); therefore, we use the ER method to evaluate the OC retailer's suppliers. At the firm level, the ER method is convenient and cost-effective as there is no specific limit to the number of experts consulted. Referencing Yang and Singh (1994) and Yang and Xu (2002), we apply the ER method to conduct supplier evaluation in three steps.

(i) Constructing the evaluation analysis model, which includes the main criteria and sub-criteria shown in Table 2, in which the criteria weights are determined by the results of BWM and a set of evaluation grades including *best, good, average, poor, worst*;

(ii) Using the ER algorithm to obtain each supplier's distribution evaluation of each criterion, including the distributed scores of the main criteria according to the assessment value/distribution of the sub-criteria, and repeating this process at the main criteria level to determine the distributed score for each supplier;

(iii) Systematically comparing and ranking the suppliers using a ranking method based on utility intervals, considering that there might be incompleteness or uncertainty in the assessment information.

3.2 Phase 2: OC retailer SS&DA under disruption risks

3.2.1 Problem description

We consider an OC retailer-dominant supply chain (Figure 2). The supply chain consists of $n_1 + n_2$ suppliers $i \in I = \{1, \dots, n_1, n_1 + 1, \dots, n_1 + n_2\}$, including n_1 local suppliers and n_2 regional suppliers that are located in R geographic regions. I^r is the subset of suppliers in region r, $r \in \{1, \dots, R\}$. Moreover, there are $m_1 + m_2 + m_3$ demand nodes $k \in K = \{1, \dots, m_1, m_1 + 1, \dots, m_1 + m_2, m_1 + m_2 + 1, \dots, m_1 + m_2 + m_3\}$, including m_1 nodes of warehouse delivery, m_2 nodes of physical store delivery, and m_3 nodes in which end-customers prefer delivery via drop-shipping. The OC retailer uses warehouses, physical stores, and vendor-managed inventory to fulfill consumer demand. We assume that the demand for different delivery modes is known and independent of one another. To ensure a non-differentiated shopping experience across channels, suppliers provide the same products via the three delivery channels (Hübner et al., 2022).

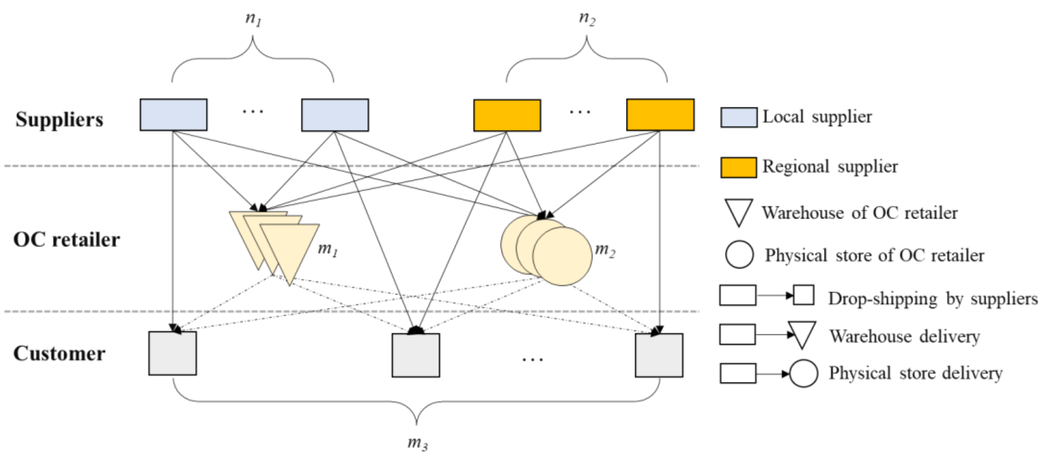


Figure 2. The OC supply chain framework.

We consider disruption risks due to risk events such as natural disasters, geopolitical events, and public health emergencies, which have strong regional attributes (PrasannaVenkatesan and Goh, 2016). Therefore, we analyze three potential disruptions according to the size and location of the risk outbreak, including local disruption (with a probability of p_0), regional disruption (with a probability of $p_r, r \in R: r \geq 1$), and super disruption (with a probability of p_{su}). Suppliers are of the all-or-nothing type, indicating that they are completely reliable in normal times or completely fail when disruptions happen (Esmaeili-Najafabadi et al., 2021). We assume that local and regional disruptions do not occur simultaneously because risk occurrences frequently have geographical boundaries. Moreover, in-store pick-up is not available when a local disruption occurs, and physical stores are considered mini fulfillment centers for fulfilling online orders (Sodhi and Tang, 2021). Therefore, physical store demand remains during a local disruption. In summary, four scenarios and their corresponding probability are as follows (notations are presented in Table 3):

Type 1: When no disruption occurs (normal circumstances), we have:

$$\mathcal{P}_0 = (1 - p_{su})(1 - p_0) \prod_{r \in R, r \geq 1} (1 - p_r). \tag{1}$$

Type 2: When a super disruption occurs, we have:

$$\mathcal{P}_1 = p_{su}. \tag{2}$$

Type 3: When a regional disruption event occurs, we have:

$$\mathcal{P}_2 = (1 - p_{su}) \prod_{r \in s_t} p_r \prod_{r \notin s_t} (1 - p_r). \tag{3}$$

Type 4: When a local disruption event occurs, we have:

$$\mathcal{P}_3 = (1 - p_{su}) p_0. \tag{4}$$

In this setting, the OC retailer executes flexible contracts with its suppliers in which suppliers can provide products over a certain percentage of the ordered quantity to manage disruption risks (PrasannaVenkatesan and Goh, 2016). For example, as shown in Figure 3, when no disruption occurs, the retailer will assign demand to three suppliers (Q_1, Q_2, and Q_3). When supplier 3 fails due to a disruption, it cannot supply any products. The buyer can obtain replacement supplies from suppliers 1 and 2 and may face stockout if the replacement supplies are less than the original provisions from supplier 3 ($q_1 + q_2 < Q_3$). We assume that the undisrupted suppliers will make up for the shortfall in the ordered units at no extra cost (Meena et al., 2011).

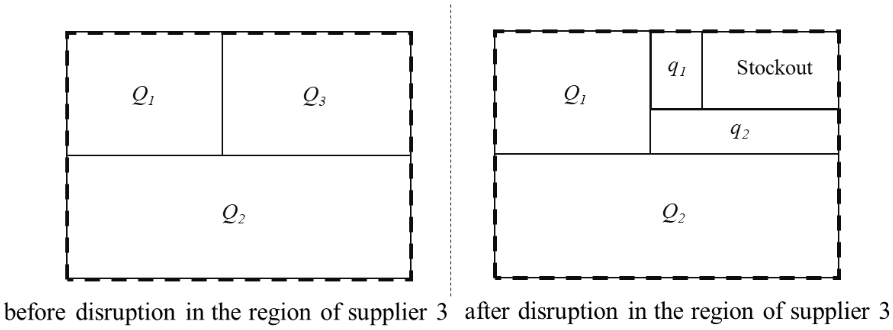


Figure 3. An example of procurement of replacement supplies from undisrupted suppliers.

The model incorporates the following sourcing strategies to enable resilient sourcing and mitigate disruption risks:

- *Multiple sourcing*: This approach helps reduce various supply disruption risks that firms face (e.g., Yousefi et al., 2021), such as strikes, natural disasters, and public health events, to maintain competitiveness among suppliers (Elmaghraby, 2000).
- *Geographical diversification*: Sourcing from suppliers in different geographic regions is an effective risk mitigation strategy (Hosseini et al., 2019; Esmaeili-Najafabadi et al., 2021). For example, during the COVID-19 pandemic, when some regions closed their borders, a geographically diversified supply network could effectively disperse disruption risks.
- *Local sourcing*: Local suppliers have significant advantages in terms of having lead times, meeting frequent low-quantity deliveries, and cultivating close cooperative relationships. In particular, when other areas are disrupted, local suppliers can still fulfill order deliveries.

3.2.2 Assumptions and notation

We propose a multi-objective MILP model that balances economic benefit, procurement value, and GS to determine the optimal selection of suppliers and assign demand. The multiple objectives include minimizing the total cost, maximizing TPV, and maximizing the distances between suppliers. We make the following assumptions for the model:

(1) The OC retailer purchases a single product with no quantity discount in a single period (Sawik, 2022; Mohammadivojdan et al., 2022);

(2) The demand from each channel in a planning period is known, deterministic, and stable (Lücker and Seifert, 2017), as physical stores can function as fulfillment centers for online orders during a disruption (Sodhi and Tang, 2021);

(3) The geographical regions and capacity levels of the suppliers are known;

(4) The fixed cost of ordering from a specific supplier is known and varies among potential suppliers;

(5) Each supplier has different capacity and flexibility levels;

(6) Warehouses and physical stores can fully accommodate the purchased products, so the capacity limitations of the facilities are not considered;

(7) Inventory cost is not considered in the model because the total demand in the single planning period is deterministic, and the OC retailer will sell the goods as soon as the supply arrives.

Table 3. Definitions of study notations.

Symbol	Meaning

Index	
i	Supplier node i, $i \in I$.
k	Demand node k, $k \in K$.
r	Potential suppliers' geographic region, $r \in R = \{0,1,\dots,R\}$, where r=0 is the local region.
t	Potential regional disruption scenarios $t \in T = \{1,\dots,2^R - 1\}$.
Sets	
R	Set of regions $r \in R$.
I^r	Set of suppliers in region r, $r \in R$, e.g., the set of potential local suppliers is $I^0 = \{1,\dots,n_1\}$.
S	Set of all subsets of regional disruption scenarios s_t. For example, if there are three regions (r=1, 2, 3) outside the local region (r = 0), the set of potential scenarios $S = \{s_1, s_2, \dots, s_7\} = \{(1),(2),(3),(1,2),(1,3),(2,3),(1,2,3)\}$, where $(\cdot)$ represents the region under disruption. The total number of subsets of potential regional disruption scenarios is then 2^R-1.
Parameter	
D, D_k	Original total demand, type-1 demand of warehouse delivery k, $k \in K: k \leq m_1$; type-2 physical store delivery k, $k \in K: m_1 < k \leq m_1 + m_2$; and drop-shipping by suppliers, i.e., type-3 demand, $k \in K: m_1 + m_2 < k \leq m_1 + m_2 + m_3$, $D = \sum_{k=1}^{m_1+m_2+m_3} D_k$.
C_i	The capacity of supplier i to provide products ($i \in I: n_1 < i \leq n_1 + n_2$) is exogenous and does not depend on the order quantity.
a_i	Fixed cost of ordering the products from supplier i, $i \in I: i \leq n_1 + n_2$.
b_i	The unit purchasing cost of the product from supplier i, $i \in I: i \leq n_1 + n_2$.
h_{ik}	The unit shipment cost from supplier i to demand node k (the definition of k mirrors the above) $i \in I, k \in K$.
d_{ij}	Shortest distance between locations of suppliers i and j, $i,j \in I: i < j$; $i,j \leq n_1 + n_2$.
v	Stockout cost per unit of unmet demand due to supplier failure.
p_{su}, p_r, p_0	Probability of a region r or local super disruption, respectively. Note that each region r has an independent disruption probability, $r \in R: r \geq 1$.
$\mathcal{P}$	Probability of occurrence of different types of potential scenarios (i.e., no disruption, super disruption, regional disruption, and local disruption).
w_i	OC retailers' preference value of supplier i $i \in I: i \leq n_1 + n_2$
F_i	Percentage index indicating the maximum amount that the order quantity from supplier i, $i \in I: i \leq n_1 + n_2$ can be increased, $F_i \in [0,1]$. $min\{C_i/D, (1+F_i)Q_i\}$ refers to the maximum supply fraction of supplier i.
Binary variable	
X_i	X_i = 1 if supplier i is selected; X_i = 0, otherwise, $i \in I: i \leq n_1 + n_2$
Y_{ij}	Y_{ij}= 1 if suppliers i and j are both selected; Y_{ij} = 0, otherwise, where $i < j; i,j \leq n_1 + n_2$.
Continuous variable	
Q_{ik}	Fraction of each demand k assigned to supplier i, $i \in I, k \in K$, $Q_i = \sum_{k=1}^{m_1+m_2+m_3} Q_{ik}$ is the total demand assigned to supplier i.
q_{ik}	Replacement of each demand k received from undisrupted supplier i when there are disruption risks; $q_i = \sum_{k=1}^{m_1+m_2+m_3} q_{ik}$ is the total replacement supply by an undisrupted supplier i.

3.2.3 Model formulation

Objective 1: Expected total cost

As illustrated in Figure 4, ETC includes the fixed cost (FC), purchasing cost (PC), transport cost (TC), and expected stockout cost (ESC). We express the ETC as follows:

$$\mathrm{ETC} = \mathrm{FC} + \mathrm{PC} + \mathrm{TC} + \mathrm{ESC}, \tag{5}$$

where,

$$FC = \sum_{i=1}^{n_1+n_2} a_i X_i, \tag{6}$$

$$PC + TC = \sum_{i=1}^{n_1+n_2} \left(\sum_{k=1}^{m_1+m_2+m_3} (b_i + h_{ik}) Q_{ik} D_k \right). \tag{7}$$

Two scenarios can cause stockout loss. One scenario is all regional suppliers fail when a super disruption occurs. The second scenario occurs when the available supply of the supplier(s) that do not fail is lower than the allocated demand of the failed supplier(s), in which case the retailer may face stockout. Consequently, we express the ESC under different disruption scenarios.

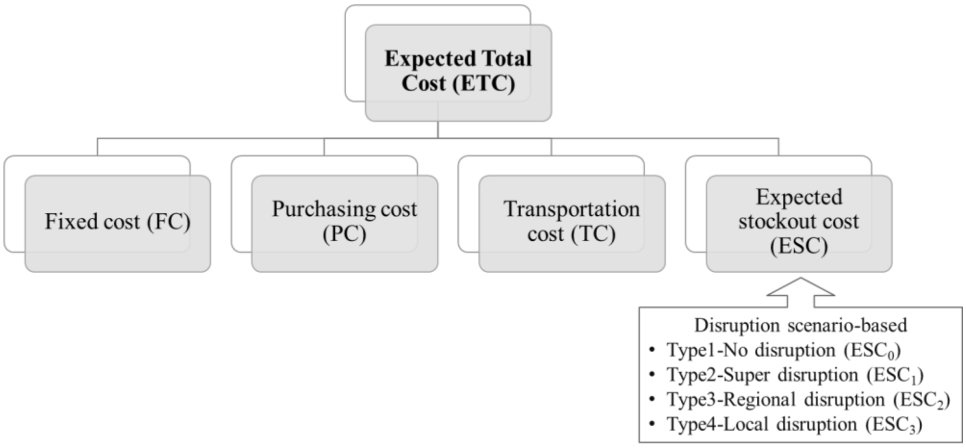


Figure 4. The composition of the expected total cost.

Type 1: When no disruption occurs (normal circumstances), there is no possibility of stockout, and $ESC_0 = 0$.

Type 2: When a super disruption occurs, both local and regional suppliers fail

$$ESC_1 = \mathcal{P}_1 Dv. \tag{8}$$

Type 3: When at least one regional disruption occurs, $r \in R: r \geq 1$; thus,

$$ESC_2 = \sum_{t=1}^{2^R-1} \mathcal{P}_2 \left(\sum_{i \in I^r, r \in s_t} Q_i - \sum_{i \in I^r, r \notin s_t} q_i \right)^+ Dv, \tag{9}$$

where $(x)^+ = max\{x, 0\}$. Noting that when some regional disruptions occur, if the replacement supplies from undisrupted suppliers fall short of the demands assigned to disrupted suppliers, an out-of-stock loss will occur.

Type 4: When a local disruption occurs, we have

$$ESC_3 = \mathcal{P}_3 \left(\sum_{i=1}^{n_1} Q_i - \sum_{i=n_1+1}^{n_1+n_2} q_i \right)^+ Dv. \tag{10}$$

Objective 2: Total purchasing value

TPV represents the retailer's utility function based on preferences for different suppliers that are obtained by supplier evaluation (Mafakheri et al., 2011). We obtain the TPV by taking the sum of the products of each supplier preference value and the corresponding order quantity as follows:

$$TPV = \sum_{i=1}^{n_1+n_2} w_i Q_i. \tag{11}$$

Objective 3: Geographical segregation

To improve SCR, OC retailers must thoroughly segregate the suppliers; therefore, we use the sum of the distances between selected suppliers to determine the degree of GS. Notably, only when both suppliers *i* and *j* are selected (i.e., $Y_{ij} = 1$) is the shortest distance (d_{ij}) meaningful (Hosseini et al., 2019). d_{ij} is usually determined by using geographic information systems or online services such as Google Maps. The expression of GS is as follows:

$$GS = \sum_{i=1}^{n_1+n_2-1} \sum_{j=i+1}^{n_1+n_2} Y_{ij} d_{ij}. \tag{12}$$

Multi-objective optimization

We propose a multi-objective MILP model with constraints on capacity and demand to address the OC retailer SS&DA problem. The multiple objectives include: (i) minimizing ETC, which satisfies the OC retailer's economic benefit; (ii) maximizing TPV, which increases the OC retailer's purchasing value (i.e., sourcing more products from suppliers with higher preference values); and (iii) maximizing GS to ensure suppliers' GS. The multi-objective MILP model is constructed as follows:

Objective functions:

$$Min\ ETC$$
$$Max\ TPV$$
$$Max\ GS$$

Constraints:

$$Q_i D \leq C_i X_i, i \in I: i \leq n_1 + n_2, \tag{13}$$
$$q_i \leq (C_i/D - Q_i)X_i, \tag{14}$$
$$q_i \leq F_i Q_i, \tag{15}$$
$$\textstyle\sum_{i=1}^{n_1+n_2} Q_{ik} = D_k, k \in K: k \leq m_1 + m_2 + m_3, \tag{16}$$
$$Q_{ik} \geq 0, i \in I: i \leq n_1 + n_2, \tag{17}$$
$$q_{ik} \geq 0, i \in I: i \leq n_1 + n_2, \tag{18}$$
$$I_{(\sum_{k=1}^{m_1} Q_{ik})(\sum_{k=m_1+1}^{m_1+m_2} Q_{ik})(\sum_{k=m_1+m_2+1}^{m_1+m_2+m_3} Q_{ik})=0)} X_i = 0, i \in I: i \leq n_1 + n_2, \tag{19}$$
$$X_i \in \{0,1\}, i \leq n_1 + n_2, \tag{20}$$
$$Y_{ij} \leq X_i, i < j; i,j \leq n_1 + n_2, \tag{21}$$
$$Y_{ij} \leq X_j, i < j; i,j \leq n_1 + n_2, \tag{22}$$
$$Y_{ij} \geq X_i + X_j - 1, i < j; i,j \leq n_1 + n_2. \tag{23}$$

Eqs. (13)–(18) represent suppliers' capacity and demand satisfaction constraints, respectively. Noting that the replacement supply fraction (q_i) is constrained by both supply capacity and maximum flexible supply, and each undisrupted supplier can offer a replacement supply that is more than its original allocation by an amount $min\{C_i/D - Q_i, F_i Q_i\}$, Eq. (19) requires that each selected supplier must be able to satisfy all types of demand, or it will not be selected. The indicator function I_x is used, where I_x= 1 if *x* holds, otherwise it is 0, which is nonlinear. We examine linearization below:

Proposition 1. The nonlinear constraint in Eq. (19) is linearized by introducing a large value *M* as follows:

$$X_i \leq M \textstyle\sum_{k=1}^{m_1} Q_{ik}, \tag{24}$$
$$X_i \leq M \textstyle\sum_{k=m_1+1}^{m_1+m_2} Q_{ik}, \tag{25}$$
$$X_i \leq M \textstyle\sum_{k=m_1+m_2+1}^{m_1+m_2+m_3} Q_{ik}. \tag{26}$$

Proof. Considering similarities, we only provide proof for the constraints on Q_{ik}. Noting that $X_i \in \{0,1\}$ is a binary variable, $Q_{ik} \in [0,1]$ is the proportion of the demand that D_k assigned to supplier *i*. This can be shown for all three cases that can arise in this study.

(i) When $\sum_{k=1}^{m_1} Q_{ik} = \sum_{k=m_1+1}^{m_1+m_2} Q_{ik} = \sum_{k=m_1+m_2+1}^{m_1+m_2+m_3} Q_{ik} = 0$, $X_i = 0$;

(ii) When $\sum_{k=1}^{m_1} Q_{ik} = 0$, $\sum_{k=m_1+1}^{m_1+m_2} Q_{ik} = 0$, or $\sum_{k=m_1+m_2+1}^{m_1+m_2+m_3} Q_{ik} = 0$, supplier *i* cannot meet the three types of demand simultaneously; thus, based on Eqs. (24)–(26), $X_i = 0$;

(iii) When $\sum_{k=1}^{m_1} Q_{ik} \neq 0$, $\sum_{k=m_1+1}^{m_1+m_2} Q_{ik} \neq 0$, and $\sum_{k=m_1+m_2+1}^{m_1+m_2+m_3} Q_{ik} \neq 0$, based on Eqs. (24)–(26), $X_i = 1$.

According to Hosseini et al. (2019), Eqs. (21)–(23) are the constraints of Y_{ij}, which are obtained from the following cases: (i) when $X_i = X_j = 1$, $Y_{ij} = 1$; (ii) when $X_i = 0$, $X_j = 1$, or $X_i = 1$, $X_j = 0$, $Y_{ij} = 0$; (iii) when $X_i = X_j = 0$, $Y_{ij} = 0$.

3.2.4 Solution procedure

The popular MOEAs to solve the multi-objective models are NSGA-II, MOPSO, and multi-objective genetic algorithm (MOGA) (Anwar and Ahsan, 2014). Due to their adaptability and speed, the MOGA and NSGA-II are the most extensively used among them in many different fields. With the help of these algorithms, a final population with improved characteristics is produced after an initial population. The benefits of MOPSO, on the other hand, include being less dependent on the characteristics of the objective function, being able to escape from the local minimum with the right design, and having fewer operator settings (Alejo-Reyes et al., 2021). The key benefit of this technique over other global optimization algorithms is also how quickly it converges.

Using a real-world case study as our starting point, we discuss the various performances of the aforementioned algorithms in the section that follows in this paper. We use MOGA to benchmark the numerical results and use the Taguchi method to tune the parameters of the other two algorithms because MATLAB R2022b includes a “gamultiobj solver”. To compare the utilized algorithms, five multi-objective standard measure metrics are chosen, including Number of Pareto Solution (NPS), Mean Ideal Distance (MID), Spread of Non-dominated Solution (SNS), Maximum Spread (MS), and Computational time (CPU time). It should be mentioned that these metrics are widely used in the literature (e.g., Maghsoudlou et al., 2016). Roghanian and Cheraghalipour (2019) provided extensive definitions and formulations of these metrics.

4. Numerical case study based on a real company

4.1 Case description and related parameters

To verify the operability and effectiveness of the proposed model and solution procedure, we apply the model to an OC retailer in China and numerically solve the corresponding SS&DA problem using the retailer’s real data. Company $\mathbb{A}$ is an OC retailer in China that is headquartered in Beijing. It sells luxury goods and personal care products from numerous brands, and its primary sources are mostly significant domestic and foreign distributors. Because of this, Company $\mathbb{A}$ has numerous alternative suppliers for the same product that is marketed under the same brand. Products can be purchased by customers in physical stores, online, or through drop-shipping from suppliers. The supply chain used in the numerical study is based on a specific luxury product produced by five suppliers located in three regions, two local physical stores (D_2 and D_3), and a local warehouse (D_1) (see Figure 5).

Figure 5. Arrangement of the supply chain nodes of company 𝔸.

The demand node of drop-shipping by suppliers is virtualized as D_4 due to the similarities in China's freight rates. Following desensitization treatment, the basic parameters of each supply chain node are presented in Table 4, and the fixed cost of ordering the products a_i (CNY/product) = 0, the stockout cost per unit of unmet demand is v (CNY/product) = 200. The probabilities of the three types of disruption risks are estimated by monitoring and identifying the key locations for catastrophic risks in a supply chain. Considering existing related research indicating that the probability of a super disruption is lower than that of a regional disruption, and local sourcing is more controllable and reliable than sourcing outside of the local region (PrasannaVenkatesan and Goh, 2016; Esmaeili-Najafabadi et al., 2021), we set $p_{su} = 0.002, p_0 = 0.010, p_1 = 0.015,$ and $p_2 = 0.015$. We list the values for the other parameters in Tables 4 and 5.

Table 4. Input parameters in the numerical study: Supplier- and demand-related data.

			$n_1 = 1$		$n_2 = 4$		
i			1	2	3	4	5
r			$r = 0$	$r = 1$	$r = 2$	$r = 2$	$r = 2$
C_i (pieces/period)			200	400	500	550	400
b_i (CNY/product)			900	1000	1500	1600	2000
F_i (%)			10%	20%	15%	20%	15%
w_i			0.6227	0.6247	0.4870	0.3692	0.3374
			h_{1k}	h_{2k}	h_{3k}	h_{4k}	h_{5k}
k	$m_1 = 1$	$D_1 = 400$	15	50	60	65	80
	$m_2 = 2$	$D_2 = 300$	15	50	60	65	80

	$D_3 = 200$	15	50	60	65	80
$m_3 = 1$	$D_4 = 100$	15	70	150	150	150

Table 5. Input parameters in the numerical study: Distances between regional supplier locations.

d_{ij} (km)	2	3	4	5
1	2000	7500	7800	8700
2	--	9000	8800	10000
3		--	1900	1300
4			--	1600

4.2 Preference value obtained using the integrated BWM–ER method

First, we invited five supply chain managers (with more than ten years of experience) in the case company as the expert group to evaluate the importance of each criterion and sub-criterion (February 7-February 9, 2022). The final result takes the experts' average evaluation results. All consistency ratios are less than 0.1, confirming the reliability of the assigned weights. We present the results of BWM for the main criteria and sub-criteria in Table 2.

Having determined the optimal weights for each criterion and sub-criterion, we then rank the suppliers using evidential reasoning. Due to the quantitative criteria included in the evaluation framework, we do not disclose the five suppliers' original assessment scores to preserve confidentiality. We fed the evaluation criteria and the original assessment scores of the five suppliers into the IDS software developed by Yang and Xu (2002), which is a useful tool for supplier evaluation and applies the ER method for MCDM. The computation starts at the sub-criteria level as a stepwise process. We show the calculation results in Appendix Table A1. Notably, in our case study, when there is complete information on each supplier, the suppliers' maximum and minimum values are equal.

4.3 Examining Pareto optimal solutions using different MOEAs

4.3.1 Benchmark results using the MOGA

According to the principle of MOGA (https://ww2.mathworks.cn/help/gads/gamultiobj-algorithm.html), We benchmark our results using "gamultiobj solver" in MATLAB R2022b on a DELL laptop with an Intel Core i5 processor running at 1.8 GHz with 8 GB of RAM. The default parameters are as follows: the population size = "500"; the mutation function = "Gaussian"; the number of generations = "1000"; and the function tolerance = "10^{-4}".

Figure 6 shows the Pareto-frontier using the MOGA. The ETC ranges from 1,239,545 CNY to 1,543,125 CNY, the TPV from 0.5021 to 0.5690, and the GS from 18,500 km to 58,600 km.

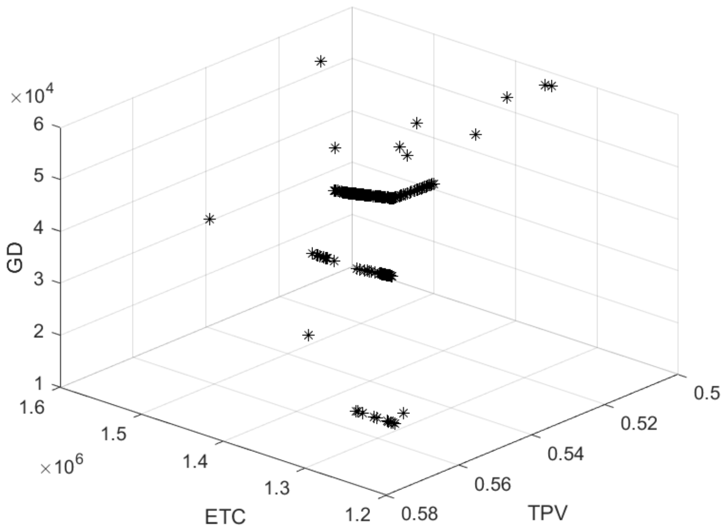


Figure 6. Pareto frontier for the numerical case study using MOGA.

Regarding the demand allocation illustrated in Figure 7, the Pareto optimal results indicate that almost all of the total demand is assigned to local supplier 1 (approximately 20%), regional supplier 2 (approximately 40%), and regional supplier 3 (approximately 40%). This is because of regional supplier 2's lower cost, higher order flexibility, and higher preference; regional supplier 3's higher supply capacity; and local supplier 1's lowest cost. In addition, a large proportion of the type-1 demand is allocated to regional supplier 3, followed by regional supplier 2 and local supplier 1; a large proportion of the type-2 demand is allocated to regional supplier 2, followed by local supplier 1 and regional supplier 3; and the type-3 demand is allocated to regional supplier 2, followed by regional supplier 3 and local supplier 1.

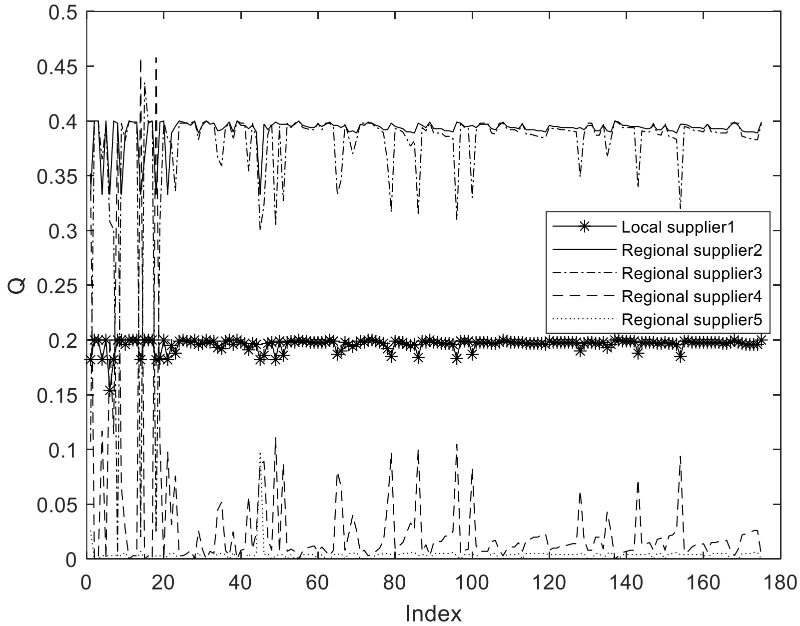


Figure 7. Demand allocation results.

4.3.2 Tuning the parameters of algorithms

The Taguchi approach is used to adjust each algorithm's parameters for maximum performance (Taguchi, 1986). This method was used by Taguchi, a quality advisor in Japan, to avoid performing numerous trials by taking into account a collection of elements based on orthogonal arrays. This approach attempts to maximize the impacts of the controllable features and to reduce the effects of the noise components by dividing the aforementioned factors into control and noise factors. The value of answer deviation is computed in this manner using the signal to noise ratio. In line with Roghanian and Cheraghalipour (2019), "the smaller is better" is used to tune the parameters of each method, as illustrated in the following equation:

$$^{S}/_{N} = -10 \times \log(\sum (Y^2)/n)$$

where Y represents the response value and n is the number of orthogonal arrays. Furthermore, $MCOV = MID/MS$ shows the proposed response for the Taguchi method in this study (Roghanian and Cheraghalipour, 2019).

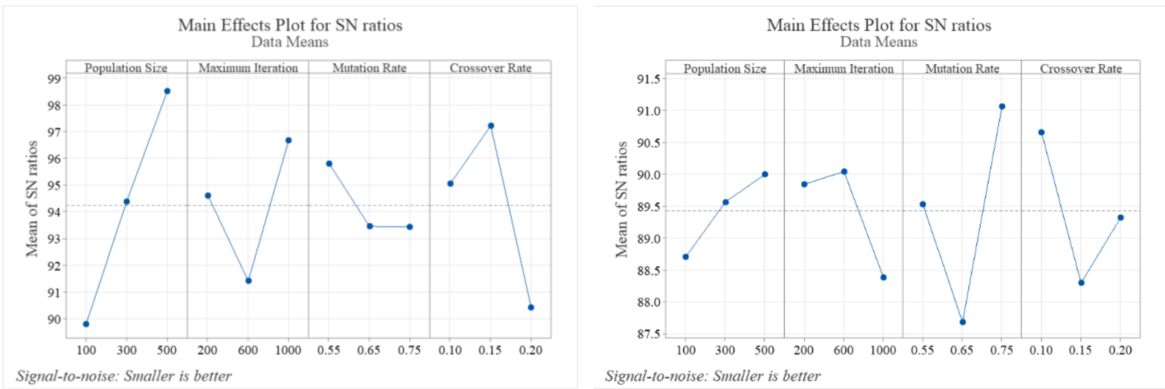
The orthogonal array is used in the Taguchi method to arrange the parameters impacting the process at the various levels so that a high number of decision variables can be studied with a limited number of experiments (Taguchi, 1986). We take into account four parameters at the three different levels (see Table 6) based on the literature and a trial-and-error experiment. Thus, by applying the Taguchi method via Minitab software, we employ the L^9 orthogonal arrays (Roy, 2001).

Table 6. Effective factors and levels in Taguchi method.

Level			Factor
1	2	3	
500	300	100	Population Size
1000	600	200	Maximum Iteration
0.75	0.65	0.55	Mutation Rate
0.20	0.15	0.10	Crossover Rate

Based on Figure 8, the best level of the parameters can be determined as follows.

- NSGA-II: Population Size = 500, Maximum Iteration = 1000, Mutation Rate = 0.55, Crossover Rate = 0.15.
- MOPSO: Population Size = 500, Maximum Iteration = 600, Mutation Rate = 0.75, Crossover Rate = 0.10.



(a) NSGA-II (b) MOPSO

Figure 8. Average S/N ratio levels for NSGA-II's and MOPSO's parameters.

4.3.3 Performance of different algorithms based on the case study

The mathematical model can be validated using actual data after fine-tuning the suggested algorithms. Recall that all algorithms are run on a Dell laptop with an Intel Core i5 CPU operating at 1.8 GHz and 8 GB of RAM using the MATLAB R2022b software. The standard measure metrics (see "sub-section 3.2.4") should be used to compare the effectiveness of the various methods because this model contains three objective functions. To this purpose, Table 7 reports the comparison of the NSGA-II and MOPSO results after tuning the parameters and the benchmark results attained by utilizing MOGA in various dimensions. MOGA is the best in terms of CPU time, as can be seen from the three last columns of this table, even though its CPU time is not the best. Moreover, MOGA allows for obtaining superior Pareto optimal solutions (i.e., the value of min-ETC in MOGA is the smallest and max-TPV in MOGA is the largest). Therefore, when performing sensitivity analysis on key parameters in the following sub-section, we mainly use the benchmark results obtained by MOGA.

Table 7. Comparison of results using different MOEAs.

		NSGA-II	MOPSO	MOGA
Standard measure metric	NPS (The lower value is better)	10	14	**175**
	MID (The lower value is better)	1.081226301	1.000775108	**0.371371002**
	SNS (The higher value is better)	26,362.31368	8,806.185366	**36,038.36843**
	MS (The higher value is better)	68,309.77392	33,251.71745	**306,217.0009**
	CPU time (The lower value is better)	**458s**	623s	602s
Extreme Pareto solutions	Min-ETC	1,282,842	1,287,598	1,239,545
	Max-TPV	0.5506	0.5509	0.5690
	Max-GS	58,600	58,600	58,600

Note: Best performing values are bolded.

4.4 Investigating the effects of the main parameters on the objective values

After obtaining the Pareto optimal solutions, there is the question of how uncertainty introduced into the key parameters changes the outcome and affects policy decisions. We select the extreme solutions under different objectives for analysis, including min-ETC, max-TPV, and max-GS. In this subsection, we select the main parameters in two categories of internal firm-related parameters (supplier preference and stockout cost) and external environment-related parameters (disruption probability and demand).

4.4.1 Effects of firm-related parameters

Supplier preference: We vary the preferences of different suppliers in the interval (0, 1), keeping other parameters constant. Although changes in supplier preference do not significantly affect the min-ETC and max-GS solutions, they increase the max-TPV. Contrary to PrasannaVenkatesan and Goh (2016), pursuing the max-TPV does not cause the suppliers located in a single region to be assigned more demand but still suggests allocating demand to suppliers with cost advantages, which allows the OC retailer to increase TPV and reduce ETC (Appendix Figure A1). Giving higher preference values for suppliers with high costs increases ETC.

Stockout cost: We varied the stockout cost per item in the interval [100, 1,000] keeping the other parameters constant. Changes in the stockout cost do not cause significant changes in max-TPV and max-GS but lead to a slight increase in the min-ETC (Figure 9). In these min-ETC solutions, local supplier 1, regional supplier 2, and regional supplier 3 are always selected based on relatively lower costs and higher preferences. There is no significant damage to TPV because the OC retailer has a higher preference for the three lower-cost suppliers. Therefore, we conclude that choosing local and regional suppliers with cost advantages can maximize TPV and alleviate the economic loss caused by rising stockout costs for the OC retailer.

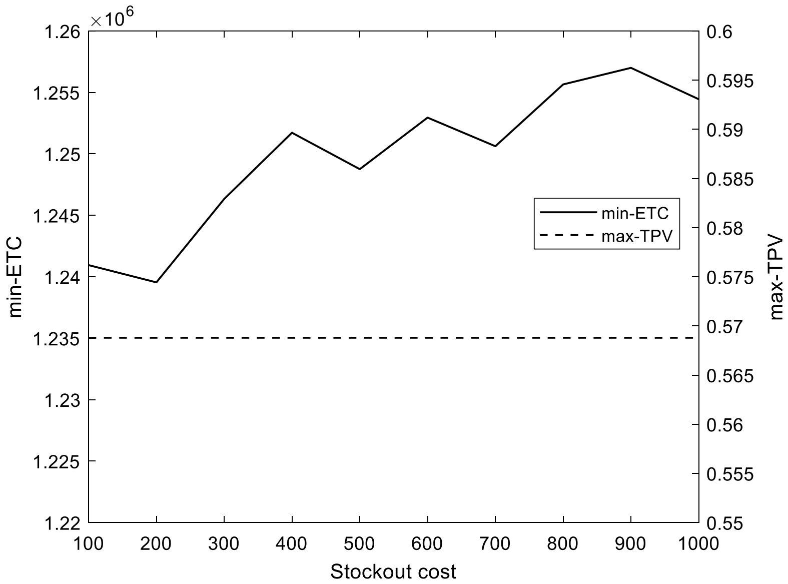


Figure 9. Effect of stockout cost on extreme solutions.

4.4.2 Effects of environment-related parameters

Disruption probability: We vary the probabilities of different disruptions' occurrence between 0 and 1 with an increment of 0.1, keeping other parameters constant. Increasing the occurrence probabilities of different types of disruption events does not affect the max-TPV and max-GS but increases the min-ETC (Figure 10). In addition, super disruption has the greatest negative impact and local disruption contributes the least. The increased risk of disruption in region 2 has a higher negative impact than the increased risk of disruption in region 1 because there are more suppliers located in region 2. Therefore, we conclude that choosing a local supplier can reduce the loss caused by disruptions for the OC retailer to a certain extent while selecting suppliers from different regions helps mitigate disruption risks.

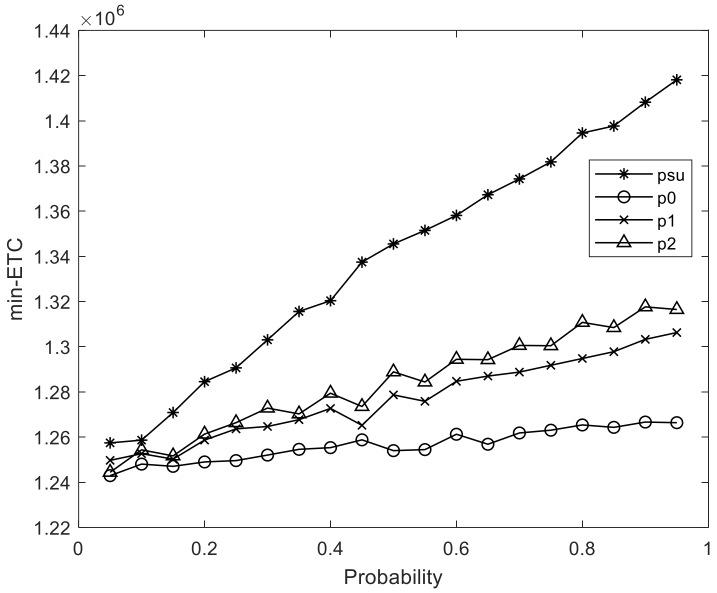


Figure 10. Effects of disruption probabilities on extreme solutions.

Demands: We next increase the demands at different nodes (D_1, D_2, D_3, D_4), with the original demand as the baseline, keeping the other parameters constant. Specifically, D_1 represents type-1 demand, D_2 and D_3 are type-2 demand, and D_4 is type-3 demand. As shown in Appendix Figure A2, increasing the three types of demand raises min-ETC and decreases max-TPV. This is because as demand increases, considering the suppliers' capacity constraints, partial demand must be allocated to less preferred suppliers, which leads to a loss in TPV. Therefore, to avoid a loss in TPV, reduce ETC, and geographically diversify the supply network, selecting regional suppliers with large supply capacity is a better choice, despite such suppliers not presenting the lowest cost.

4.5 Extension analysis by changing the constraints

To examine the impacts of different practices on solving the OC retailer's SS&DA problem, we conduct the following extensive analysis of the numerical study, including two scenarios. (i) Comparing the OC supply with separated supply in the context of multi-channel retailing by dropping the constraint in Eq. (19) that requires suppliers to meet the needs of different channels simultaneously, and (ii) adding the following constraint that the proportion of the total demand assigned to supplier s must be no less than the minimum demand assigned to the same supplier (Q_i^{min}) as follows:

$$Q_i \geq Q_i^{min}, i \in I: i \leq n_1 + n_2, \quad (27)$$

where $Q_i^{min} = 0.010$ in the case study.

The Pareto optimal solutions demonstrate that the ETC under the cross-channel separated supply policy is greater than that under the integrated supply policy (see Appendix Figure A3). Moreover, under the minimum demand assignment constraint, the optimal values of the three objective functions based on this numerical study do not exhibit obvious changes, nor do the optimal total demand assignment decisions, indicating that the optimization results obtained above are meaningful and reliable.

4.6 Main observations of the case analysis

Referencing the results of our two-phase decision-making system using a real case study, we draw the following main observations, which provide managerial insights for the case company and similar OC retailers.

4.6.1 Local suppliers are an important aspect of the supplier portfolio

Retailers such as the case company usually apply multisource strategies, which enable them to take advantage of pricing advantages and successfully reduce the risks of supply disruption. Due to the complexity and variability of the external environment, professionals and researchers have started to pay more attention to the importance of local suppliers when implementing multiple sourcing (Maersk, 2020). The Kearney Foreign Direct Investment Confidence Index survey in 2018 revealed that 89% of businesses were implementing or considering the implementation of localization initiatives, and roughly 40% were hiring local people or establishing production bases in the local market. In the presence of risk events such as geopolitical conflicts and border blockades, choosing local suppliers can significantly reduce supply disruptions and stable supply for OC retailers. As the case study shows, in terms of the local supplier with cost advantages, the Pareto optimal solution indicates that choosing this supplier can achieve economic benefits and promote GS, improving the SCR of OC retailers.

4.6.2 Different types of demand have different tendencies towards suppliers when allocated

Demand from a variety of sources is placed on OC retailers, including physical stores, live broadcast platforms, online shopping websites, and even drop-shipping from suppliers. While offline demand is predominantly fulfilled by physical stores, online demand is primarily met by warehouses, and the drop-shipping option is fulfilled by upstream suppliers (Melacini et al., 2018). Therefore, from the supply perspective, suppliers must send ordered goods to three demand points: warehouses, physical stores, and consumers who select drop-shipping. Analyzing the three demand types considering order size and delivery frequency reveals warehouse > physical shop > drop-shipping for order size and warehouse > physical store > drop-shipping for delivery frequency (Song et al., 2020). As a result, the demand for large order sizes is more likely to be awarded to suppliers with extensive supply capacity, whereas high delivery frequency is more likely to be allocated to suppliers with a closer distance.

4.6.3 The integrated supply strategy is more economical than its separated counterpart

To provide a seamless cross-channel experience for customers of the OC system, retailers must be able to offer homogenous services across various touchpoints and channels (Cai and Lo, 2020). Therefore, OC retailers like Wal-Mart have begun to implement cross-channel integrated supply, integrating the needs of different channels so that suppliers from different sources can simultaneously meet demands to benefit from economies of scale and reduce increasing fixed ordering costs caused by multiple purchases (Hübner et al., 2022). Consistent with OC retailers' practice, it demonstrates that integrated supply has certain economic benefits when seeking to meet various demands. Although creating an integrated purchase platform necessitates a certain level of cost input, the Pareto optimal solutions demonstrate that integrated supply saves 8.84% of the total cost on average compared with decentralized supply.

5. Further computational experiments using the MOGA

We operate with five distinct data sets that are randomly created with the parameters listed in Table 8 in order to show the applicability and usefulness of the proposed model for practical applications. The models are solved using the MOGA approach to produce Pareto optimum solutions. Table 9 provides the computational performance and Pareto solutions for the five test problems, where the identifier of the test problem, the number of suppliers, the number of regions, and the disruption scenarios associated with each data set are presented in columns (1)–(4), respectively. Extreme Pareto solutions are shown in other columns.

Table 8. Random data generation.

Parameter	Corresponding random distribution
The number of suppliers (i)	~ Uniform (3;8)
The number of regions (r)	~ Uniform (2;4)
The number of demand nodes (k)	3
C_i	~ Uniform (100;400)
a_i	~ Uniform (0;50)
b_i	~ Uniform (500;1,000)
F_i	~ Uniform (0;0.5)
w_i	~ Uniform (0;1)
h_{ik}	~ Uniform (5;100)
p	~ Uniform (0.05;0.5)
D_k	~ Uniform (200;1,000)
d_{ij}	~ Uniform (100;10,000)
v	~ Uniform (50;200)

Using the five test problems, the proposed multi-objective MILP model's viability is further confirmed. These conflicts between the model's three objectives confirm that various objective functions cannot be optimized concurrently, which supports the use of the multi-objective programming approach. The results also demonstrate the importance of local suppliers for reducing the risk of disruption and increasing GS.

Table 9. Summary of model results from differing scenarios and extreme Pareto optimal solutions.

Test problem	Number of suppliers	Regions		Disruption scenarios	Extreme Pareto solutions		
		Local	Foreign		Min-ETC (X_i)	Max-TPV (X_i)	Max-GS (X_i)
1	7	1	1	4	994,776 (1,1,1,0,1,1,1)	0.556 (1,1,0,1,1,1,1)	14,789 (1,1,1,1,1,1,1)
2	3	1	1	4	645,458 (1,1,1)	0.349 (1,1,1)	1,454 (1,1,1)
3	4	1	2	6	714,091 (1,1,1,1)	0.787 (1,1,1,1)	3,240 (1,1,1,1)
4	5	1	3	10	945,258 (1,1,1,1,1)	0.502 (1,1,1,1,1)	17,987 (1,1,1,1,1)
5	8	1	2	6	1,105,280 (1,1,0,1,1,1,0)	0.721 (1,0,1,1,1,0,1,0)	52,948 (1,1,1,1,1,1,1,1)

6. Summary and implications

In an increasingly dynamic environment, this paper proposes a two-phase approach to solve the SS&DA problem for OC retailers for navigating disruption risks for improving SCR from the perspective of purchasing. In the first phase, we combine BWM and the ER method to obtain the OC retailer's preference values for suppliers based on a five-dimensional evaluation framework. In the second phase, we develop a multi-objective MILP model to determine the optimal solution for the SS&DA problem. By comparing different MOEAs to find the set of Pareto optimal solutions, a real case study and several test problems are applied to validate the proposed evaluation framework and multi-objective MILP models. To the best of our knowledge, this study is the first attempt to integrate the OC characteristics and the local sourcing strategy to solve the SS&DA problem for retailers. Thus, it offers the following theoretical contributions:

(i) A two-phase approach is proposed by considering the characteristics of the OC operations, different resilience strategies, different types of disruption risk events, and suppliers in different geographical regions, providing theoretical insight for future research on procurement decisions in OCR.

(ii) The proposed approach is constructed to solve three key decision-making issues of the SS&DA problem for OC retailers, namely supplier evaluation, selection, and demand allocation, in the presence of potential disruption risks. Resilience factors are considered in each decision-making phase, which helps to enrich the research on OCR supply chain management.

(iii) The effect of geographic locations is considered comprehensively when solving the SS&DA problem, due to the geographic location-induced differences, such as dividing suppliers and disruption risks by geographical location, and using geographic segregation as one of the objective functions to improve SCR.

(iv) A real-world case study is applied to test the proposed approach and provides several related observations, this paper offers further inquiries on the SS&DA problem beyond the considered exploratory case.

In conclusion, this study offers valuable insights for practitioners, which can be summarized as follows. First, we provide a set of criteria for supplier evaluation in the OC context, spanning five practical and comprehensive dimensions of product and service quality, cost, resilience capability, human capital, and digitalization, and consequently obtain OC retailers' supplier rankings by applying the hybrid BWM and ER methods. Second, the numerical results also reveal the importance of local suppliers for OC retailers, and suggest them to allocate the demand from different channels to suppliers in different regions to maximize the overall benefit. Third, the outcomes of our research can assist OC retailers' supply chain managers to design supply networks that minimize not only traditional supply cost but also possible losses due to disruptive risks while increasing their SCR.

Our work has some limitations that should be addressed in future work. We assumed that the suppliers are all-or-nothing type, i.e., completely reliable under normal conditions and completely fail when a risk event occurs, however, there might situations when the suppliers are still able to reserve partial capacity during the disruption risk. Moreover, the focus of this work is on evaluating the impact of those low frequency but high impact disruptive risk such as natural disasters. However, other operational disruptions (e.g., bankrupt cy of suppliers, labor strike) can be investigated in future research. Last, when studying SS&DA issues under potential disruption risk, it is also worthwhile to consider the impact of demand fluctuation caused by the risk events, such as panic buying behavior during the COVID-19 pandemic.

Data statement

All data generated during this study are included in this published article and its supplementary information files. However, due to the sensitive nature of the questions asked in this study, the case retailer was assured raw data would remain confidential and would not be shared.

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Appendix

Table A1 Aggregated distributed assessments of the five suppliers.

Supplier/Expected utility	Criteria	Worst	Poor	Average	Good	Best
Local supplier 1	Total score	0.00%	22.92%	29.10%	23.93%	24.04%
(0.6227)	PS	0.00%	44.71%	23.48%	0.00%	31.80%
	CO	0.00%	0.00%	0.00%	0.00%	100.00%
	RC	0.00%	25.49%	59.03%	15.48%	0.00%
	HC	0.00%	0.00%	0.00%	100.00%	0.00%
	DG	0.00%	0.00%	2.43%	97.57%	0.00%
Regional supplier 2	Total score	1.46%	16.25%	29.74%	36.06%	16.49%
(0.6247)	PS	5.24%	0.00%	20.89%	16.25%	57.62%
	CO	0.00%	0.00%	0.00%	96.92%	3.08%
	RC	0.00%	48.19%	25.83%	25.97%	0.00%
	HC	0.00%	0.00%	28.69%	71.31%	0.00%
	DG	0.00%	0.00%	100%	0.00%	0.00%
Regional supplier 3	Total score	16.02%	10.48%	44.17%	21.35%	7.98%
(0.4870)	PS	23.26%	0.00%	38.25%	11.49%	27.00%
	CO	0.00%	80.59%	7.72%	7.72%	3.98%
	RC	26.38%	0.00%	47.76%	25.86%	0.00%
	HC	0.00%	0.00%	0.00%	100.00%	0.00%
	DG	0.00%	0.00%	100.00%	0.00%	0.00%
Regional supplier 4	Total score	8.35%	44.55%	40.15%	4.95%	2.00%
(0.3692)	PS	23.51%	34.53%	29.85%	6.42%	5.69%
	CO	16.12%	64.47%	11.58%	3.86%	3.98%
	RC	0.00%	31.44%	68.56%	0.00%	0.00%
	HC	0.00%	0.00%	57.79%	42.21%	0.00%
	DG	0.00%	100.00%	0.00%	0.00%	0.00%
Regional supplier 5	Total score	28.28%	34.30%	13.64%	21.77%	2.01%
(0.3374)	PS	54.96%	21.88%	11.87%	5.98%	5.31%
	CO	80.59%	15.43%	0.00%	0.00%	3.98%
	RC	0.00%	46.02%	6.27%	47.71%	0.00%
	HC	0.00%	0.00%	57.79%	42.21%	0.00%
	DG	0.00%	64.44%	35.56%	0.00%	0.00%

Table A2 The orthogonal array L^9 and computational results for the NSGA-II and MOPSO.

Run order	Population Size	Maximum Iteration	Mutation Rate	Crossover Rate	NSGA-II response	MOPSO response
1	500	1000	0.75	0.2	0.0000152	0.0000299
2	500	600	0.65	0.15	0.0000127	0.0000410
3	500	200	0.55	0.1	0.0000086	0.0000259
4	300	1000	0.65	0.1	0.0000143	0.0000397
5	300	600	0.55	0.2	0.0000341	0.0000310
6	300	200	0.75	0.15	0.0000142	0.0000299
7	100	1000	0.55	0.15	0.0000145	0.0000465
8	100	600	0.75	0.1	0.0000446	0.0000246

9	100	200	0.65	0.2	0.0000525	0.0000432

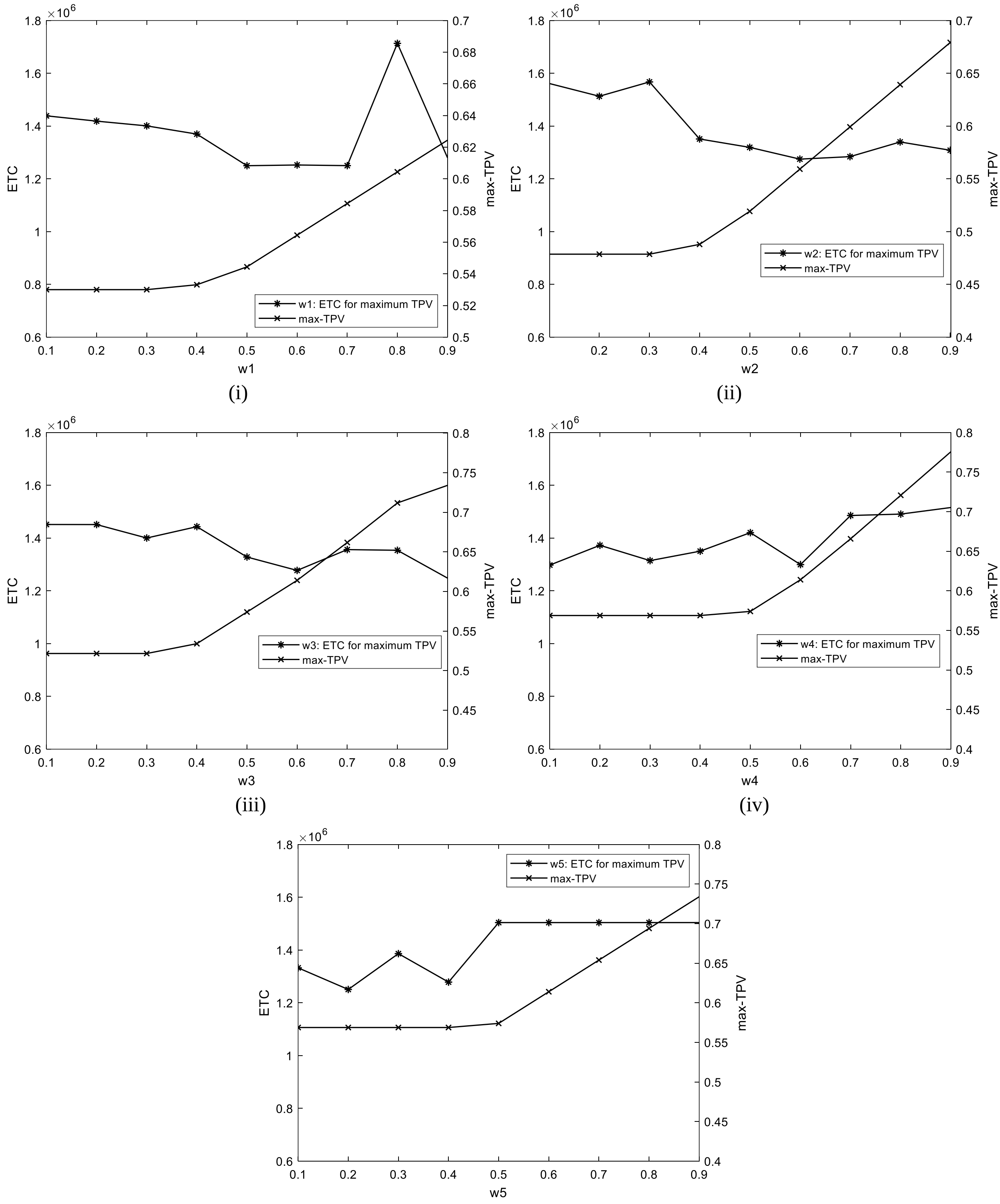
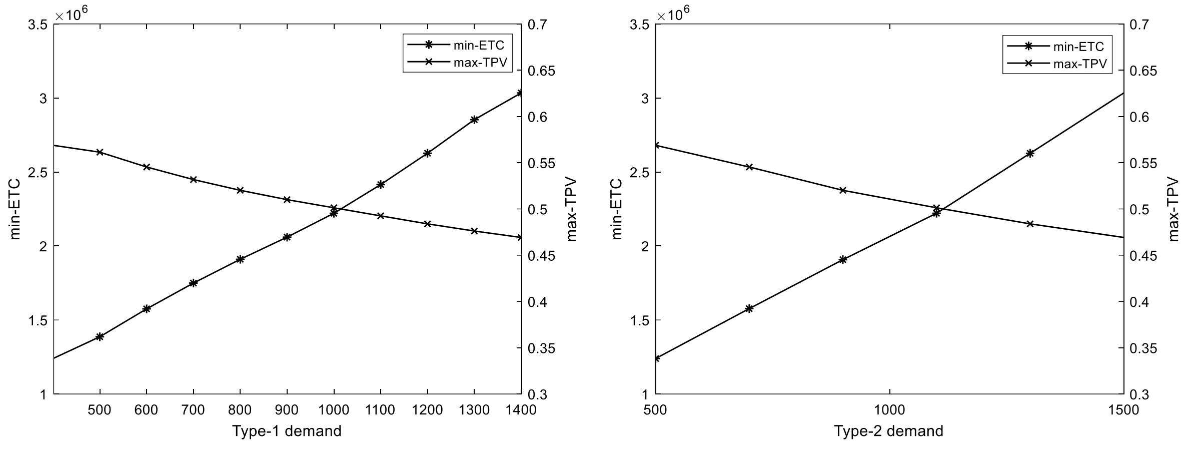


Figure A1 Effect of preferences on ETC for maximum TPV.



(a) (b)

(c)

Figure A2 Effect of demand on extreme solutions.

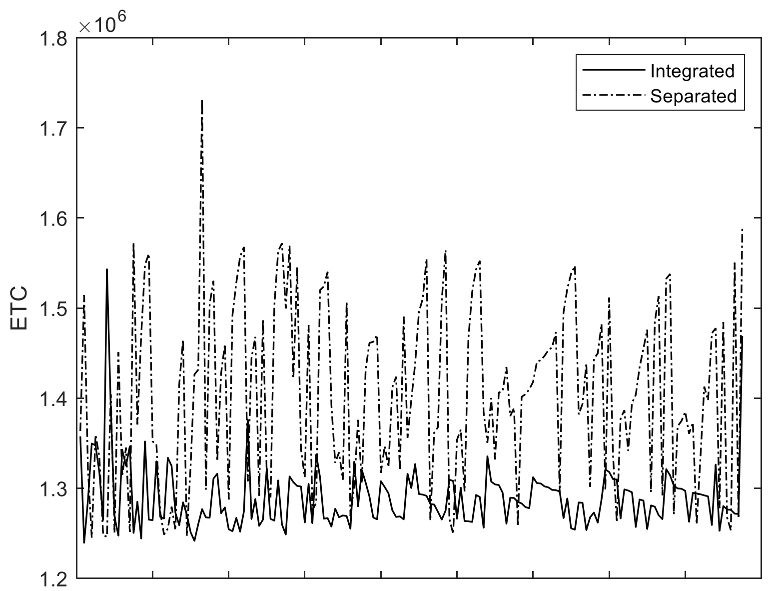


Figure A3 Integrated supply compared with separated supply.