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Resilient supply chains for essential perishable supplies: enhancing flexibility through multi-sourcing

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ABSTRACT

This study presents a quantitative model that evaluates the impact of supplier diversification on supply chain resilience. It focuses on the supply of essential perishable products, such as vaccines, from unreliable suppliers prone to delays. An optimisation model is developed to determine the optimal supplier mix and is solved using a Particle Swarm Optimization algorithm. The model accounts for constant demand, suppliers with varying reliability levels, diverse fixed and variable costs, and delivery times subject to random delays. Due to the perishability of the products, maintaining safety stock is challenging; therefore, a quadratic penalty for stock-outs is incorporated. The study reveals that multi-sourcing can substantially reduce the total cost compared to relying on a single supplier, while also enhancing resilience. Cost savings increase with the number of suppliers, particularly when the penalty for unmet demand is high; however, the marginal benefits eventually diminish. A computational study indicates that using two suppliers instead of one can reduce expected total costs by 34.65%.

KEYWORDS

Economic order quantity; random delivery time; particle swarm optimization; multisourcing; supply chain resilience

Introduction

After COVID-19, the world confronted the reality of its fragile supply chains, prompting the consideration of various strategies to handle disruptions effectively. This became particularly evident for essential life-saving products. For example, a cancer drug crisis began in 2022 when the United States Food and Drug Administration (FDA) inspected an Intas Pharmaceuticals plant in India and discovered multiple violations related to quality control and data integrity. This led to a production stoppage, causing a nationwide shortage of cancer drugs. Intas used to provide around 50% of the U.S. supply of Cisplatin, a widely used cancer drug. Therefore, when production stopped, relying on other suppliers was not possible because other manufacturers could not suddenly increase their production volumes due to capacity and manufacturing constraints, resulting in major disruptions (Willyard 2023).

Similarly, Infant Formula Milk (IFM) is a critical and irreplaceable commodity of exceptional value and importance (Floris et al. 2010; Green Corkins and Shurley 2016). Over the past decade, the IFM supply chain has faced numerous disruptions, significantly affecting its availability and posing serious risks to the health of millions of infants (Al-Khatib et al. 2024). A notable example is the 2022 contamination incident involving Abbott's products, which led to the company's shutdown in the United States. This disruption caused a severe shortage, with availability rates plummeting to below 20% in several states. Parents were left struggling to secure essential nutrition for their infants, highlighting the urgent need for resilient supply chain practices (Doherty et al. 2022; Paris 2022).

The fragility of supply chains for essential products like IFM is further exacerbated by market concentration, where a limited number of suppliers restricts flexibility. Increasing supplier diversity enhances flexibility and robustness, which is a fundamental component of supply chain resilience. Flexibility, in this context, refers to the ability to adapt to disruptions while maintaining efficient operations under normal conditions (Sheffi and Rice 2005), while robustness refers to the ability to maintain performance levels and operational continuity during disruptions, encompassing both rapid recovery and stability protection (Iftikhar, Ali, and Stevenson 2024).

These real-world disruptions highlight critical vulnerabilities in supply chain robustness and resilience. They demonstrate how heavy reliance on a limited number of suppliers, whether due to cost efficiency or market dominance, can severely impair a supply chain's ability to respond to unexpected events. In each case, whether caused by quality violations, production shutdowns, or sudden demand surges, the lack of flexibility led to delayed deliveries, severe

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shortages, and increased risks to public health, as these products are essential for well-being and their unavailability heightens health risks. These events underscore the importance of key resilience capabilities such as redundancy, responsiveness, and adaptability. Without sufficient flexibility, particularly through supplier diversification, supply chains become fragile, unable to recover quickly or maintain consistent service during disruptions, ultimately causing harm to society.

The literature review indicates that various mathematical models have been employed to address multiple sourcing strategies. Notably, the first inventory management model, the Economic Order Quantity (EOQ), was introduced by Harris (1915) over a century ago. It aims to find the optimal order quantity depending on the total costs such as holding costs and ordering costs that are directly related to the supplier characteristics while meeting the demand. Since then different extensions of the EOQ model have been proposed to adapt it and make it more realistic in the literature (Erdem, Murat Fadiloglu, and Özekici 2006; Gonzalez-Ayala et al. 2023; Hemmati and Hamid Reza Pasandideh 2021; Khakbaz et al. 2024). While existing research has examined EOQ models and multi-sourcing strategies, a critical gap remains in integrating these approaches for perishable products with unreliable suppliers that cause random delivery delays.

Motivated by these challenges, this paper develops optimisation models to strengthen the resilience of supply chains for essential perishable products by leveraging multiple suppliers. While relying on a single, highly reliable supplier may ensure high-quality supplies, such a strategy is vulnerable to unforeseen risks and disruptions. To mitigate these vulnerabilities, this research employs mathematical modelling to enhance supply chain resilience by enabling a diversified and flexible reliance on multiple suppliers. This approach aims to create a robust supply chain while minimising associated costs.

A key distinguishing feature of the proposed framework is its incorporation of random order delivery delays, which account for uncertainties in lead times. Additionally, the perishable nature of goods such as vaccines and IFM, with their limited shelf lives, imposes strict constraints on inventory management. This perishability makes it impossible to maintain substantial safety stock, necessitating precise planning of production and storage (Leuveano et al. 2023).

By systematically evaluating these factors, this study moves beyond the simplistic notion that simply increasing the number of suppliers leads to greater resilience. Instead, it provides a nuanced, data-driven framework to determine the optimal mix of suppliers and allocation strategies, balancing flexibility, cost, and reliability.

To the best of our knowledge, while existing research has investigated EOQ models and multi-sourcing strategies independently, most approaches fall short when applied to perishable products, particularly in environments with unreliable suppliers and random delivery delays. EOQ models often assume deterministic or predictable lead times and rely heavily on safety stock to buffer against uncertainty – an approach that is impractical or inefficient for perishable goods with limited shelf lives. Similarly, many multi-sourcing strategies do not adequately capture the stochastic nature of supplier reliability, overlooking the compounding effects of variable delivery delays on service levels and cost performance. These limitations make existing models insufficient for managing essential perishable products where stockouts carry high penalties and shelf-life constraints render conventional buffers ineffective.

This study addresses this critical gap by integrating multi-supplier reliability into a stochastic EOQ framework that explicitly models random delivery delays and minimises total costs without relying on safety stock, offering a more realistic and resilient solution for supply chains handling perishables. The findings offer practical insights and evidence-based recommendations for supply chain decision-makers, particularly for critical pharmaceutical supplies or perishable food products. The remainder of this paper is structured as follows. Literature review reviews relevant literature. In Optimizing order quantities for a single supplier with random Lead times, we describe and mathematically analyse a single-supplier model with random delivery times, which lays the foundation for the multiple-supplier model analyzed in Optimizing order quantities for multiple unevenly reliable suppliers. Computational study presents a computational study evaluating the benefits of the multiple-supplier strategy. Limitations and insights present some managerial insights. Finally, conclusion offers concluding remarks, key insights, limitations, and directions for future research.

Literature Review

Supply chain resilience capabilities and mitigation strategies

In recent research, there is a growing focus on the concept of supply chain resilience (SCRES), where SCRES refers to the ability of a supply chain to adjust, anticipate unforeseen events, respond to disruptions, and restore its intended level of performance and efficiency, as defined by Juttner, Peck, and Christopher (2003). Different papers dealt with building a methodology for enhancing resilience including Aldrighetti et al. (2024), Al-Khatib, Kharbeche, and Haouari (2023), and Dwaikat et al. (2022). Applications of building resilience plans for supply chains are highlighted by many studies after the

Covid-19 pandemic by different papers including but not limited to Liu et al. (2023); Ivanov and Keskin (2023); Rozhkov et al. (2022); Sawik (2022); Dube et al. (2022).

The efficiency of resilience depends on the developed capabilities used to regulate supply chain risks and reduce vulnerability to disruptions (Adobor and McMullen 2018). SCRES capabilities include robustness, agility, availability, efficiency, flexibility, redundancy, velocity, and visibility (Christopher and Peck 2004). A non-exhaustive list of recent significant exploration of these capabilities includes Mandal et al. (2016); Han, Kian Chong, and Li (2020); Piprani, Ismawati Jaafar, and Mohezar Ali (2020); Vanany et al. (2024); Mistarihi and Magableh (2023) Messina et al. (2023), and Sinaga, Simatupang, and Basri (2024).

These capabilities are addressed through various mitigation plans. Snyder et al. (2016) extensively reviewed diverse mitigation strategies that enhance supply chain resilience through preparedness and contingency planning. While, how different mitigation strategies affect each other and their effect on overall performance are covered by Namdar, Blackhurst, and Azadegan (2022); Paul et al. (2022); and Alikhani et al. (2023).

Agrawal and Alikhani (2025) shows that supply chain ambidexterity, which is the ability to leverage existing capabilities while simultaneously exploring innovative approaches, can significantly reduce the negative effects of supply, customer, and internal disruptions and thus enhance resilience. This strategic resilience aligns with broader efforts in the literature to strengthen disruption response mechanisms. For instance, Darmawan (2024) used simulation to assess the use of different reactive strategies amidst disruptions and adjust inventory control parameters based on that. Moreover, Hu, Sasha Dong, and Lev (2022) and Taleb et al. (2023) delved into supplier selection processes.

Multi-sourcing as a resilience strategy

Multi-sourcing is usually employed as a strategy to mitigate disruptions like delivery delays, which can result in backlogs and operational challenges (Thevenin, Ben-Ammar, and Brahimi 2022). In fact, selecting multiple supplier dependencies reduces the likelihood of experiencing risks associated with each supplier. These risks can include poor quality, late delivery, dispersed geographical locations, supplier failure, financial stress, supply disruptions, poor supplier service, lack of supplier involvement, supplier's economic risk, supplier's technology risk, supplier's information risk, supplier's environmental risk, and supplier's ethical risk (Yoon et al. 2018). In fact, Bentahar and Belhadi (2025) highlights the importance of integrating project management principles into supply chain management as a means to strengthen resilience in environments characterised by volatility, uncertainty, complexity, and ambiguity. They present that particularly agile practices, structured planning tools, and stakeholder management provide structured approaches that enable supply chains to better absorb and adapt to these challenges. The authors show that agile transformation enhances flexibility. Additionally, they illustrate how advanced analytics improve planning in food supply chains and how partner alignment contributes to successful logistics collaboration. In addition, Yao and Fabbe-Costes (2018) presents a framework showing that resilience emerges not only within firms and supply chains but also across the broader network of interconnected actors. A key factor highlighted is flexibility and redundancy in sourcing. The study notes that assessment models identify flexible and dispersed sourcing structures as critical capabilities that enhance a network's ability to absorb disruptions.

Consequently, numerous studies covered multiple supplier-related mitigation strategies from various quantitative perspectives. For instance, Thevenin, Ben-Ammar, and Brahimi (2022) highlighted the criticality of supplier reliability in manufacturing companies by employing robust optimisation techniques to integrate lot-sizing and supplier selection decisions under uncertainty. The study proposed a row and column generation algorithm, complemented by heuristic approaches, to efficiently solve the optimisation problem. While Deligiannis, Liberopoulos, and Pandelis (2023) explored the impact of supply capacity learning on dual-sourcing decisions in supply chains for non-storable (perishable) products from two different suppliers, where one supplier is an expensive reliable supplier and the other is a cheaper unreliable supplier. The study aims to meet deterministic, time-varying demand and reveals conditions under which splitting demand between suppliers is optimal. Similarly, Firouz, Keskin, and Melouk (2017) investigated the advantages of multiple suppliers, particularly in cases where suppliers face capacity issues or where buyers require alternative sources to mitigate disruptions and maintain competition among suppliers.

In the context of enhancing supply chain resilience after the COVID pandemic, Kim et al. (2023) studied the use of multiple suppliers, focusing on optimising production quantities and procurement strategies in electronic manufacturing. The study emphasises employing multiple sourcing strategies to improve supply chain resilience and operational efficiency, while mitigating uncertainties and managing inventory. Similarly, Pamucar, Ebadi Torkayesh, and Biswas (2023) developed a decision-making approach to address the supplier selection problem for medical face masks and shields, which was critical in preventing virus spread. Applied to a real-life case in a Turkish hospital, the methodology enables decision-makers to evaluate suppliers based on both technical and sustainability criteria.

Building on this, other studies further explain how multi-sourcing enhances supply chain resilience by increasing flexibility and enhancing robustness. Sallwa and Paul Kabelele (2024) stated that selecting from a diverse pool of suppliers enhances the ability to mitigate supply chain risks, especially when combined with strategic material storage and flexible production processes, which strengthen resilience and reduce the negative impact of disruptions on overall supply chain performance. While Marcucci et al. (2022) highlights that multisourcing is identified as a critical strategy for enhancing supply chain resilience. It increases sourcing flexibility, reduces dependency on single suppliers, and mitigates the ripple effects of disruptions. By improving supplier reliability and flexibility in outsourcing multi-sourcing has a positive total effect on SCR. It also supports supply chain visibility and enables managers to counteract negative disruption cycles by offering alternative supply options. Thus, it enhances supply chain robustness.

EOQ models for multi-supplier inventory management

The literature review indicates that various mathematical models have been employed to address multiple sourcing strategies. Notably, the first inventory management model, the Economic Order Quantity (EOQ), was introduced by Harris (1915) over a century ago. It aims to find the optimal order quantity depending on the total costs such as holding costs and ordering costs that are directly related to the supplier characteristics while meeting the demand. Since then different extensions of the EOQ model have been proposed to adapt it and make it more realistic in the literature.

Erdem, Murat Fadiloglu, and Özekici (2006) enhanced the EOQ model by integrating multiple suppliers with random capacities. The study presents a framework that optimises order quantities under yield uncertainty and supplier diversification. By equalising the expected number of unfulfilled units across suppliers, the model minimises total costs. Analyses using uniform and exponential capacity distributions demonstrate that diversification effectively reduces risk as the number of suppliers increases. Building on the supplier diversification theme, Gonzalez-Ayala et al. (2023) proposed a modified EOQ model that integrates supplier selection and order allocation under complex non-linear freight rate structures. Using Modified Simulated Annealing algorithm, the study underscores the practical value of advanced metaheuristics for efficient inventory decision-making in complex procurement environments. Further expanding EOQ applications in real-world retail logistics. Meanwhile, Khakbaz et al. (2024) introduced a novel EOQ model tailored for a multi-item, multi-supplier, multi-retailer cross-docking system. The model simultaneously optimises holding and ordering costs aiming to reduce total inventory costs while enhancing operational efficiency. A sensitivity analysis also reveals the influence of demand patterns and cost parameters on optimal policies, providing actionable managerial insights.

Sustainability considerations were addressed by Hemmati and Hamid Reza Pasandideh (2021), who integrated the EOQ model into a bi-objective mixed-integer nonlinear programming framework for a two-echelon supply chain. Their model simultaneously handles supplier location, selection, and order allocation decisions under green constraints. Employing stochastic programming and scenario-based analysis, the model minimises both total supply chain costs including ordering, holding, shortage, and transportation, and carbon emissions. However, for highly perishable items White and Censlive (2015) found that many studies recommend adding a safety margin to replenishment orders to account for losses due to shelf-life expiration, even in the absence of shortages or when postponement strategies are employed. Despite the time-sensitive nature of perishable goods, most studies rely on traditional EOQ models, with limited application of system dynamics techniques capable of capturing the dynamic behaviour of spoilage and expiration. This highlights an area where further methodological advancement is needed.

Literature review gap

Various studies have explored mitigation strategies such as multi-sourcing, which enhances the flexibility and robustness of the supply chain. These studies specifically address methodologies, criteria, and quantitative approaches related to supplier selection.

While existing research has examined EOQ models and multi-sourcing strategies, a critical gap remains in integrating these approaches for perishable products with unreliable suppliers that cause random delivery delays. This paper addresses this gap by employing an EOQ model that incorporates stochastic delivery delays to minimise total costs for essential perishable products without relying on safety stock. Unlike prior studies that focus solely on deterministic or planned delays, this work highlights the critical impact of stockouts for perishable products. It provides a framework to mitigate supply chain disruptions caused by stochastic delivery delays while optimising costs. By integrating multi-supplier reliability with demand fulfilment, this study advances sourcing strategies in contexts where minimising stockouts is vital to ensuring supply chain continuity.

Our key contributions are as follows:

Enhanced single-supplier EOQ model: We extend the classical EOQ model by incorporating random supplier delays, addressing the critical challenge of highly penalised stockouts for essential perishable products.

Optimization for Multiple Suppliers: We integrate the enhanced EOQ model into an optimisation framework to address the multiple-supplier variant of the problem, where suppliers differ in reliability and costs. The resulting nonlinear optimisation problem is solved using a Particle Swarm Optimization (PSO) algorithm.

Comprehensive Computational Study: We conduct an extensive computational study to evaluate the sensitivity of various model parameters on supply chain resilience and overall performance. This analysis quantifies the benefits of leveraging multiple suppliers to enhance supply chain resilience and mitigate disruptions.

Optimising order quantities for a single supplier with random lead times

Throughout this paper, we focus on the management of a single essential perishable product. The study addresses a realistic scenario where global disruptions – such as logistical delays, production bottlenecks, or geopolitical issues – significantly impact the supply chain, leading to major shipment delays. Unlike conventional models that assume unmet demand is lost, this study considers a more practical assumption: delayed orders are eventually fulfilled after a random stochastic delay. The primary objective is to minimise the impact of these uncertainties on product availability, ensuring a consistent and reliable supply of essential perishable products.

We begin by investigating the single-supplier case in this section. The results derived here will then be used, in Optimizing order quantities for multiple unevenly reliable suppliers, for solving the multiple-supplier case. To this end, we will first provide a formal description of the problem, including the main assumptions, and introduce the notation. Subsequently, we will outline the solution approach.

Assumptions and notation

The main model assumptions are as follows:

(1) **Constant demand rate**: Denoted by D. The demand is assumed to be relatively stable, with only minor fluctuations. This assumption is common in settings such as public hospitals administering the Diphtheria-Tetanus-Pertussis (DTP) vaccine, a combination vaccine that serves as a cornerstone of infant immunisations worldwide as part of national immunisation programmes, where demand remains consistent with minor weekly variations.

(2) **Fixed ordering cost**: Denoted by F. This cost includes the transportation fees as well as the setup costs for preparing the order.

(3) **Linear variable purchasing cost**: The item unit cost is denoted by c.

(4) **Linear holding cost**: The holding cost of one unit of the item for one unit of time is denoted by h and is proportional to the purchase cost.

(5) **Perishability constraint**: Due to perishability, the maximum duration between receiving an item and using it to fulfil demand should not exceed an upper bound $\bar{T}$. Therefore, the maximum order size is $\bar{Q} = D\bar{T}$.

(6) **No safety stock**: Maintaining a safety stock could lead to spoilage and waste. Especially sensitive drugs, which often have a limited shelf life.

(7) **Nominal lead time**: An order is placed when the inventory level matches the demand expected to be fulfilled during this duration.

(8) **Random delivery delays**: Deliveries are subject to random delays. The nominal lead time can be prolonged by a random delay, denoted by u, having a continuous probability distribution function (PDF) denoted by $f(u)$.

(9) **Quadratic shortage penalty cost**: Since no safety stock is maintained, a delivery delay u causes a shortage of Du units. This shortage incurs a penalty of $\pi(Du)^2$, where π represents the penalty for a shortage of one unit during one period of time. Unlike the standard linear shortage penalty function, the quadratic function penalises large stock-outs more severely. This is justified for essential products (such as critical drugs), where prolonged shortages could have extremely serious consequences.

Assuming a constant order size, denoted x, the single-supplier problem requires finding the optimal order size that minimises the expected total cost per unit of time. This cost includes the purchase cost, ordering cost, holding cost, and shortage cost.

To improve clarity in the assumptions and notation section, Table 1 provides a summary of the notation used as a reference throughout this paper.

Model analysis

Based on the model assumptions, the inventory level function is periodic as displayed in Figure 1.

Table 1. Summary of notation.

Notation	Definition	Notation	Definition
D	Constant demand rate	F	Fixed ordering cost
c	Linear variable purchase cost	π	Penalty for shortage
h	Linear holding cost	$\bar{Q}$	Maximum order size
x	Order size	x^*	Optimal order size
u	Random delay	$f(u)$	Continuous probability distribution function (PDF
$\bar{T}$	Product shelf life	CK	Total cycle cost
$K(x,u)$	Total cost per unit of time	$\bar{K}(x)$	Expected cost per unit of time

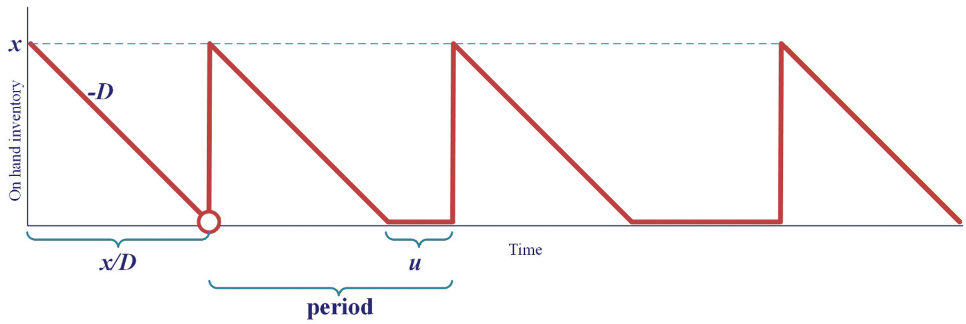

Figure 1. Variation of the inventory level over time.

Each cycle begins with the replenishment of an order of size x. The fixed and variable costs are F and cx, respectively. This order satisfies the demand for $\frac{x}{D}$ units of time, incurring a holding cost of $\frac{hx^2}{2D}$. If the next delivery is delayed by u units of time, the inventory level will remain at zero during this period, resulting in a shortage cost of $\pi(Du)^2$.

Therefore, the total cycle cost is:

$$CK(x,u) = F + cx + \frac{hx^2}{2D} + \pi(Du)^2$$

Since the duration of one cycle is random and equal to $\frac{x}{D} + u$, the total cost per unit of time during one cycle is:

$$K(x,u) = \frac{F + cx + \frac{hx^2}{2D} + \pi(Du)^2}{\frac{x}{D} + u}$$

Therefore, the expected cost per unit of time is:

$$\bar{K}(x) = \int_0^\infty K(x,u)f(u)du$$

The optimal order size x^* is the solution to the following problem:

$$(\mathbf{S}) : Minimize_{0\le x\le \bar{Q}}\bar{K}(x)$$

Before moving on to solve the problem defined by (4), we make a very reasonable assumption which will greatly simplify our analysis and will be applied in the following:

Assumption (A1): We assume that the unit purchase cost is lower than the order cost ($c < F$) and also lower than the penalty cost for unsatisfied demand of one unit over a period of time ($c < \pi$).

Proposition 1. *If Assumption (A1) is satisfied, then for any continuous PDF $f(.)$ associated with delays, the expected cost per unit of time, $\bar{K}(.)$, is a strictly convex function with respect to the order size x.*

Proof. A necessary and sufficient condition for the strict convexity of $\bar{K}(x)$ is

$$\frac{\partial^2 \bar{K}}{\partial x^2} > 0.$$

We have

$$\frac{\partial^2 \bar{K}}{\partial x^2} = \int_0^\infty \frac{\partial^2 K(x,u)}{\partial x^2} f(u)du.$$

Hence, a sufficient condition that guarantees that the right-hand side of this equality is strictly positive is:

$$\frac{\partial^2 K(x,u)}{\partial x^2} > 0, \text{for all } u \ge 0.$$

For the sake of clarity, we rewrite $K(x,u)$ as follows:

$$K(x,u) = \frac{\alpha x^2 + cx + \beta}{\gamma x + u},$$

where $\alpha = \frac{h}{2D}$, $\beta = F + \pi(Du)^2$, and $\gamma = \frac{1}{D}$.

Using this notation, we get

$$\frac{\partial K(x,u)}{\partial x} = \frac{\alpha\gamma x^2 + 2\alpha u x + cu - \beta\gamma}{(\gamma x + u)^2},$$

and,

$$\frac{\partial^2 K(x,u)}{\partial x^2} = \frac{2}{(\gamma x + u)^3}\left(\alpha u^2 - \gamma c u + \beta\gamma^2\right).$$

We set $g(u) = \alpha u^2 - \gamma cu + \beta\gamma^2$. Clearly, we see from (10) that $\frac{\partial^2 K(x,u)}{\partial x^2}$ and $g(u)$ have the same sign. Using the genuine parameters, we express $g(u)$ as follows:

$$g(u) = \left(\frac{h}{2D} + \pi\right)u^2 - \frac{c}{D}u + \frac{F}{D^2}.$$

We observe that $g(0) > 0$. On the other hand, we can check that the sign of $g(u)$ never changes. This can be verified as follows. Let us consider the quadratic equation $g(u) = 0$ and check that this equation has no solutions. Indeed, the discriminant of the equation $g(u) = 0$ is

$$\Delta = \frac{c^2}{D^2} - \frac{4F}{D^2}\left(\frac{h}{2D} + \pi\right) = \frac{1}{D^2}\left(c^2 - 4F\left(\frac{h}{2D} + \pi\right)\right).$$

From Assumption **(A1)**, we derive:

$$c^2 < \pi F.$$

Thus, we infer that $\Delta < 0$. Therefore, $g(u) > 0$, for all $u \geq 0$.

Hence, we conclude that $\frac{\partial^2 K(x,u)}{\partial x^2} > 0$, for all $u \geq 0$. Therefore, $\bar{K}(.)$ is a strictly convex function with respect to x.

The significance of Proposition 1 is underscored by the unique property of strictly convex functions: they possess a single global minimum. Consequently, any local minimum is also the global minimum, streamlining the search for the minimum value. However, in our problem setting, the function $\bar{K}(x)$ lacks a closed form, and computing this integral accurately is exceedingly complex for a general probability density function $f(u)$. Therefore, conventional numerical methods that rely on the function's derivative to locate the minimum point – such as gradient descent or Newton's method – are not applicable. Instead, to address Problem **(S)**, we have employed the Golden Section Search method. This technique is especially advantageous for pinpointing the minimum of a strictly unimodal function when the function is devoid of a closed form, and its derivatives are inaccessible. The following pseudo-code outlines the Golden Section Search method for determining the minimum of $\bar{K}(x)$ within the interval $[0, \bar{Q}]$:

(1) **Initialisation**: Set $a = 0$ and $b = \bar{Q}$.
(2) **Calculate Key Points**: Determine the points c and d within the interval $[a, b]$ using the golden ratio ϕ, where $\phi = \frac{1+\sqrt{5}}{2}$. These points are computed as:
   - $$c = b - \frac{b-a}{\phi}$$
   - $$d = a + \frac{b-a}{\phi}$$
(3) **Evaluate the Function**: Compute the values of $\bar{K}(x)$ at the points c and d, denoted $\bar{K}(c)$ and $\bar{K}(d)$.
(4) **Narrow the Interval**:
   - If $\bar{K}(c) < \bar{K}(d)$, the new interval is set to $[a, d]$.
   - Conversely, if $\bar{K}(d) < \bar{K}(c)$, the new interval is set to $[c, b]$.
(5) **Repeat the Process**: Continue steps 2 to 4 with the updated interval until the interval's length falls below the desired precision level.
(6) **Find the Minimum**: The function's minimum resides within the final interval. The midpoint of this interval serves as an approximate location for the minimum.

In Step 3, evaluating $\bar{K}(x)$ necessitates the exact calculation of a typically very complicate integral. For our implementation, this evaluation is executed numerically using Simpson's method (Hamming 1973). Hence, by combining the Golden Search Method with numerical integration of the expected cost function, the Economic Order Quantity for an essential product with random delivery times can be efficiently calculated.

In summary, Figure 2(a) presents the flowchart used to determine the optimal order quantity Q^* that minimises the expected cost function $\bar{K}(x)$, where the procedure for calculating $\bar{K}(x)$ is illustrated in Figure 2(b).

Optimising order quantities for multiple unevenly reliable suppliers

Derivation of the multi-supplier model

Multi-sourcing, a well-established strategy, strengthens supply chain resilience by reducing dependence on any single supplier. This approach ensures that disruptions from one source do not cause a complete halt in the supply chain, thereby addressing resilience through its robustness capability. In this model, we evaluate resilience primarily by metric of shortage cost, which directly reflects the supply chain's ability to meet demand even in the face of disruptions. The infrequency of supply shortages makes the probability of concurrent stockouts from two different suppliers within the same time minimal. Furthermore, multi-sourcing offers economic advantages, particularly for essential and time-sensitive perishable goods, by mitigating the risk of stockouts that can have significant

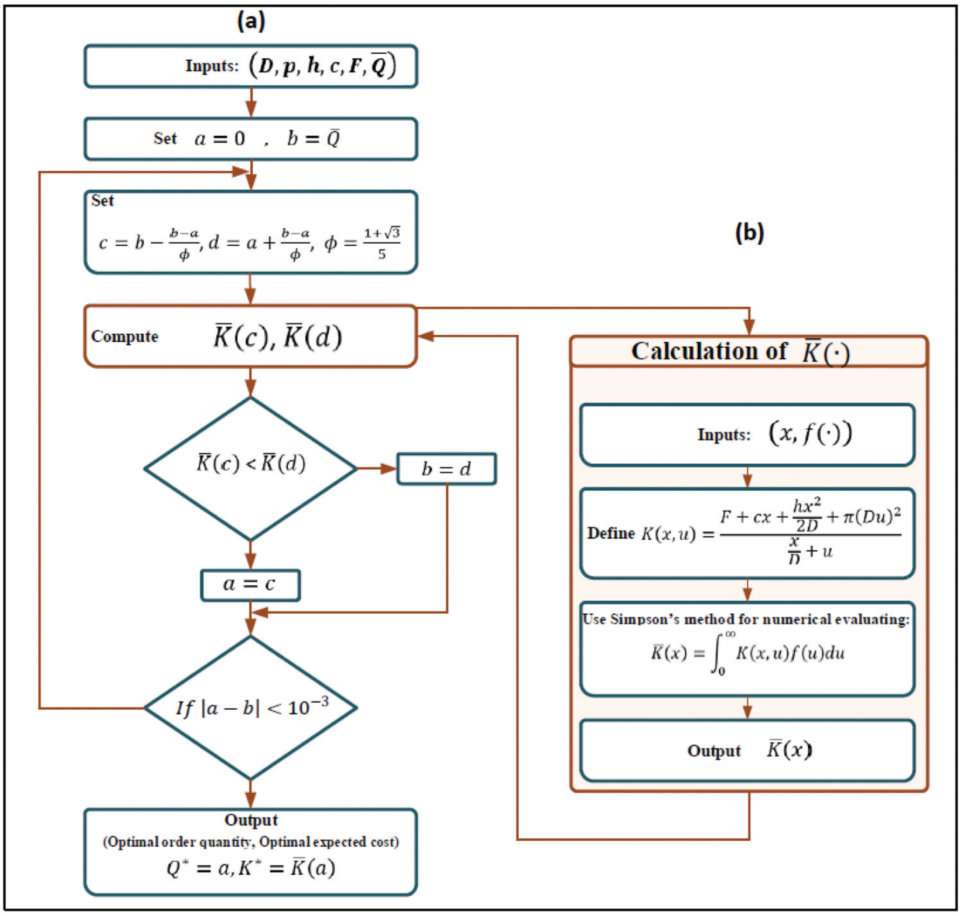

Figure 2. Flowchart for the calculation of the optimum order quantity.

repercussions. The disruptive events, which are represented by delivery delays, are modelled as random variables having a continuous PDF function $f(u)$. The model's objective to minimise stockouts, ensuring that the supply chain can absorb such disruptions with minimal impact on overall availability and cost. Thus, resilience in this context is evaluated through robustness by the system's ability to continuously meet demand and avoid shortages through strategic supplier diversification.

Figure 3 illustrates the impact of using multiple suppliers on stockout duration through three separate panels representing the dependence only on the first supplier, the dependence on the second supplier, and combined demand fulfilment using both suppliers. We observe that utilising dual suppliers significantly reduces the severity of stockouts because, at any given time, only a fraction of the demand will be unfulfilled rather than the entire demand. Hence, this combined inventory strategy can potentially reduce stockout rates compared to relying on individual suppliers. Therefore, by employing multiple suppliers, it is expected that the inventory system will exhibit enhanced stability and robustness in the face of supply disruptions. Subsequently, a detailed examination of this strategy involving multiple suppliers will be presented.

We assume that we have m suppliers. Each supplier i $(i = 1, \ldots, m)$ is characterised by a fixed ordering cost F_i, a unit variable purchasing cost c_i, a unit holding cost h_i, and a PDF $f_i(.)$ of the delivery delays. We denote by x_i the order size from supplier i, and by y_i the demand rate that is fulfilled by supplier i.

From (2), we deduce that, for supplier i, the total cost per unit of time during one cycle is:

$$K_i(x_i, y_i, u) = \frac{F_i + c_i x_i + \frac{h_i x_i^2}{2y_i} + \pi(y_i u)^2}{\frac{x_i}{y_i} + u}, \text{for } y_i > 0,$$

and $K_i(x_i, y_i, u) = 0$ for $y_i = 0$.

Therefore, the corresponding cost expected cost per unit of time for supplier i is:

$$K_i(x_i, y_i) = \int_0^\infty K_i(x_i, y_i, u) f_i(u) du$$

For each demand rate $y_i \geq 0$, we set

$$K_i^*(y_i) = \min_{0 \leq x_i \leq \bar{Q}} \bar{K}_i(x_i, y_i), \text{for } y_i > 0,$$

and $K_i^*(0) = 0$.

The problem now involves determining the optimal demand rate to be fulfilled by each supplier and the corresponding order size from each supplier.

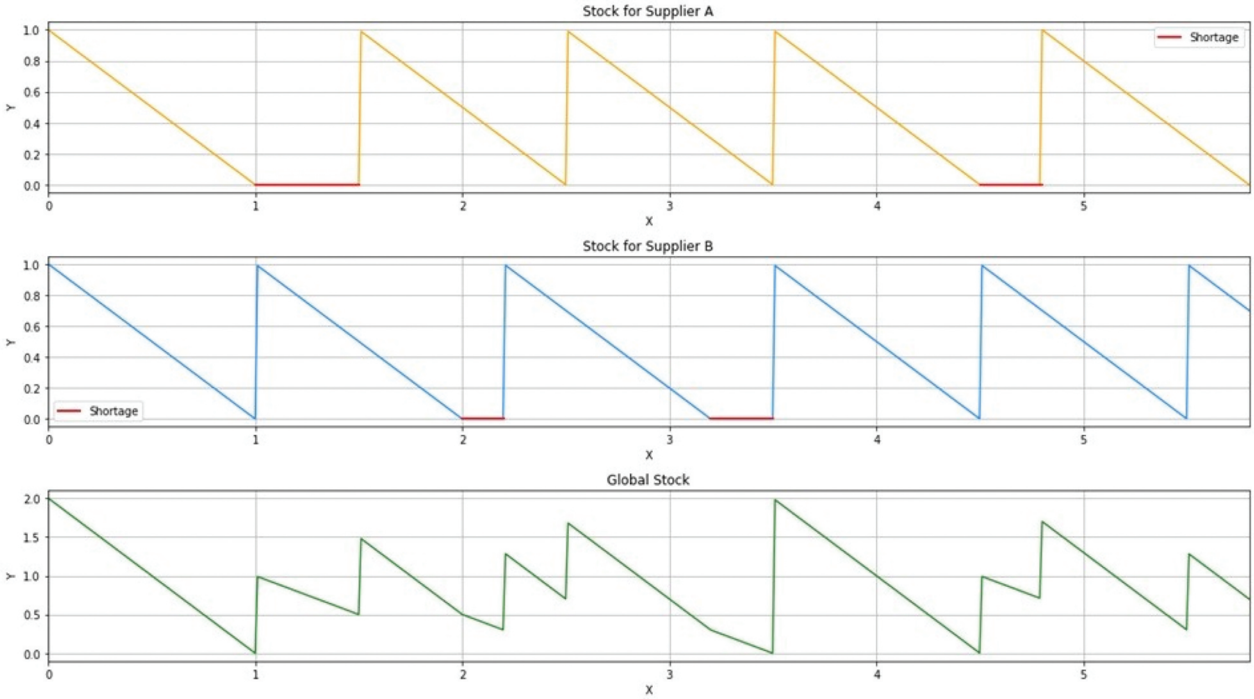

Figure 3. Effect of multiple suppliers on demand fulfillment.

Mathematical formulation and solution algorithm

The objective is to minimise the expected total cost per unit of time, which includes the ordering, purchasing, holding, and stockout costs.

The optimal demand rates can be computed by solving the following optimisation problem:

$$(M) : Minimize \sum_{\{i=1\}}^{\{m\}} K_i(y_i)$$

$$Subjectto : \sum_{\{i=1\}}^{\{m\}} y_i = D$$

$$y \geq 0, \quad i = 1, \ldots, m$$

The objective function 17 aims to minimise the expected total costs of the inventory system. Constraint 18 guarantees that all demand will be met, with the exception of unmet demand due to unforeseen delivery delays. Constraint (19) mandates that each demand rate must be positive.

It is important to note that, for a given y_i, the computation of $K_i^*(y_i)$ involves solving a single-supplier problem using the Golden Section Search algorithm, as elaborated in the flowchart in Figure 2. Consequently, the exact optimisation of Problem **(M)** appears to be unattainable. As an alternative, we suggest an approximate solution to Problem **(M)** by utilising a Particle Swarm Optimization (PSO) algorithm (Wang, Tan, and Liu 2018).

Particle Swarm Optimization (PSO) is a population-based stochastic optimisation technique inspired by the social behaviour of birds flocking or fish schooling (Wang, Tan, and Liu 2018). One of the significant advantages of PSO is its ability to handle non-linear, non-differentiable, and multi-modal objective functions, making it particularly suitable for solving Problem **(M)**. In PSO, each solution is represented by a 'particle' in the swarm. Each particle has its own position and velocity. These particles move through the problem space by following the current optimum particles. Each particle adjusts its movement based on its own experience and the experience of the entire swarm. It keeps track of its coordinates in the problem space, which is associated with the best solution it has achieved so far (personal best) and the best value found by the swarm (global best). The goal is to guide a set of particles towards the best position, which will be a close approximation of the real solution in this search space.

For each iteration, each particle updates its velocity and position using the following formulas (Marini and Walczak 2015):

$$\mathbf{v}[k+1] = \mathbf{v}[k] + c_1 \cdot r_1 \cdot (\mathbf{pbest}[k] - \mathbf{y}[k]) + c_2 \cdot r_2 \cdot (\mathbf{gbest} - \mathbf{y}[k])$$

$$y[k+1] = y[k] + v[k]$$

where:

- $\mathbf{v}[k]$ is the particle's velocity for particle k,
- $\mathbf{y}[k]$ is the current position of particle k,
- $\mathbf{pbest}[k]$ is the best-known position of particle k,

- **gbest** is the best-known position of the whole swarm,
- c_1 and c_2 are learning factors,
- r_1 and r_2 are random numbers in $[0, 1]$.

To ensure compliance with constraint ([func18]), during each iteration, we normalise the position of each particle. Specifically, for each particle $\mathbf{y}[k]$, we divide the i^{th} component by the sum of all components of the particle and then scale it by D. This normalisation process guarantees that the sum of all y_i values equals D, thus maintaining the feasibility of all particles within the swarm.

In our implementation, we used a population size of 10, and the following parameter settings: $c_1 = 2$, $c_2 = 2$, r_1, and r_2 are randomly generated in $[0, 1]$ for each iteration.

Computational study

We conducted a thorough computational study to evaluate the empirical performance of our proposed models and algorithms. For all experiments, we assumed that delivery delays are randomly distributed according to a negative exponential function with parameter $p > 0$. This function is defined as:

$$f(u) = \begin{cases} pe^{-pu} & \text{for } u \geq 0, \\ 0 & \text{for } u < 0. \end{cases}$$

Assuming that delay events represent a Poisson process (a common model for random events occurring independently over time), the delay durations are exponentially distributed. This makes the negative exponential function a natural choice for modelling delivery delays.

All the computational experiments were implemented using Python Version 3.11. The tests were carried out on a Windows machine with Processor: Intel(R) Core(TM) i5-9300 H CPU @ 2.40 GHz, 4 core(s), 8 logic processor(s) (9th Gen) and 8GB of RAM.

In what follows, we shall present the results of four experiments. The first experiment assesses the cost savings that may result from using multiple suppliers instead of just one. This experiment is carried out for different problem parameters. In the second and third experiments, we shall investigate the impact of varying two important parameters: the penalty coefficient (π) and the demand rate (D), respectively. In the fourth experiment, we investigate a procedure for finding the optimal number of suppliers.

Comparative cost analysis of single vs. multiple sourcing

In this first experiment, we randomly generated instances with m suppliers. For each instance, we began by solving m single-supplier problems, calculating for each supplier i the optimal order x_i^* and the corresponding optimal expected cost $K(x_i^*)$. Let $K_S^* = \min_{i=1,\dots,m} K(x_i^*)$ denote the minimal expected cost if a single supplier is used. Next, we used PSO to solve the multiple-supplier problem and calculate the optimal expected cost K_M^*. The percentage savings ε achieved by using multiple suppliers instead of a single supplier is given by:

$$\varepsilon = 100 \times \left(1 - \frac{K_M^*}{K_S^*}\right).$$

The instances were generated as follows: The number of suppliers $m \in \{2, 3, 4, 5\}$. The demand rate D was set to 50, and the maximum storage duration D to 50. The holding cost h to 10% of the purchase cost. Data was generated in two versions: one with tight ranges for the randomly generated variables and another with relaxed ranges. Table 2 displays the main characteristics of the instances. To ensure accuracy, 20 instances were randomly generated for each scenario.

The results are summarised in Table 3. In this table, we provide, for each problem class, the average, median, standard deviation, maximum, minimum the distribution of the percentage savings and the cumulative CPU time for solving the 20 instances.

We observe that PSO achieved convergence within a maximum runtime of 20 min for the largest test cases involving 5 suppliers. Our findings reveal significant cost savings are achievable by utilising multiple suppliers compared to a single supplier. The average cost savings tend to increase as the number of suppliers grows. This trend is particularly evident for the tight penalty coefficient range. Here, increasing the supplier count leads to a substantial rise in average savings, jumping from 17.86% to 25.43% with a penalty cost of 2, and from 34.65% to 55.32% with a penalty of 10.

While the relaxed penalty coefficient range generally yields lower savings due to higher supplier quality variability, a similar pattern emerges. Savings increase from 6.50% to 13.83% with a penalty coefficient of 2, and from 23.85% to 38.08% with a penalty of 10. Importantly, in both scenarios, the cost savings increase as stockout penalties become more severe.

Table 2. Generated data specifications.

Variable	Tight range	Relaxed range
Purchase cost c	1–3	1–8
Fixed cost F	200–500	100–2500
PDF parameter p	0.75–0.99	0.6–0.99

Table 3. Percentage savings.

Range	π	m	Average ε	Median ε	σ	ε max	ε min	CPU Time (sec)
Tight Range	2	2	17.86	19.07	4.26	25.14	8.04	458.70
		3	20.83	20.80	5.39	28.21	7.14	710.84
		4	24.67	25.33	7.46	39.18	11.04	896.65
		5	25.43	26.71	5.57	33.58	13.17	1069.24
	10	2	34.65	34.88	3.51	41.13	28.77	470.95
		3	46.58	46.69	3.86	52.12	40.42	718.46
		4	52.00	51.52	2.73	57.26	46.97	954.51
		5	55.32	55.42	2.47	60.13	50.12	1190.87
Relaxed Range	2	2	6.50	5.95	5.29	17.23	0.00	399.98
		3	9.07	10.32	7.34	21.26	0.00	533.32
		4	12.34	12.98	8.93	31.69	0.00	685.85
		5	12.28	15.88	8.11	23.63	0.00	732.54
	10	2	23.85	24.04	6.36	36.85	13.72	471.27
		3	32.52	31.49	7.39	46.08	16.16	695.84
		4	35.52	36.22	6.54	44.41	17.35	861.16
		5	38.08	38.98	6.77	49.99	20.86	1027.61

Table 4. Characteristics of the five suppliers for penalty coefficient sensitivity.

i	F_i	c_i	p_i
1	250	3.5	0.98
2	350	1.2	0.6
3	1000	1	0.7
4	200	1	0.7
5	750	3	0.95

Penalty coefficient sensitivity analysis

This subsection analyzes how the penalty coefficient (π) affects percentage savings. We generated data for five suppliers with varying fixed costs (F_i), purchase costs (c_i), and PDF parameters (p_i) as detailed in Table 4. The demand rate (D) was set to 50 units. The penalty coefficient was varied from 0 to 20. Four scenarios were investigated: using suppliers 1–2, 1–3, 1–4, and all five (1–5). Figure 4 presents the percentage savings as a function of the penalty coefficient.

We observe that as the penalty coefficient goes up, savings initially increase significantly, showing the benefits of using multiple suppliers to avoid expensive delays. However, after a certain point, the rate of savings slows down, and further increases in penalty costs lead to only a small additional savings. This means that with higher penalty costs there is more advantage of using multiple suppliers; however, there is a limit to how much extra savings can be achieved.

Demand rate sensitivity analysis

This third experiment analyzes how the coefficient rate (D) affects percentage savings. We generated data for five suppliers with varying fixed costs, purchase costs, and PDF parameters as detailed in Table 5. The demand rate D was varied from 0 to 200. Four scenarios were investigated: using 2, 3, 4, and 5 suppliers. Figure 5 shows the impact of demand variation on percentage cost savings.

We observe from Figure 4 that below a certain demand rate threshold, there is no significant benefit to using multiple suppliers. However, as the demand rate surpasses this threshold, savings increase significantly. This highlights the advantages of employing multiple suppliers to mitigate costly shortages due to delays. However, the relationship between demand rate and savings is concave, indicating that while higher demand positively impacts savings, the benefits grow at a decreasing rate as demand continues to rise.

Optimal number of suppliers

Increasing the number of suppliers clearly leads to additional management complexity and costs. Specifically, administrative and management expenses, such as paperwork, processing, and labour, add to the fixed costs of placing orders. This financial burden does not depend on the frequency or size of orders but solely on the number of suppliers, and it increases with the number of suppliers, m, due to more intricate order management and storage processes. To account for this, we incorporate a managerial cost, denoted as (A_m), into our analysis. To find the optimal number of suppliers, we evaluate model **(M)** for different values of m, selecting the solution that minimises the overall cost, inclusive of A_m.

We model A_m as a nonlinear function:

$$A_m = am^{\beta},$$

where, a represents the administrative cost per unit time for a single supplier, and β is a nonnegative parameter that captures the relationship between m and A_m. A linear relationship occurs when $\beta = 1$, indicating that A_m increases proportionally with the number of suppliers. When $\beta > 1$, the relationship is convex, meaning A_m increases at an accelerating rate with each additional supplier. Conversely, for $0 < \beta < 1$, the relationship is concave, indicating that while A_m increases with more suppliers, it does so at a decreasing rate, with each new supplier contributing less to the overall cost. In our experiment, we generated data for five suppliers using four values of $\beta = 0.5$, 1, 1.2, and 2.1,

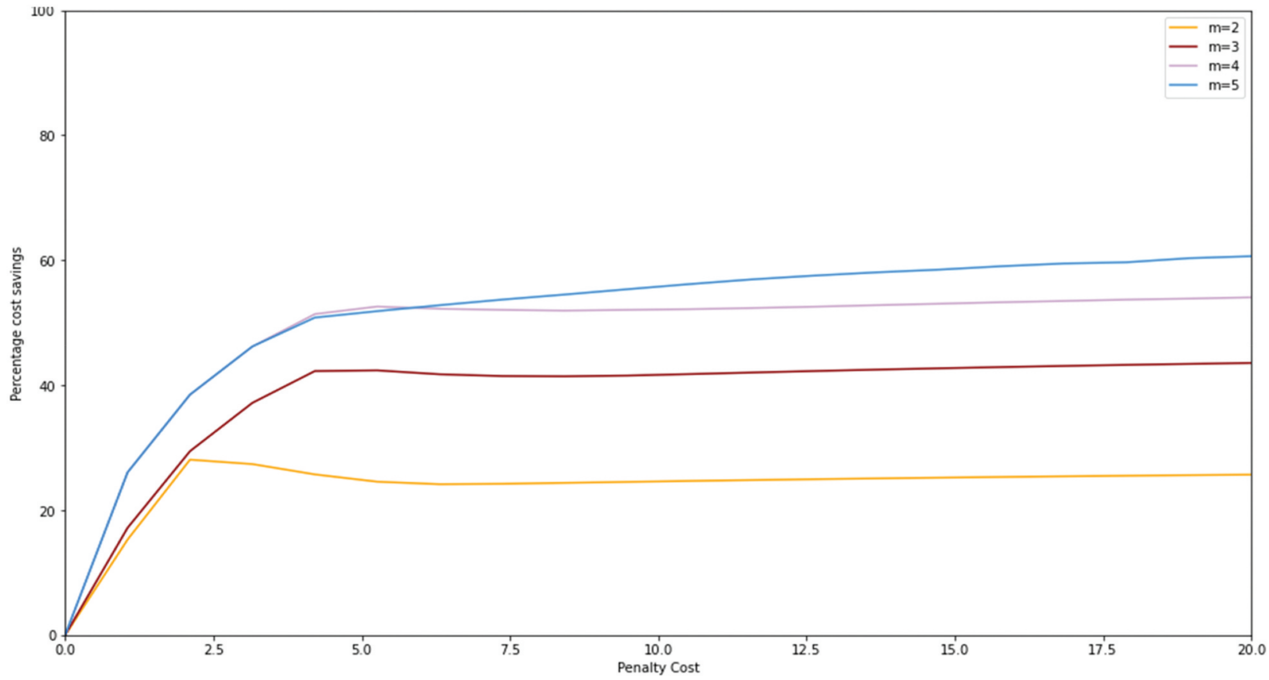

Figure 4. Effect of penalty coefficient on percentage cost savings.

Table 5. Characteristics of the five suppliers for demand rate sensitivity.

i	F_i	c_i	p_i
1	400	4.0	0.98
2	2000	1.2	0.8
3	1000	2.0	0.4
4	2000	2.0	0.9
5	750	3.0	0.9

respectively, with the data specifications provided in Table 6. We set $\alpha = 200$, the penalty cost $\pi = 20$, and the demand rate $D = 50$ units.

The results are summarised in Table 7. In this table, 'IC Cost' refers to the expected total inventory cost as defined in equation (17), while 'AD Cost' represents the administrative cost A_m. Columns labelled 'TC' indicate the total cost for different values of β. Table 7 reveals that the optimal number of suppliers is highly sensitive to the value of β. Specifically, when the managerial cost follows a concave function ($\beta = 0.5$), the optimal solution involves utilising all five suppliers. However, when $\beta \geq 1$, the optimal number of suppliers is consistently less than the maximum. An extreme case occurs when $\beta = 2.1$, where the cost of adding a second supplier outweighs the operational savings, rendering additional suppliers no longer cost-effective. In such instances, alternative strategies for enhancing resilience should be explored. This experiment underscores the importance of the cost function's shape in determining the most efficient number of suppliers.

Limitations and insights

Global supply chains face increasing disruptions from geopolitical tensions, pandemics, and natural disasters, threatening the availability of essential perishable goods like vaccines, infant formula, and critical drugs. Because modern supply chains are complex, a single failure can cause widespread shortages. Building resilience – particularly through strategies like multi-sourcing – improves flexibility and robustness, helping prevent stockouts when suppliers fail.

This study addresses a critical gap by integrating multi-sourcing and random delivery delays into a stochastic EOQ model that minimises total costs without relying on safety stock. This realistic approach offers practical guidance for managing perishable supply chains and ensuring the timely delivery of life-saving products. However, several limitations must be acknowledged to guide future advancements:

- Our model assumes the purchase cost is constant and independent of the order size. However, in many practical settings, economies of scale come into play. Specifically, when dealing with multiple suppliers, the order sizes from different suppliers tend to be relatively small, resulting in higher unit purchase costs and potentially increasing overall procurement expenses. This may lead to overestimating total costs in real-world cases where larger order quantities result in discounts. It also overlooks pricing structures based on order volume, which could identify more cost-effective procurement strategies.
- The model assumes a deterministic demand rate, which may not reflect real-world demand variability and uncertainty in all cases. As a result, its applicability may be limited in environments where demand is highly volatile.

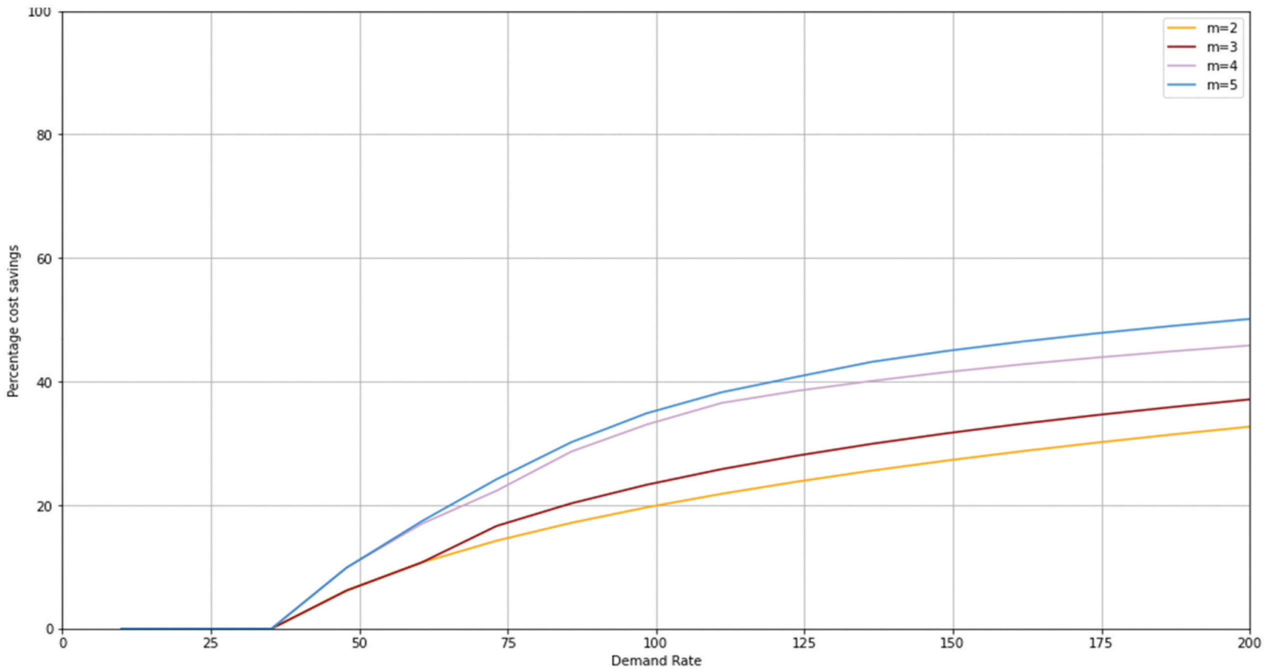

Figure 5. Effect of demand rate on percentage cost savings.

Table 6. Characteristics of the five suppliers for the optimal number of suppliers sensitivity.

i	F_i	c_i	p_i
1	250	3.5	0.98
2	350	1.2	0.6
3	1000	1.0	0.7
4	200	1.0	0.7
5	750	3.0	0.95

- Our model treats different suppliers as independent entities. Yet, managing suppliers in a coordinated manner can lead to synchronised deliveries, potentially reducing overall transportation costs and optimising logistics. Incorporating supplier coordination could reveal additional cost-saving opportunities and enhance supply chain efficiency
- The model considers only a single product type, assuming independent supply chains for each item. It does not account for scenarios where multiple product types are sourced from the same supplier, potentially overlooking shared constraints such as lead times or combined ordering costs.

Given these limitations, several theoretical and managerial insights and recommendations offer practical guidance for strengthening supply chain robustness by researchers and managers, respectively.

Theoretical insights

- Extending the model to incorporate dynamic and uncertain problem characteristics would broaden its applicability.
- Our empirical analysis indicates that the relationships between demand and saving rate, as well as between penalty cost and percentage cost savings, are concave. Confirming these observation through formal theoretical proofs warrants further investigation.
- Incorporating variable purchase costs and evaluating supplier synergies could improve cost accuracy and overall supply chain efficiency. Managing dependent supplier relationships requires greater coordination and communication compared to independent management, which should be explicitly reflected in the model.
- Coordinated management may also enable joint transportation planning and shared warehousing, enhancing both cost efficiency and environmental sustainability. Furthermore, analysing interdependencies between suppliers – such as shared infrastructure or subcontracting – can provide deeper insights into supply chain vulnerability and resilience. In this study, we modelled the additional cost of multiple suppliers using a simple nonlinear function based solely on the number of suppliers, without accounting for potential synergies. Developing a more accurate cost model that includes these synergies would be a valuable direction for future research.
- Integrating emergency ordering mechanisms would enable a more responsive strategy for managing disruptions. This added flexibility, combined with an enhanced model, could provide a more realistic approach to mitigating delivery delays and ensuring supply reliability. Emergency procurement can also serve as a contingency

Table 7. Total cost including managerial cost of managing different numbers of suppliers.

Suppliers No.	IC Cost	AD Cost $\beta = 0.5$	AD Cost $\beta = 1.0$	AD Cost $\beta = 1.2$	AD Cost $\beta = 2.1$	TC $\beta = 0.5$	TC $\beta = 1.0$	TC $\beta = 1.2$	TC $\beta = 2.1$
1	2547.06	200.00	200.00	200.00	200.00	2747.06	2747.06	2747.06	***2747.06***
2	1892.92	282.84	400.00	459.48	857.42	2175.77	2292.92	2352.40	2750.34
3	1437.46	346.41	600.00	747.44	2009.02	1783.87	2037.46	***2184.90***	3446.49
4	1170.16	400.00	800.00	1055.61	3675.83	1570.16	***1970.16***	2225.76	4845.99
5	1002.53	447.21	1000.00	1379.73	5873.09	***1449.75***	2002.53	2382.26	6875.63

buffer when conventional suppliers are affected by regional disruptions. Additionally, analysing when emergency ordering becomes cost-effective could provide managers with strategic thresholds for activating such measures.

- Expanding supplier evaluation criteria to include environmental impact, compliance history, and sustainability metrics would offer a more holistic framework for decision-making.
- Furthermore, it would be worthwhile to explore the inclusion of an additional mitigation strategy in the model – one that involves emergency orders with premium shipping fees and higher purchase costs. Incorporating this flexibility, along with an enriched model, could result in a more realistic approach that helps mitigate the impact of delivery delays and ensures a more reliable supply chain. Emergency procurement can also serve as a contingency buffer when conventional suppliers are simultaneously affected by regional disruptions. Moreover, analysing the conditions under which emergency ordering becomes cost-effective could provide managers with strategic thresholds for activating such measures.

By addressing these areas, future studies can further develop this model into a comprehensive decision-support tool that aligns with the complexities of real-world supply chains and enhances resilience in the face of growing global uncertainties.

Managerial insights

- Supplier Diversification: Increasing supplier diversity can be crucial. Relying on a single supplier exposes supply chains to higher risks of disruptions in case this supplier fails. For example, hospitals should source vaccines from multiple suppliers to avoid disruptions caused by disruptions such as bankruptcy, contamination, strikes, or cyberattacks. The study highlights that adopting a multi-supplier strategy can significantly bolster robustness by minimising the effect of risks by depending on multiple suppliers while minimising the possible associated costs depending on the case setting.
- Supplier Mix Optimisation: Managers need to carefully balance their supplier choices. Our model shows that the right mix of suppliers enhances supply chain reliability, cost, and flexibility, thus significantly improving supply chain robustness. Decision-makers should prioritise suppliers to reduce total costs and strengthen resilience.
- Cost Management: The quantitative approach in this research reveals that supplier diversification can not only mitigate risks but also reduce total supply chain costs. By diversifying orders among multiple suppliers, businesses can minimise the impact of delays and stockouts, leading to an average cost reduction of 34.65%. Managers need to weigh the trade-offs between cost efficiency and supply chain reliability based on the suppliers' parameters. For instance, the medical system should procure critical medications from a major international pharmaceutical company while also engaging a local supplier to balance cost and delivery time, even if the local supplier is less reliable.
- Geographic Diversification: While having multiple suppliers is essential, this research emphasises the importance of ensuring these suppliers are geographically diversified. Relying on suppliers from the same region exposes supply chains to the risk of simultaneous disruptions caused by regional events, such as natural disasters or geopolitical conflicts. By sourcing from different geographic locations, managers can minimise the likelihood of concurrent disruptions, ensuring supply chain continuity. For instance, managers can choose supplier storage facilities – either from the same company or different ones – across multiple continents to reduce the impact of natural disaster risks.
- The proposed mathematical model empowers industry managers to make data-driven supplier management decisions and thereby lead to less vulnerable supply chains.

Conclusion

The COVID-19 pandemic has exposed significant vulnerabilities in global supply chains, particularly for critical products such as pharmaceuticals and essential food items. This situation highlighted the need for robust mitigation strategies to enhance supply chain resilience, such as reducing dependency on a single supplier. Our research addresses this challenge by proposing an advanced economic order quantity model that considers random delivery delays, especially for essential perishable products that cannot depend on safety stock. The model accounts for constant demand, multiple unevenly reliable suppliers with varying fixed and purchasing costs, and delivery times subject to random delays. To address the criticality of stock-outs, we incorporate a quadratic shortage penalty function that heavily penalises significant stock-outs.

Our model *quantitatively* demonstrates that engaging multiple suppliers can significantly enhance supply chain resilience through robustness while minimising total costs. Through theoretical and computational analysis, we have shown that using multiple suppliers not only provides financial benefits but also improves the reliability of supply chains, making them more robust against disruptions. This research underscores the importance of diversifying suppliers to mitigate risks and ensure a steady supply of essential goods.

To conclude, this model offers valuable support for procurement managers who deal with vital perishable products such as pharmaceutical and medical industries by helping identify optimal supplier combinations under uncertainty. This enables a reduction in the risk of stockouts for critical perishable products while maintaining cost-efficiency. Thus, enhancing its supply chain resilience. The study provides a foundational step towards resilient and data-driven supplier management.

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

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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/or] its supplementary materials.

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