Effect of rework strategy on sourcing decisions under uncertainty

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Abstract

We address the challenge of allocating orders among multiple suppliers before a sales season (modeled as a single period) with uncertain demand and unreliable suppliers, driven by two key risks: capacity uncertainty and quality variability. Using a two-stage stochastic framework, we first model the buyer's decisions on supplier order allocation and internal capacity investment, followed by a second stage where supply and demand uncertainties are realized, and the buyer utilizes internal capacity to produce new items and rework defective ones. Reworking is especially advantageous when the cost of returns is prohibitive, and it offers higher revenue potential while being less resource intensive compared to recycling. Our study examines how rework strategies affect profit, waste reduction, and yield improvement, finding that rework provides financial benefits, especially under constrained supply capacity, with greater advantages for more risk-averse buyers. The appeal of rework increases further with waste-related taxes, such as landfill levies. In addition, we show that firms investing in internal capacity for rework operations tend to rely on fewer suppliers, relying on their own production capabilities to cushion against supply volatility. Using synthetic data inspired by the fast fashion industry, we offer managerial insights to implement sustainable sourcing strategies when exposed to both demand and supply uncertainty.

Keywords: Supplier selection, Supplier uncertainty, Rework and Reuse, Yield loss, Demand Uncertainty, Circular Economy

1 Introduction

Globalization of supply chains has led organizations to source from geographically distributed suppliers, creating exposure to disruption risks that include logistic interruptions, natural disasters, geopolitical instability, and production challenges such as fluctuation of capacity and quality issues that can affect procurement capabilities and erode financial performance (Rujeerapaiboon et al. 2023). Hendricks and Singhal (2003, 2005) analyzed more than 500 companies that faced supply chain disruptions in the 1990s, empirically demonstrating significant adverse effects on both short-term operational performance and stock market returns. Subsequent research by Ambulkar et al. (2015), Kim et al. (2015) and Shekarian et al. (2020) has corroborated these findings. Recent research by Baghersad and Zobel (2021) examines both short-term and long-term impacts of supply chain disruptions, revealing that manufacturing-dependent sectors such as semiconductors, vaccine manufacturing, agribusiness, etc. are particularly vulnerable (Tang and Kouvelis 2014). For example, semiconductor shortages have disrupted operations in companies such as Apple, Sony, Tesla, and BMW, leading to production delays and backlogs (Bailey 2020, Mohammad et al. 2022, Ramani et al. 2022, Voas et al. 2021). These disruptions contributed to estimated global losses of $110 billion (Wayland).

An industry that faces even more acute challenges is fast fashion, as fashion brands must simultaneously navigate supply-side risks and demand volatility, a dual pressure that significantly amplifies operational complexity (Bruce and Daly 2011, Brun and Castelli 2008). Fashion brands typically place advance orders with their suppliers, primarily based in Asia, prior to the sales season. These suppliers are often non-exclusive. As a result, brands face significant risks of low order fulfillment due to supplier capacity fluctuations, which can arise from machine downtime, labor shortages, or prioritization of other customers. In addition, inconsistent product quality further complicates supply reliability (Shen and Chen 2020). Given the long lead times, there is a limited opportunity for mid-season replenishment. As a result, fashion brands often overorder in anticipation of potential supply shortages and demand fluctuations. This frequently results in excess inventory in stores at the end of the season, which is usually cleared through markdowns (Broughton and Maurer 2022). Recently, apparel brands such Abercrombie & Fitch, Guess, and Gap changed their pricing strategy to increase profit margins while closely monitoring stock levels (Maurer and Trentmann 2021). An unintended outcome of these sourcing practices is the accumulation of items that do not meet strict brand quality standards. These substandard items cannot be sold directly to consumers, and distributing them through gray channels risks cannibalizing seasonal sales of the latest collection. Since returning them to suppliers is cost-prohibitive, they are often discarded in landfills. This environmentally harmful practice has prompted regulatory responses. In particular, France's 2025 legislation introduces an eco-tax on textile and apparel waste.

The advent of digital technologies and Industry 4.0 has greatly strengthened supplier-buyer collaboration, offering effective solutions to many of the previously identified supply challenges. Such brand-supplier collaborations are particularly prevalent in industries where long-term partnerships are the norm, such as automotive and industrial goods, where suppliers play a crucial role in R&D and product innovation, becoming key contributors to the value chain. In contrast, fashion brands work with expansive supplier networks spread across diverse regions, as they rely on short production cycles and low-cost, single-season transactions. For example, Inditex, the parent company of Zara, partners with more than 6,600 suppliers in Europe, Asia, and North Africa. Similarly, VF Corporation sources from 273 contract manufacturers in 30 countries, while Adidas collaborates with 388 external manufacturing partners. This global scale complicates collaborative planning and introduces significant coordination challenges. According to Jain et al. (2022), the supplier diversification strategy is counterproductive, as it prevents brands from capitalizing on volume advantages and discourages suppliers from investing in capabilities that enable faster recovery after disruption. In addition, most garment suppliers, particularly in Asia, operate under a basic cut-make-trim (CMT) model with narrow profit margins, restricting their ability to invest in advanced technologies. Furthermore, the prevalence of short-term supplier relationships, often lasting only a few seasons, discourages brands from supporting digital upgrades at the supplier. Researchers also found that garment manufacturers continue to lag in technological maturity (Nipa 2020, Salman et al. 2024, Majumdar et al. 2021).

Therefore, to reduce supply side vulnerabilities, many brands are now developing internal production capabilities, while others secure strategic equity positions in large suppliers (Tier1) to guarantee uninterrupted access to supply and command greater accountability. For example, in 2023, New Balance, an American athleisure brand, invested $70 million to establish its sixth manufacturing facility in Londonderry, New Hampshire, while also operating an existing facility in Flimby, England. Zara employs a hybrid sourcing strategy, combining near-shoring (own production) for European markets with offshore production (contract manufacturers) in Asia and North Africa to optimize both cost and speed. The Prada Group acquired a 15% stake in the Italian knitwear manufacturer Luigi Fedeli e Figlio in June 2023. Similarly, Zegna Group has strategically expanded its manufacturing capabilities through acquisitions, including textile producer Bonotto (year 2016), fashion accessory manufacturer Cappellificio Cervo (year 2018), knitwear manufacturer Dondi (year 2019), and Tessitura Ubertino (year 2021). In addition, some forward-thinking fashion brands are now investing in sustainable infrastructure, exemplified by The Hong Kong Research Institute of Textiles and Apparel (HKRITA) and H&M Foundation's collaborative Open Lab initiative for advanced garment recycling. Fashion's growing embrace of manufacturing ownership and vertical integration signals a new paradigm in which brands are directly trying to influence quality, reliability, and speed.

The fast fashion sourcing challenge can be framed as a single-period newsvendor problem, where procurement quantities must be allocated across multiple unreliable suppliers before the sales season begins. Research identifies three main types of supplier unreliability: (1) yield uncertainty, where a supplier may only partially fulfill an order, the quantity delivered depending on the amount ordered (Giri 2011, Xie et al. 2021, Yuan et al. 2021) (2) capacity uncertainty, which arises when a supplier's production capacity is reduced due to internal failures (Feng et al. 2020, Gholami and Mirzazadeh 2018, Arbabian and Rikhtehgar Berenji 2023) and (3) major disruptions, where a supplier completely fails and delivers nothing, commonly referred to as an all-or-nothing supplier (Mohammadivojdan et al. 2022, Sawik 2024). Existing research typically addresses risk factors in isolation, proposing mitigation strategies that focus on maximizing expected profit or minimizing costs, with limited attention given to incorporating service-level targets. Typical hedging strategies include: (1) backup supplier agreements, often in the form of option contracts (Heydari et al. 2024, Mohammadivojdan et al. 2022); (2) spot market purchases (Mohammadivojdan et al. 2022)); (3) use of revenue share or buyback contracts (Jadidi et al. 2024); and (iv) sourcing mix (reliable and unreliable suppliers) (Hu and Kostamis 2015, Jiang et al. 2025)). The existing literature provides limited information on supply chain contexts that simultaneously consider the three main sources of supply uncertainty: yield variability, capacity constraints, and disruption, in addition to stochastic demand. Research that examines rework as a viable strategy to mitigate supply risk while simultaneously addressing environmental concerns, such as waste reduction, is even more scarce. Rework emerges as a particularly compelling strategy under two key conditions: (1) when returning defective products to suppliers is no longer economically viable or when landfill taxes are imposed by regulatory authorities, and (2) when rework consumes fewer resources than conventional recycling methods. These conditions are especially relevant in the fast fashion industry, positioning rework as a timely and contextually appropriate recourse mechanism.

We address this gap by formulating the problem as a two-stage decision model. In the first stage, the buyer must simultaneously determine (1) optimal order quantities and (2) labor allocation to build internal production capacity. The second stage commences once demand and supply reliability become known and the buyer leverages internal capacity to rework defective items and in some cases produce new ones. We assume that suppliers operate independently and that demand, supplier capacity, and yield distributions can be effectively represented through a finite set of discrete scenarios. Furthermore, we consider a context in which the brand lacks pricing power. Our modeling approach jointly maximizes profit and minimizes waste by directing reworked items to meet demand, preventing them from going to landfill, and simultaneously producing new items for unforeseen surges in demand. Traditional supply chain procurement literature often assumes risk-neutral conditions, assessing portfolio value primarily through expected profit. However, understanding risk preferences is essential, especially in environments marked by demand uncertainty and supply-side risks. In such cases, even rare but significant losses can jeopardize a firm's financial stability, making downside risk mitigation a critical consideration for decision makers (Sawik 2024, Merzifonluoglu 2024). Consequently, our optimization models use the Conditional Value-at-Risk (CVaR) metric to distinguish procurement strategies between risk-averse and risk-neutral decision makers and to evaluate the impact of risk-averse behavior on overall profitability.

Given this context, our aim is to examine the following four core research questions.

1. What are the benefits for a risk-neutral buyer when implementing rework to mitigate supply chain uncertainties?
2. To what extent do these benefits diminish when the buyer becomes risk-averse?
3. To what extent do regulations such as the landfill tax modify the value proposition of rework?
4. What is the profit sensitivity when implementing rework under i) demand uncertainty, ii) supply disruptions, and iii) quality variance?

The remainder of the paper is organized as follows. Section 2 provides a detailed review of the literature that highlights the unique contributions of our study. In Section 3, we introduce the problem statement, outline the assumptions, and provide a comprehensive description of the sequence of events. Section 4 explores the model, explaining the notational conventions and the solution process. Section 5 presents the findings and insights obtained from the numerical analysis. Finally, Section 6 covers the conclusion, discusses the managerial implications, and suggests possible areas for future research.

2 Literature Review

Our study integrates four streams of literature: (1) supply chain risks, (2) multiple procurement channels, (3) quality management in the supply chain, and (4) rework in production systems.

The first stream of literature focuses on supply chain risks, which are broadly categorized into three main types. The first category, yield uncertainty, refers to cases where suppliers fulfill only part of the ordered quantity. This issue typically arises due to factors such as quality defects, the use of inferior raw materials, or product damage during shipment (see, e.g. Agrawal and Nahmias (1997), Merzifonluoglu and Feng (2014), Chen et al. (2001b)). The second category relates to capacity uncertainty, which arises when a supplier's production capability is reduced due to localized disruptions such as labor strikes or equipment failures (see, e.g., Ciarallo et al. (1994), Li et al. (2013), Golmohammadi and Hassini (2021)). To mitigate the risk of yield and capacity uncertainty, researchers propose several strategies. These include increasing production or maintaining buffer inventory (Henig and Gerchak 1990, Hewitt and Pantuso 2024), diversifying their supplier base to leverage risk aggregation and reduce variability in supply output (Federgruen and Yang (2008, 2009); Anupindi and Akella (1993), Dada et al. (2007), Feng et al. (2020), Li et al. (2013), Hu and Kostamis (2015), Dong et al. (2012), Kouvelis et al. (2018), Tan et al. (2016), Feng et al. (2019), Yuan et al. (2021)), trade credit (Yang and Birge 2013, Brunet and Babich 2012, Klapper et al. 2012)), liability sharing (Chao et al. 2009), buyback and revenue share contracts (Xie et al. 2021, Tang and Kouvelis 2014) and investing in efforts to improve supplier reliability (Wang et al. 2010, Golmohammadi and Hassini 2021). Recent research has explored how monopoly buyer pricing decisions can be used to mitigate supply chain risks (Kouvelis et al. 2021, Dong et al. 2022). The third category includes major disruptions that occur when a supplier is unable to deliver any goods due to unforeseen and extraordinary events, such as natural disasters, international trade disputes, or pandemics. Suppliers exposed to such risks are often referred to as 'all-or-nothing' suppliers, reflecting the binary nature of their delivery outcomes. For an extended review of the supply chain disruption literature, see Sodhi and Tang (2012) and Snyder (2012). According to Katsaliaki et al. (2022), supply chain disruptions can result from a variety of events, including (i) catastrophic and macrolevel risks (Gunessee et al. 2018, Ivanov 2020), (ii) legal, regulatory and financial incidents (Dwivedi et al. 2018, Griffith et al. 2019), (iii) fluctuations on the demand and supply side (Babich et al. 2007, Hu and Kostamis 2015, Sawik 2013, 2017), and (iv) logistics and transportation-related issues (Maiyar and Thakkar 2019, Dupont et al. 2018). Recently, Sawik (2024) and Merzifonluoglu (2024) examined risk-averse decision-making strategies aimed at improving supply chain resilience in worst-case disruption. Both authors emphasize the importance of studying risk aversion through the lens of Conditional Value at Risk (CVaR), suggesting that minimizing downside risk is suitable in environments characterized by uncertainty. The existing supply chain risk literature typically analyzes yield, capacity, and disruption risks separately, with few studies integrating all three within a single framework. Most models focus on maximizing expected profit or minimizing cost, occasionally incorporating Conditional Value at Risk (CVaR) with service-level targets. Studies that integrate sustainability considerations into supply chain risk management, such as waste reduction or emissions control, remain relatively rare.

In the second stream of literature, scholars examine the use of multiple procurement channels to mitigate supply uncertainty. These strategies include engaging with multiple suppliers, employing option or forward contracts, and participating in spot markets. Many researchers (Seifert et al. 2004, Wu and Kleindorfer 2005, Martínez-de Albéniz and Simchi-Levi 2009, Fu et al. 2010, Saghafian and Van Oyen 2012, Luo and Chen 2017, Xue et al. 2020) analyze optimal ordering decisions in supply chains with stochastic yields, focusing on sourcing through option contracts and spot markets following demand realization. Merzifonluoglu (2015, 2017), Mohammadivojdan et al. (2022), Moinzadeh and Nahmias (2000) investigate single-period procurement models incorporating forward contracts, option contracts, and spot markets, and propose methods for supplier selection and order placement. More recently, research has focused on two-stage sourcing models that incorporate resource actions under risk aversion, utilizing Conditional Value-at-Risk (CVaR) optimization techniques (Fan et al. 2020, Merzifonluoglu 2024). These studies commonly assume that supply uncertainty results in partial fulfillment of orders, without explicitly distinguishing whether randomness stems from yield variability or capacity unavailability. Furthermore, specific recourse strategies may not be universally applicable across product categories. For example, fashion brands cannot purchase current season collections from spot markets in the event of supply disruptions, and neither option nor forward contracts adequately address challenges related to waste disposal.

The third stream of literature focuses on quality management within supply chains, exploring the strategies firms employ to improve product quality. Within this domain, three main approaches emerge. First, an investment-based approach involves the buyer committing resources to improve supplier reliability by improving supplier internal processes. These are also known as prevention approaches, which have been studied by various researchers such as Liker and Choi (2004), Sako (2004), Krause et al. (2007), Zhu et al. (2007), Lee and Li (2018), Nikoofal and Gümüş (2018), Bondareva and Pinker (2019) and the references therein. They establish a compelling case that buyer-initiated quality improvement is crucial in improving product quality. In some cases, the supplier and the buyer collaborate by jointly investing in quality improvement and inspection efforts (Hsieh and Liu 2010). The second is the avoidance approach, which encompasses various mechanisms such as rewards and incentives (Baiman et al. 2001, Lee and Li 2012, Chen et al. 2001a), certifications (Hwang et al. 2006), and cooperative quality investments (Chen et al. 2015) and deferred payment (Babich and Tang 2012, Rui and Lai 2015). One of the serious consequences of poor quality management is the risk of product recalls. Although traditional mechanisms such as product warranties can help address this risk, they are often ineffective when dealing with distant suppliers in emerging markets (Reyniers and Tapiero 1995, Lim 2001, Balachandran and Radhakrishnan 2005, Chao et al. 2009). The incentive-based strategy is attractive and promotes supplier participation; however, it is plagued by moral hazard issues and the risk that defects reach the final consumer, which could lead to recalls and liability charges (Chao et al. 2009). The third and most widely adopted approach, the inspection-based strategy, addresses these limitations by requiring the buyer to inspect the incoming units. Dong and Tomlin (2012) showed that an incoming inspection strategy is effective not only in multi-tier supply chains but also in managing product adulteration risks posed by foreign suppliers (Babich and Tang 2012). Chen et al. (2022) compared two ways to manage product quality: using inspections or buying insurance. They found that inspections work better when the buyer has limited funds, but insurance becomes a better choice once the buyer has enough working capital. However, the inspection process comes with drawbacks, including its labor-intensive nature and vulnerability to human errors. In this study, we examine a buyer who engages with pre-qualified suppliers on a seasonal basis. Due to the short-term nature of these relationships, inspection is identified as the most suitable method for quality control. For simplicity, we assume a 100% inspection rate for the incoming items, with the inspections being perfectly accurate and free from errors. Future research could explore incorporating misclassification rates into the model, using our inspection policy as a benchmark. We refer readers to Raouf et al. (1983) and Duffuaa and Khan (2002) to explore this topic further.

The fourth stream deals with rework in the production system. A substantial body of literature highlights that in industries where defective units retain significant value -such as semiconductors, glass, metal processing, chemicals, pharmaceuticals, and automotive manufacturing - there is a strong incentive to rework these elements (Buscher and Lindner 2007, Chiu et al. 2007, Sarker et al. 2008, Widyadana and Wee 2012). Recent studies that investigate rework more thoroughly include Sonntag and Kiesmüller (2017), which assumes a perfect rework process in which reworked items are restored to meet primary demand. Their primary objective was to determine the optimal base stock level in production environments where discarded items are reworked and retained in the system. They show that rework is a favorable strategy when rework time is short and its cost is lower than that of new production and disposal. In addition, they find that the safety stock levels under a rework regime are lower compared to scenarios where defective items are simply discarded. Recently, Berling and Sonntag (2022) extended these results under the assumption of imperfect rework. Our paper builds on the context of Sonntag and Kiesmüller (2017) by extending it to a sourcing context, investigating how the decision to rework or discard defective items affects profitability and waste reduction. We have summarized the key literature in a table and highlighted our contributions in relation to them in the appendix C.

This study investigates the use of rework and internal production as hedging strategies in environments where buyers simultaneously face yield variability, capacity uncertainty, and stochastic demand. The disruption risk is incorporated into our study by modeling scenarios in which the supplier capacity is reduced to zero with specified probabilities. We provide insights into how rework influences economic performance (e.g., profitability) and sustainability outcomes (e.g., waste reduction), particularly as decision-making shifts from risk-neutral to risk-averse behavior. Rework is operationalized through the investment in internal capacity, which can be prohibitively expensive in specific contexts, limiting its widespread adoption. This research identifies the conditions under which rework becomes financially viable and examines its potential to offset the economic burden of waste disposal taxes. Ultimately, our goal is to equip practitioners with evidence-based guidance on the feasibility and benefits of adopting rework strategies in their specific operational environments.

3 Problem Formulation

3.1 Preliminaries

Our research setting focuses on the fast fashion industry, where buyers, such as fashion brands, procure items from suppliers in preparation for an upcoming sales season. These suppliers are often based in low-cost countries. It is well documented that suppliers frequently fail to fulfill orders due to capacity limitations caused by machine malfunctions, labor strikes, or local disruptions. In addition, items received from suppliers undergo quality control and inspection, where less desirable products are screened. Fashion brands prefer to discard rejected items rather than sell them at salvage value to avoid gray-market transactions. However, with the government introducing waste penalties and increasing consumer awareness of sustainable fashion, brands are now adopting environmentally friendly strategies such as reworking. Products that do not meet quality standards are reworked and sold as new. The rework strategy is feasible only if the buyer invests in its internal production capacity by hiring workers before the season. We base our analysis on the key assumption that the buyer, typically a fashion brand, is located in a mature economy such as the U.S., EU, or Japan, while the suppliers are primarily based in low-cost exporting countries across Asia. Sourcing from external suppliers is typically more cost effective than setting up in-house production, largely due to wage arbitrage between advanced economies and lower-cost countries such as India, Bangladesh, and Vietnam. The trend of outsourcing and waste generation in a fast fashion has been thoroughly examined in the works of Rauturier (2020), Zanjirani Farahani et al. (2022), White et al. (2017) and Ma et al. (2016). Brands typically resort to internal production only under exceptional circumstances, such as addressing critical supply chain risks—often at a higher cost. This forms the foundation of our investigation into whether investing in internal production capacity is a viable strategy for fashion brands to manage supply and demand uncertainties, and under what circumstances it may still be more advantageous to continue sourcing from unreliable suppliers.

This problem closely resembles a single-period newsvendor model with rework capability. If the realized demand exceeds the sum of sourced items and internal production, sales will be lost, as new collections are in vogue for only one season. Conversely, if the total supply exceeds the realized demand, the buyer will have surplus inventory that must be discarded, incurring an unwanted penalty as a municipal tax.

The objective is to select the optimal supplier portfolio and determine the order sizes that maximize procurement profit. To address this problem, we formulate a two-stage stochastic model with rework as a recourse mechanism. The buyer aims to meet the uncertain demand for each product in their portfolio $\mathcal{M}$. Each product $m \in \mathcal{M}$ has a set $\mathcal{K}_m$ of suppliers. We let $\mathcal{K} = \cup_{m \in \mathcal{M}} \mathcal{K}_m$ denote the set of all suppliers. The demand for all products is a multivariate random vector denoted $D \in \mathbb{R}^m_+$, following a known probability distribution. In the first stage, the buyer decides to hire workers τ at a unit cost of c^{lab} and place an order quantity q_{mk} for product $m \in \mathcal{M}$ at the supplier $k \in \mathcal{K}_m$ at a unit outsourcing cost of c^o_{mk}. At this point, both demand and supply are unknown. The suppliers have a random capacity denoted by U_{mk} with a known distribution. If the order quantity q_{mk} exceeds the capacity U_{mk}, the supplier can only fulfill the order up to its capacity limit. Consequently, the resulting supplier yield Y_{mk} is the minimum of the quantity ordered and the supplier's capacity, i.e., $Y_{mk} = \min(q_{mk}, U_{mk})$.

In the second stage, D_m and Y_{mk} are revealed, and the items of type $m \in \mathcal{M}$ received from the supplier $k \in \mathcal{K}_m$ are sent for inspection. The inspection process classifies incoming products as good, re-usable, or poor. We let G_{mk} denote the proportion of the yield Y_{mk} that is classified as good quality. Therefore, of the supplier's yield, $Y_{mk}G_{mk}$ are good quality items. We define R_{mk} as the fraction of defective yield that is reworkable. Specifically, since $Y_{mk}(1 - G_{mk})$ units are not of acceptable quality, the number of garments of type m from the supplier $k \in \mathcal{K}_m$ that can be reworked is given by:

$$R_{mk}(1 - G_{mk})Y_{mk}$$

The proportions of G_{mk} and R_{mk} are treated as random variables, with their distributions inferred from historical data. The remaining portion is classified as rejected and subsequently discarded. As a result, the interplay between capacity availability and quality levels introduces uncertainty into the supply process. To mitigate the risk of supplier uncertainty, the buyer uses its internal capacity τ in three ways: (i) internal production of product $m \in \mathcal{M}$ in regular time, p_m, at a cost c_m, (ii) production over time of product $m \in \mathcal{M}$, o_m, at a cost c^e_m, and (iii) rework of product $m \in \mathcal{M}$ from supplier $k \in \mathcal{K}_m$, r_{mk}, at a cost c^r_m. The buyer is constrained by the number of re-usable items such that $r_{mk} \leq R_{mk}Y_{mk}(1 - G_{mk})$. Therefore, the items discarded from the product $m \in \mathcal{M}$ from the supplier $k \in \mathcal{K}_m$ after the rework operation are D_m - $Y_{mk}G_{mk} - r_{mk}$. Let a_m denote the capacity consumed to produce an item internally and a^r_m represent the capacity required for rework. Therefore, the second stage decisions are the quantities r_{mk}, p_m, and o_m, for each product $m \in \mathcal{M}$ and supplier $k \in \mathcal{K}_m$ that are related to the first stage decision τ such that $a_m p_m + a^r_m r_{mk} \leq \tau$ and $a_m o_m \leq \beta\tau$. The allowance limit β indicates the proportion of workers allowed to work overtime according to regulations. Figure 1 illustrates the decision sequence of our model. The number of products that buyers avoid discarding due to the rework operation is $\sum_{m \in \mathcal{M}} \sum_{k \in \mathcal{K}_m} r_{mk}$. Sustainable fast fashion brands monitor and highlight this metric in their marketing campaigns and annual reports.

3.2 Assumptions

The following assumptions underpin our study:

1. External sourcing is more cost-effective than internal production, i.e., $c^o_{mk} < c_m < c^e_m$. We note that this assumption is not required for our modeling approach, but reflects the current situation in which production in the west is more expensive than in the global south.

2. The product pricing is exogenous

3. The suppliers are not correlated

4. The buyer's quality inspection process covers 100% of the supply and is assumed to be error-free.

5. Rework is cost-efficient and consumes fewer resources, i.e., $c^r_m < c_m < c^e_m$ and $a^r_m \leq a_m$.

6. Customers perceive reworked items as equivalent in quality to new products, leading to no decline in demand

7. Landfill taxes are lower than the per-unit cost of returning defective items to the supplier

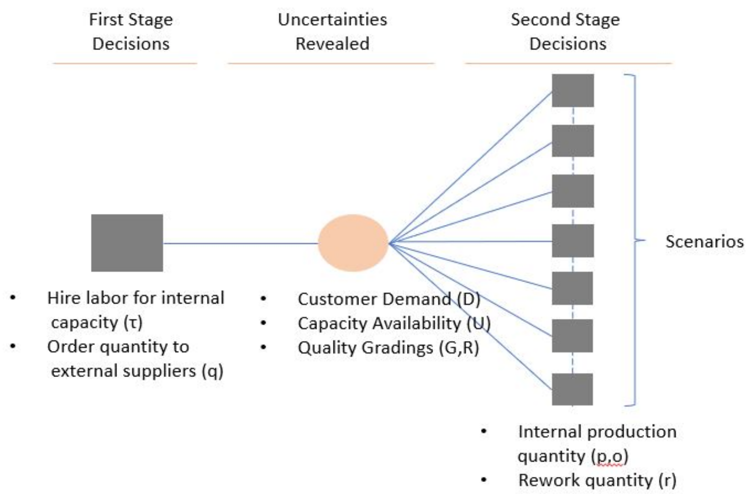

Figure 1: Decision sequence.
Source: Author

3.3 Model formulation

We outline all the sets, parameters, and variables used in our model in Table 1 for easy reference. This table also includes the notation used for a two-stage stochastic linear programming formulation to be developed later.

We let $\mathbf{G}$, $\mathbf{R}$, $\mathbf{U}$, $\mathbf{D}$ denote the vectors or matrices that contain, respectively, G_{mk}, R_{mk}, U_{mk}, and D_m for $m \in \mathcal{M}$ and $k \in \mathcal{K}_m$. Similarly, we let $\mathbf{q}$, $\mathbf{p}$, $\mathbf{o}$, and $\mathbf{r}$ denote matrices or vectors containing, respectively, q_{mk}, p_m, o_m, and r_{mk} for $m \in \mathcal{M}$ and $k \in \mathcal{K}_m$. Our objective is to explore the impact of rework capacity within the context of stochastic supply and demand conditions, alongside traditional supplier selection and order allocation issues. We have formulated our problem as a single period two-stage stochastic optimization problem. The first stage objective V maximizes the difference between the expected second stage profit, represented by $\Pi(.)$, and the

Table 1: Sets, Parameters, and Decision Variables

Symbol	Description
Sets	
$\mathcal{M} = \{1, 2, ..., M\}$	Set of items to be sourced or produced
$\mathcal{K}_m = \{1, 2, ..., K_m\}$	Set of external suppliers for item $m \in \mathcal{M}$
Parameters	
c^{lab}	Marginal cost of fixed labor capacity
c_m	Marginal cost of internal production per item $m \in \mathcal{M}$
c^e_m	Marginal cost of overtime production per item $m \in \mathcal{M}$
c^r_m	Average rework cost per item $m \in \mathcal{M}$
c^o_{mk}	Outsourcing cost per item $m \in \mathcal{M}$ from supplier $k \in \mathcal{K}_m$
a_m	Capacity consumed to produce item $m \in \mathcal{M}$
a^r_m	Capacity consumed to rework item $m \in \mathcal{M}$
l_m	Penalty for losing one sale of item $m \in \mathcal{M}$
α	Confidence level represents the probability that a given statistic will fall within a specified range under repeated sampling.
β	Proportion of plant's workforce that is allowed to overtime where $\beta \in [0, 1]$
λ	Proportion of product cost levied as environmental waste tax
ν	Parameter that control the level of risk aversion where $\nu \in [0, 1]$
y_m	Revenue the buyer makes by selling one unit of product $m \in \mathcal{M}$
VaR_α	Value at Risk
$CVaR_\alpha$	Conditional Value at Risk
Random Variables	
U_{mk}	Realized capacity of supplier $k \in \mathcal{K}$ to produce item $m \in \mathcal{M}$
D_m	Demand for product $m \in \mathcal{M}$
G_{mk}	Proportion of acceptable items of product $m \in \mathcal{M}$ with from supplier $k \in \mathcal{K}_m$
R_{mk}	Proportion of reworkable items of product $m \in \mathcal{M}$ from supplier $k \in \mathcal{K}_m$
First Stage Decision Variables	
τ	Positive integer variable to indicate the number of people to hire for rework and production
q_{mk}	Positive integer decision variable denoting the number of units of product $m \in \mathcal{M}$ to buy from supplier $k \in \mathcal{K}_m$
Second Stage Decision Variables	
Y_{mk}	Yield realization for product $m \in \mathcal{M}$ sourced from supplier $k \in \mathcal{K}_m$
L_m	Unfulfilled demand (Lost sale) for $m \in \mathcal{M}$
S_m	Total quantity of item sold $m \in \mathcal{M}$
r_{mk}	Quantity for rework of item $m \in \mathcal{M}$ from supplier $k \in \mathcal{K}$
p_m	Quantity for internal production during the season of item $m \in \mathcal{M}$
o_m	Quantity for internal production during the season of item $m \in \mathcal{M}$ during overtime hours

initial investment in labor capacities τ as outlined in Equations (1) through (5). The maximum value achieved by $V(.)$ is denoted by V^*.

$$V^* = \max_{q_k, \tau \geq 0} \mathbb{E}\left[\Pi(\mathbf{q}, \tau \mid \mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D})\right] - c^{\text{lab}}\tau \tag{1}$$

$$\begin{aligned}
\Pi(\mathbf{q}, \tau \mid \mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D}) : \max_{\mathbf{p}, \mathbf{o}, \mathbf{r}} \sum_{m \in \mathcal{M}} \Bigg[& y_m \min\left(D_m, p_m + o_m + \sum_{k \in \mathcal{K}_m} r_{mk} + \sum_{k \in \mathcal{K}_m} \min(q_{mk}, U_{mk}) G_{mk}\right) \\
& - l_m \left(D_m - p_m - o_m - \sum_{k \in \mathcal{K}_m} r_{mk} - \sum_{k \in \mathcal{K}_m} \min(q_{mk}, U_{mk}) G_{mk}\right)^+ \\
& - c_m p_m - c_m^r \sum_{k \in \mathcal{K}_m} r_{mk} - c_m^e o_m - \sum_{k \in \mathcal{K}_m} \left[c_{mk}^o \left(\min(q_{mk}, U_{mk}) G_{mk} + r_{mk}\right)\right] \\
& - \sum_{k \in \mathcal{K}_m} c_{mk}^o \lambda \left(\min(q_{mk}, U_{mk})(1 - G_{mk}) - r_{mk}\right) \Bigg]
\end{aligned} \tag{2}$$

Subject to:

$$\sum_{m \in \mathcal{M}} a_m o_m \leq \beta\tau \tag{3}$$

$$\sum_{m \in \mathcal{M}} a_m p_m + \sum_{m \in \mathcal{M}} \sum_{k \in \mathcal{K}_m} a_m^r r_{mk} \leq \tau \tag{4}$$

$$r_{mk} \leq \min(q_{mk}, U_{mk})(1 - G_{mk}) R_{mk} \qquad \forall m \in \mathcal{M}, k \in \mathcal{K}_m \tag{5}$$

In the first stage (1), the buyer incurs costs to hire τ labor associated with the establishment of internal capacity, prior to the realization of demand and supply yield. The second stage is represented by (2). The first term captures the revenue component, calculated as the product of the unit price (y_m) and the minimum of demand (D_m) and the total available inventory. The second term accounts for the penalty associated with lost sales when demand (D_m) exceeds the available inventory. The subsequent terms represent the production costs of new items ($c_m p_m$ and $c_m^e o_m$) and reworked items ($c_m^r r_m$). The final two terms reflect the cost of externally sourced items (c_{mk}^o), which includes both the proportion of good items (G_{mk}) and reworked items (r_{mk}), and the penalty cost (λc_{mk}^o) associated with the proportion of rejected items that were not reworked - i.e,$(1 - G_{mk}) - r_{mk}$) - and consequently sent to landfill. Constraint (3) models the proportion of labor (β) allowed to work overtime, while Constraint (4) limits the total capacity consumed in producing new items and reworked items to not exceed the available labor force (τ). Finally, constraint (5) ensures that the quantity of reworked items (r_{mk}) does not exceed the reworkable portion of externally sourced items, represented by $R_{mk}(1 - G_{mk})$. A detailed explanation of the terms involved and the sequence of events in the first and second stages is provided in Section (3.1).

The optimization problem presented above is not analytically tractable, despite its superficial resemblance to a constrained news-vendor problem. This complexity stems from four sources of randomness ($\mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D}$) which influence not only the objective function but also the constraints, specifically (5). Therefore, the optimization problem above is not a generalization of the newsvendor problem in that the optimal purchase quantities, $\mathbf{q}$ cannot be expressed as critical fractiles of some random variable of interest in general. Furthermore it is not a convex problem. As a result, we proceed to analyze this problem numerically by reformulating it into a two-stage stochastic linear program using auxiliary variables, which will be detailed in the following subsection.

3.4 Solution Approach

The stochastic optimization problem (1) can be recast as a two-stage stochastic linear program by introducing auxiliary variables. The resulting two-stage stochastic linear program can be solved efficiently using the sample average approximation (SAA) technique (Birge and Louveaux 1997). This approach is similar to the one used by Fleuren et al. (2024) and Mohammadivojdan et al. (2022) to address two-stage problems. For a detailed explanation of the Sample Average Approximation (SAA) method, we refer the reader to Shapiro and Philpott (2007) and Wang (2007).

In the following, we present the reformulation of the problem in linear form. The application of the SAA method to this reformulated model follows standard procedures, and more details are provided in Appendix A. Linearization of the formulation requires the introduction of the following auxiliary variables: product yield $m \in \mathcal{M}$ from supplier $k \in \mathcal{K}_m$, $Y_{mk} \equiv \min(q_{mk}, U_{mk})$, sales for product $m \in \mathcal{M}$, S_m, as well as lost sales L_m. The two-stage problem can be expressed linearly with these auxiliary variables as follows:

$$V^* = \min_{q_{mk}, \tau \geq 0} \quad \mathbb{E}\left[\Pi(\mathbf{q}, \tau \mid \mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D})\right] - c^{\text{lab}}\tau \tag{6}$$

where

$$\begin{aligned}\Pi(\mathbf{q}, \tau \mid \mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D}) : \max_{\mathbf{p},\mathbf{o},\mathbf{r}} \quad \sum_{m\in\mathcal{M}} \Bigg[& y_m S_m - l_m L_m - c_m p_m - c^r_m \sum_{k\in\mathcal{K}_m} r_{mk} - c^e_m o_m \\ & - \sum_{k\in\mathcal{K}_m} \left(c^o_{mk} \left(Y_{mk} G_{mk} + r_{mk}\right)\right) \\ & - \sum_{k\in\mathcal{K}_m} \left(c^o_{mk} \lambda \left(Y_{mk}(1 - G_{mk}) - r_{mk}\right)\right) \Bigg]\end{aligned} \tag{7}$$

Subject to:

$$\sum_{m\in\mathcal{M}} a_m p_m + \sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m} a^r_m r_{mk} \le \tau \tag{8}$$

$$\sum_{m\in\mathcal{M}} a_m o_m \le \beta\tau \tag{9}$$

$$Y_{mk} \le q_{mk} \qquad \forall m\in\mathcal{M}, k\in\mathcal{K}_m \tag{10}$$

$$Y_{mk} \le U_{mk} \qquad \forall m\in\mathcal{M}, k\in\mathcal{K}_m \tag{11}$$

$$r_{mk} \le R_{mk} Y_{mk}\,(1-G_{mk}) \qquad \forall m\in\mathcal{M}, k\in\mathcal{K}_m \tag{12}$$

$$S_m \le p_m + o_m + \sum_{k\in\mathcal{K}_m} r_{mk} + \sum_{k\in\mathcal{K}_m} Y_{mk}G_{mk} \qquad \forall m\in\mathcal{M} \tag{13}$$

$$S_m \le D_m \qquad \forall m\in\mathcal{M} \tag{14}$$

$$L_m \ge D_m - S_m \qquad \forall m\in\mathcal{M} \tag{15}$$

$$\tau, p_m, o_m, r_{mk} \ge 0 \qquad \forall m\in\mathcal{M}, k\in\mathcal{K}_m \tag{16}$$

Constraints (8) and (9) model the limited availability of labor. Constraints (10) and (11) linearize the Supplier Yield condition, i.e., $Y_{mk} = \min(q_{mk}, U_{mk})$. Constraint (12) sets the upper limit on the number of reworkable items. The constraint (13) ensures that sales do not exceed available inventory, while constraint (14) ensures that sales do not exceed demand. Constraint (15) accounts for the lost sales. The above formulation is linear and can be solved by sample average approximation (SAA) (see Appendix A for details).

3.5 Objectives for different risk attitudes

The formulation presented in the previous section assumes that the decision maker is risk neutral and simply seeks to maximize expected profit. Decision makers in real life often also seeks to avoid losses or very low profits. Therefore this sections presents an alternative objective functions that can model the decision maker's attitude towards risk by using the so-called conditional-value-at-risk.

Before delving into Conditional Value-at-Risk (CVaR), it is essential to understand the Value-at-Risk (VaR), which is widely utilized in financial and economics literature (Duffie and Pan 1997, Tardivo 2002). We let

$$\Psi = \Pi(\mathbf{q}, \tau \mid \mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D}) - c^{\text{lab}}\tau$$

denote the profit for some given first-stage ordering decisions $\mathbf{q}$ and labor hiring decision τ when second-stage decisions are made optimally. It is a random variable with continuous distribution as we assume that all uncertain parameters $\mathbf{G}$, $\mathbf{R}$, $\mathbf{U}$, $\mathbf{D}$, are also continuously distributed. The value-at-risk at level $\alpha \in (0,1)$ for our problem is defined as the lower $(1-\alpha)$-quantile of Ψ:

$$VaR_\alpha = \min\{z \mid \mathbb{P}(\Psi \le z) \ge 1-\alpha\} = F_\Psi^{-1}(1-\alpha), \tag{17}$$

where $F_\Psi(\cdot)$ is the distribution of Ψ and $F_\Psi^{-1}(\cdot)$ is its inverse. The value-at-risk represents the expected profit below a specified confidence level α. In this context, the buyer chooses the confidence level $\alpha \in (0,1)$ to manage risks associated with supply uncertainty, demand variability, or major disruptions.

The conditional value at risk is then defined as follows for any $\alpha \in (0, 1)$:

$$CVaR_\alpha = \mathbb{E}[\Psi \mid \Psi \leq VaR_\alpha]. \tag{18}$$

Conditional value-at-risk is introduced to minimize expected worst-case losses beyond VaR_α. The $CVaR_\alpha$ is a coherent and consistent risk measure with second (or higher)-order stochastic dominance, ensuring that minimizing CVaR never conflicts with maximizing the expectation of any risk-averse utility function (Ogryczak and Ruszczynski 2002).

To model the buyer's risk-averse behavior, we balance the firm's risk with its overall expected profit to create a mean-risk supplier selection model. In particular, we suggest the following objective function for our first stage:

$$(1 - \nu)\mathbb{E}[\Psi] + (\nu)CVaR_\alpha \tag{19}$$

for some $\nu \in [0, 1]$ and $\alpha \in (0, 1)$. The objective function (19) is a convex combination of the risk-neutral (6) and the CVaR (18) objective, incorporating all constraints from the original model (8) to (16). The parameter ν allows decision-makers to assign a weight to risk. When ν is zero, the resulting problem is identical to the risk-neutral one; when ν is one, the problem fully reflects a risk-averse objective.

For $\nu \in (0, 1)$, the formulation is not linear, but can be linearized in a sample average approximation using standard techniques (e.g. Merzifonluoglu 2024). We provide details on our numerical approach in Appendix A.

4 Numerical Study and Results

We define key metrics that help answer the research questions and present them in Table 2. Each metric is evaluated by comparing scenarios in which rework is enabled ($r_{mk} \geq 0$) with those where rework is disabled for all $m \in \mathcal{M}$ and $k \in \mathcal{K}_m$. Without rework, the metrics remain unchanged except that r_{mk} is zero.

Table 2: Metrics and Formulae

Metrics	**Formulae**
Risk-Adjusted Mean Profit	$\nu\mathbb{E}[\Psi] + (1 - \nu)\text{CVaR}_\alpha$
Waste Proportion	$1 - \frac{\mathbb{E}\left[\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m}(Y_{mk}G_{mk}+r_{mk})\right]}{\mathbb{E}\left[\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m}Y_{mk}\right]}$
Net Yield	$\frac{\mathbb{E}\left[\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m}(Y_{mk}G_{mk}+r_{mk})\right]}{\mathbb{E}\left[\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m}q_{mk}\right]}$
Capacity Utilization	$\frac{\mathbb{E}\left[\sum_{m\in\mathcal{M}}a_m o_m+\sum_{m\in\mathcal{M}}a_m p_m+\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m}a^r_m r_{mk}\right]}{(1+\beta)\tau}$
Active Supplier Base	$\frac{\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}}\mathbf{1}(q_{mk}>0)}{\sum_{m\in\mathcal{M}}\lvert\mathcal{K}_m\rvert}$

Our numerical explorations will begin with a foundational instance of the problem, which we outline here. The base instance has 5 products ($M = 5$) and 10 suppliers for each product ($K_m = 10$ for all $m \in \mathcal{M}$). The overtime fraction $\beta = 0.2$ is the proportion of overtime allowed labor and we will focus on the conditional value at risk at the level 95%, denoted as $\alpha = 0.95$.

Each fashion season lasts 75 working days and a worker works 8.5 hour shifts during those days.

Thus, a worker has a total available labor time of 39,100 minutes per fashion season. The average time required to produce a garment, including quality evaluation, is 45 minutes for a men's jacket or a women's ensemble, resulting in a capacity utilization of approximately $45/39,100 = 0.12\%$ per garment per worker. The time required for an internal worker to produce the product $m \in \mathcal{M}$ is given by the formula $a_m := \frac{1+m/M}{1000}$, which represents 0.12% (for $m = 1$) of the total available labor capacity. The value of a_m increases with m, indicating that more complex products require a higher labor capacity. Reworking a garment takes only 20% of a_m, i.e. $a^r_m = 0.2 \cdot a_m$, according to industry standards.

We assume that the cost per product for $m \in \mathcal{M}$ is given by $c_m := 10 + 3m$ so that it increases with m, ranging from 13 (for $m = 1$) to 25 (for $m = 5$). These cost parameters are consistent with the average hourly wages in European countries, which range from 12 € to 25 €. We omit the cost of raw material as these can be considered sunk when they are included both in the sales and purchase/production prices. Moreover, we assume that the cost of rework is 10% of the product cost, i.e., $c^r_m := 0.1 \cdot c_m$, while the cost of overtime is 1.5 times the regular production cost, i.e. $c^e_m := 1.5 \cdot c_m$. Furthermore, we estimate that the cost of hiring labor, training, and initial setup is approximately 1,500 € per worker. We set the cost of ordering product $m \in \mathcal{M}$ from supplier $k \in \mathcal{K}_m$ as

$$c^o_{mk} := (c_m + c^r_m)\delta \left(1 - \frac{1}{k+m+1}\right)$$

with $\delta = 0.9$. Then $\delta \left(1 - \frac{1}{k+m+1}\right)$ is the factor by which sourcing the product m from the supplier k is cheaper than producing the product m in-house. Thus, this factor is smaller for more complicated products (recall that $m = 1$ is the simplest product and $m = 5$ is the most complicated product), and suppliers are ordered from the most competitive ($k = 1$) to the least competitive ($k = 10$). The factor δ indicates the competitiveness of outsourcing compared to in-house production. It is important to note that this choice guarantees that sourcing a product is always cheaper than internal production, i.e., $c_m > c^o_{mk}$ for all $m \in \mathcal{M}$ and $k \in \mathcal{K}_m$.

Finally, the sales price of product m is given by

$$y_m = (c_m + a_m c^{\text{lab}}) \left(3 + \frac{m}{MK_m}\right).$$

The first part of the equation sums the variable and fixed labor costs, while the latter part ensures that a higher value of m results in a higher price. This ensures that it is always profitable to sell a product, regardless of whether it is produced internally or sourced from a supplier. We assume that the loss of goodwill associated with losing a sale is equal to the sales price of the product, i.e., $l_m := y_m$ for all $m \in \mathcal{M}$. We assume that the proportion of good quality products (G_{mk}) is approximately 60%, while the proportion of re-workable products (R_{mk}) is 70%, ensuring sufficient leeway available for the re-work activities to deliver benefit. We ensure that both G_{mk} and R_{mk} increase with m, as this indicates a business practice in which the company invests more resources in higher-priced products, leading to higher quality.

All parameters utilized in the numerical experiment are summarized as follows.

4.1 Results and Insights

Our experimental design systematically addresses each research question through targeted analyses. For RQ1, we evaluate the effectiveness of the rework strategy using three key performance

Table 3: Parameters in the numerical study

Symbol	Value
Parameter	
M	5
K_m	10
Ω	500
β	0.2
α	0.95
δ	0.9
ϕ	0.5
a_m	$\frac{1+\frac{m}{M}}{1000}$
a_m^r	0.2 a_m
c_m	$10 + 3m$
c_m^r	0.1 c_m
c_m^e	1.5 c_m
c^{lab}	1500
c_{mk}^o	$(c_m + c_m^r)\,\delta\left(1 - \frac{1}{k+m+1}\right)$
y_m	$\left(c_m + a_m c^{lab}\right)\left(3 + \frac{m}{MK_m}\right)$
l_m	y_m
Random Variable	
D_m	Γ distribution with $\mu_{D_m} = 50000 - 5000m$ and $CV_{D_m} = 0.3\ \forall m$
U_{mk}	Γ distribution with $\mu_{U_{mk}} = \phi\mu_{D_m}$ and $CV_{U_{mk}} = 0.1$ for all m and k
G_{mk}	β distribution with $\mu_{G_{mk}} = \left(0.6 + \frac{m}{MK_m}\right)$ and $CV_{G_{mk}} = 0.05\ \forall m, k$
R_{mk}	β distribution with $\mu_{R_{mk}} = \left(0.7 + \frac{m}{MK_m}\right)$ and $CV_{R_{mk}} = 0.05\ \forall m, k$

indicators: (i) mean profit adjusted for risk, (ii) percentage of waste reduction, and (iii) supplier yield rates. Furthermore, we investigate how these benefits are affected when the buyer exhibits risk aversion, with $\nu \in 0.2, 0.4$, thereby addressing RQ2. To answer RQ3, we introduce a waste disposal penalty parameter (λ) to examine its moderating effect on the RQ1 results. We further explore how rework affects supplier diversification and order allocation, and evaluate whether the traditional view that "Cost is an order qualifier and reliability is the order winner" (Dada et al. 2007) still holds. Finally, in addressing RQ4, we examine the sensitivity of profit under the rework regime to (i) demand variability (CV_{D_m}), (ii) disruption and (iii) quality variability ($CV_{G_{mk}}$)

We generated 500 randomized problem instances for a supply network consisting of 10 suppliers, each offering five products. The capacity levels were systematically varied according to the utilization ratio $\frac{\mathbb{E}[U_{mk}]}{\mathbb{E}[D_m]}$, ranging from 10% to 100% by adjusting $\mathbb{E}[U_{mk}]$ (see Appendix A.1 for details). Each instance was evaluated in two operational regimes: (1) with rework and (2) without rework, allowing a comparative analysis of the system performance in both configurations.

4.1.1 Risk Adjusted Mean Profit

We compute the average profit in the 500 randomized scenarios and plot it against supplier capacity levels $\mathbb{E}(U_{mk})$ ranging from 10% to 100% (Figure 2). For example, a supplier capacity of 10% implies that each supplier can satisfy only 10% of the total demand, corresponding to $\frac{\mathbb{E}[U_{mk}]}{\mathbb{E}[D_m]} = 0.1$. All suppliers $k \in \mathcal{K}_m$ are assumed to have identical and independently distributed U_{mk}. For the remainder of this analysis, we will refer to the risk-adjusted mean profit simply as "profit."

From Figure 2a we see that the rework regime yields higher financial returns when supplier capacity is restricted. As capacity increases, profits increase, but at a diminishing rate. When the supply capacity fully matches the demand (i.e $\frac{\mathbb{E}[U_{mk}]}{\mathbb{E}[D_m]} = 1$), the rework regime no longer provides a financial advantage over the non-rework regime. We then calculate Δ profit, which measures the percentage increase in average profit from the rework regime compared to the no-rework regime (see Figure 3). Δ profits range from 5.4% when $\frac{\mathbb{E}(U_{mk})}{\mathbb{E}(D_m)} = 0.1$ to 0.8% when $\frac{\mathbb{E}(U_{mk})}{\mathbb{E}(D_m)} = 1$.

When supplier capacity is limited, buyers face two risks: insufficient supply (quantity risk) or defective goods (quality risk). To mitigate this, the buyer can invest in labor (τ) early on to rework defective items or produce internally, ensuring sufficient supply. Table 6 compares the labor investment τ across supplier capacity levels for both regimes. Below 30% capacity, the rework regime requires consistently lower τ than the no-rework regime. Beyond this threshold, τ drops to zero in the no-rework regime, while remaining positive when rework is allowed. This cost reduction occurs because rework offers both economic ($c^r_m < c_m$) and capacity ($a^r_m < a_m$) advantages, decreasing the labor required to address supply shortages. Figure 4 further shows that worker utilization improves substantially with rework enabled. By prioritizing rework over internal production, buyers can mitigate supply shortages more cost-effectively, driving the Δ profit.

When the supplier capacity exceeds 40%, the behavior of the system diverges sharply between regimes. Although labor investment τ drops to zero in norework regime, it persists ($\tau > 0$) when rework is allowed, representing an additional operational cost. Without rework capability, buyers address supply shortages by increasing external orders $\left(\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} q_{mk}\right)$ rather than investing in internal capacity τ. Table 7 quantifies this difference in ordering strategy between regimes. Consequently, the economic value of rework diminishes, as external procurement retains its cost advantage under abundant supplier capacity.

Furthermore, higher risk aversion (ν) leads to increased labor investment (τ) (Table 6) and improved resource utilization (Figures 4b,c), and reduced external orders when rework is enabled (Table 7). While rework preserves profitability, the Δ profit (a) diminishes relative to the risk-neutral benchmark and (b) decreases monotonically with risk aversion ν, as evidenced in Figures 3(b,c).

In summary, the rework regime generates profit through two synergistic mechanisms: (i) lower labor investments (τ) and (ii) greater labor utilization. This approach yields significant financial returns under constrained supplier capacity, with benefits gradually diminishing as capacity improves. A similar but moderated pattern occurs for risk-averse buyers, with the profit premium (Δ profit) shrinking relative to risk-neutral benchmarks.

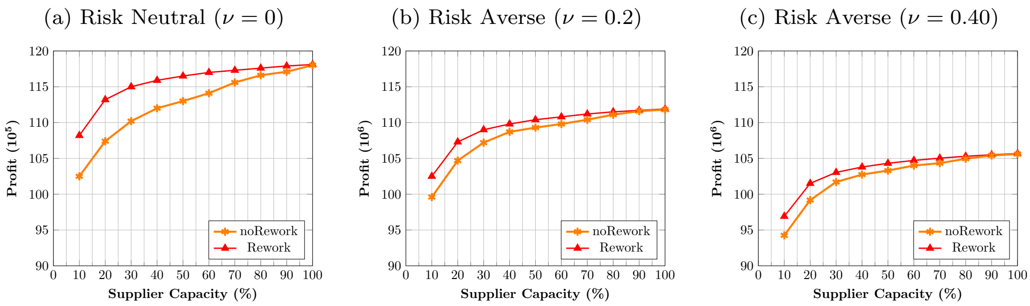

Figure 2: Profit under no penalty

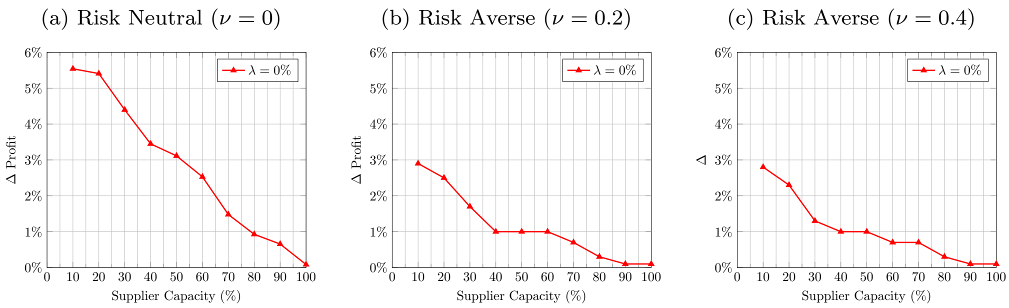

Figure 3: Δ Profit

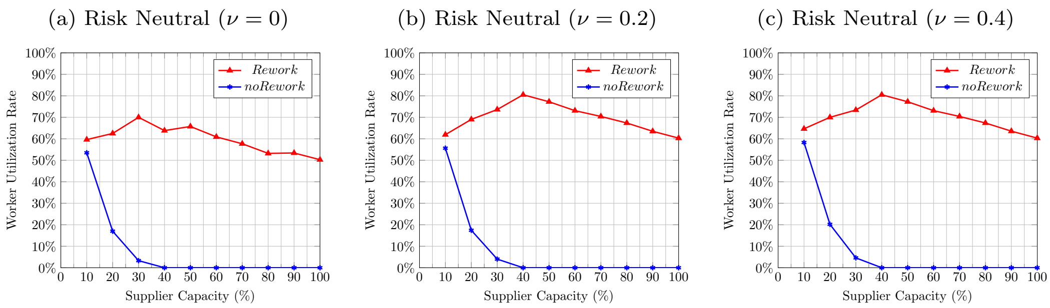

Figure 4: Worker Utilization Rate

4.1.2 Waste

Our model makes the explicit assumption that non-reworked items have zero salvage value, with the entire unsalvageable quantity $Y_{mk}(1-G_{mk})-r_{mk}$ treated as waste destined for landfill disposal. Since most garments contain synthetic fibers, this practice raises significant ecological concerns. Therefore, we investigate whether implementing rework operations reduces waste. We define waste as

$$\text{Mean Rejection Rate} = 1 - \frac{\mathbb{E}\left[\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m}(Y_{mk}G_{mk}+r_{mk})\right]}{\mathbb{E}\left[\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m}Y_{mk}\right]}.$$

Our results are presented through two complementary trends: (i) waste proportion (Figure 5) and (ii) net waste avoidance which indicates the number of items salvaged from landfill due to rework compared to the baseline without rework (Figure 6). These trends offer distinct, yet related perspectives on the same underlying performance measure.

Figure 5 presents the mean rejection rate of 500 simulation runs per capacity level, indicating the proportion of final yield (Y_{mk}) discarded as waste. The no-rework regime shows a constant 34% waste proportion across all capacity levels because, without rework ($r_{mk} = 0$), waste equals $1-G_{mk}$, where the initial quality rate $G_{1k} = 0.6$ for all suppliers $k \in \mathcal{K}_m$ and improves monotonically with $m \in \mathcal{M}$; The average quality in all $m \in \mathcal{M}$ calculated as $\frac{1}{|\mathcal{M}|}\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_{\Updownarrow}} G_{mk} = 66\%$ produces a constant waste rate 34%. In Figure 5a, we see that under the rework regime (i.e., $r_{mk} > 0$), the waste proportion decreases to 24% at 10% supplier capacity. Then shows a gradual increase before stabilizing at 30% for capacity levels exceeding 50%. Consequently, it consistently remains below the 34% level observed in the no-rework regime. This reduced waste proportion resulting from rework can be attributed to two factors: (i) as supplier capacity improves, the buyer places smaller orders with external suppliers, leading to a decrease in Y_{mk}; and (ii) when $\tau > 0$, the buyer relies on rework operations instead of internal production. These two effects simultaneously influence the "Mean Rejection Rate", resulting in lower waste.

When we examine waste from a different perspective, specifically items salvaged from landfills (see Figure 6), we find that rework consistently prevents products from ending up in landfills. As ν increases, we observe greater variations in the total number of salvaged items, but the overall trend remains positive due to rework.

Finally, the trend in waste proportion is fundamentally different from that of profit. We see that the profit advantage of the rework decreases (Δ profit $\to 0$) as the supplier capacity increases $\left(\frac{\mathbb{E}[U_{mk}]}{\mathbb{E}[D_m]} \to 1\right)$, while the net waste avoidance from the rework remains positive at all levels of capacity. Furthermore, increasing risk aversion ($\nu \uparrow$) among buyers further reduces waste, leading to greater diversion from landfills.

(a) Risk Neutral ($\nu = 0$) (b) Risk Neutral ($\nu = 0.2$) (c) Risk Neutral ($\nu = 0.4$)

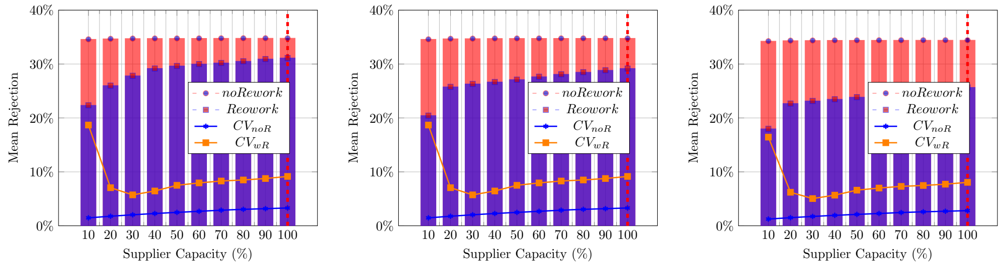

Figure 5: Waste Proportion

4.1.3 Net Yield

After examining profit and waste, we now focus on the final metric, 'Net Yield', which is defined as the percentage of the ordered quantity that is ultimately accepted and used to meet demand. A higher Net Yield reduces the need to order surplus quantities from suppliers and minimizes the necessity for diversification to compensate for yield losses.

Figure 7 illustrates net yields at various levels of supplier capacity, revealing different trends for scenarios with and without rework. The findings show that enabling rework improves net yield in capacity-constrained situations, especially when $\frac{\mathbb{E}[U_{mk}]}{\mathbb{E}[D_m]} < 30\%$. As supplier capacity increases, the yield gap between the rework and no-rework scenarios gradually closes, though it remains statistically significant up to a capacity level of 60%. Notably, this trend persists even among risk-averse buyers.

(a) Risk Neutral ($\nu = 0$) (b) Risk Averse ($\nu = 0.2$) (c) Risk Averse ($\nu = 0.4$)

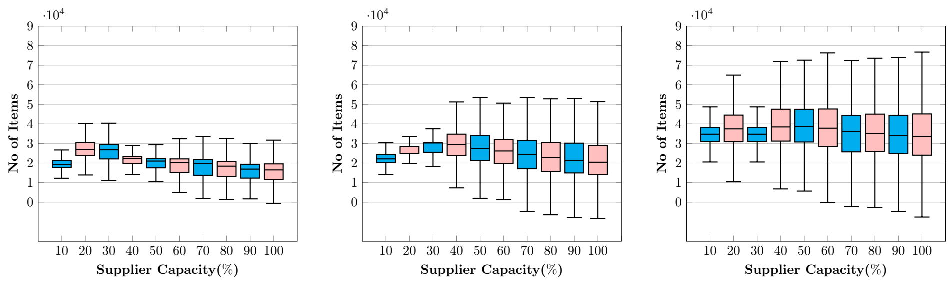

Figure 6: Net Wastage Avoidance

(a) Risk Neutral ($\nu = 0$) (b) Risk Neutral ($\nu = 0.2$) (c) Risk Neutral ($\nu = 0.4$)

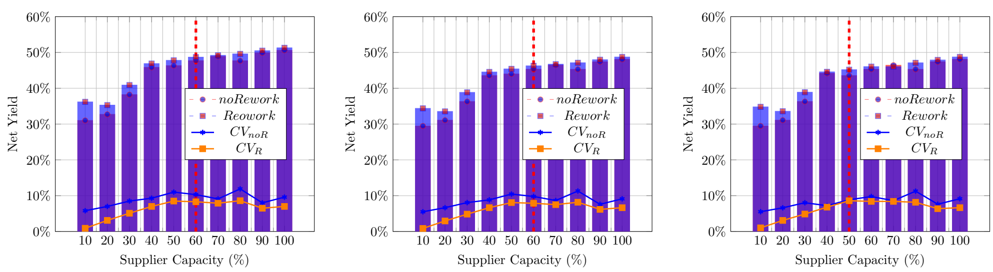

Figure 7: Net Yield

In summary, rework improves profits, increases net yield, and decreases waste. While the advantages in profit and yield diminish as supplier capacity rises, waste reduction remains consistently positive even when capacity is abundant. Therefore, rework remains a valuable strategy, especially for buyers who prioritize both environmental sustainability (i.e., waste minimization) and profitability.

4.1.4 Order Allocation at Different Supplier Yields

We examine the critical factors that impact order allocation and determine whether the active supplier base differs when rework is an option. For each of the five products, there are 10 suppliers ($|\mathcal{K}_m| = 10$ for all $m \in \mathcal{M}$). For each product $m \in \mathcal{M}$, we rank the suppliers from least expensive to most expensive, that is, we assume without loss of generality that $c^o_{m,1} \leq c^o_{m,2} \leq \cdots \leq c^o_{m,10}$.

In previous experiments, $\mu_{G_{mk}} := \mathbb{E}[G_{mk}]$ was the same for all suppliers. Now, we consider the case where the supplier yield, as measured by $\mu_{G_{mk}}$, increases with the price c^o_{mk}. To this end, we set $\mu_{G_{mk}} = 0.6 + \zeta k$, where we consider $\zeta = 2\%$ so that $\mu_{G_{m,1}} \leq \mu_{G_{m,2}} \leq \cdots \leq \mu_{G_{m,10}}$. This setting is in line with the common notion that suppliers with higher costs tend to offer greater reliability. Note that when $\zeta = 0\%$, we refer to the setting when the supplier's reliability is homogeneous.

We vary the supplier capacity from 10% to 100% of the demand, i.e., $\frac{\mathbb{E}[U_k]}{\mathbb{E}[D]} \in [0.1, 1]$, and examine the selection frequency of each supplier $k \in \mathcal{K}_m$. The selection frequency is defined as the count of instances in which supplier $k \in \mathcal{K}_m$ receives a positive order (i.e $q_{mk} > 0$), aggregated across 10 levels of expected supplier capacity. A supplier preferred due to its cost effectiveness and reliability will obtain a positive order for all five products at each capacity level, resulting in a maximum score of 50. In contrast, a less preferred supplier will achieve a substantially lower score.

Authors such as Merzifonluoglu and Feng (2014) and Dada et al. (2007) have suggested that the high expected reliability can sometimes justify the choice of a more expensive supplier. We aim to examine whether this trend persists when the buyer invests in its capacity to address supply uncertainty. Specifically, we want to study whether the selection frequency and order allocation change when rework is enabled.

Figure 8 illustrates the active supply base (that is, the percentage of suppliers that have a positive order) at different levels of supply capacity, ranging from 10% to 100% of the expected demand $\sum_{m\in\mathcal{M}} D_m$. We observe that when supplier capacities are below 40%, all suppliers remain active in the rework and no-rework regimes. However, as supplier capacity exceeds 40%, differences in the active supplier base emerge and become more pronounced as capacity increases. When capacity is abundant (at 100%), the total active supply base is 46% under the rework regime, compared to 48% without rework. A similar pattern emerges even as the buyer's preference shifts from risk-neutral to risk-averse, as shown in Figures 8(b) and 8(c). We observe that the increase in risk aversion results in a slight decrease in the order quantity when rework is enabled (see Table 7) compared to when rework is not an option. However, a change in the order quantity has little impact on supplier selection; thus, the active supply base remains unchanged. Thus, our analysis demonstrates that with homogeneous reliability between suppliers, enabling rework induces marginal consolidation when supplier capacity is abundant (i.e. $\frac{\mathbb{E}[U_k]}{\mathbb{E}[D]} > 0.7$). Furthermore, we demonstrate that risk aversion has a minimal impact on supplier consolidation beyond what is observed in a risk-neutral scenario.

In the next set of experiments, we increase ζ to 2%. This implies that the reliability now varies between the suppliers and corresponds to the cost of the product c^o_{mk}, i.e, reliability increases with supplier cost. Figure 9 shows the active supplier base as different supplier capacity levels.

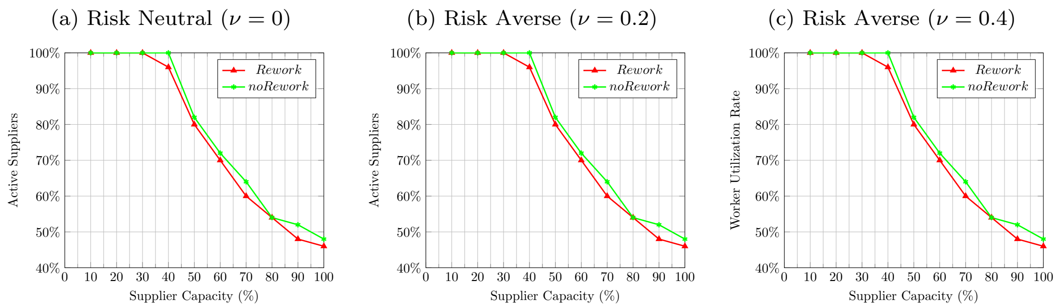

Figure 8: Active Supplier Base ($\zeta = 0$)

Similarly to the case where $\zeta = 0$, the active supply base remains relatively stable at 100% below the capacity threshold 40%. That is, all suppliers receive positive orders regardless of their cost and reliability performance. However, above this critical level, the rework exhibits progressive supplier consolidation. When the supplier capacity is abundant, 40% of the suppliers were active in the rework regime compared to 50% when rework is absent. Therefore, it is evident that supplier consolidation as a result of rework is more pronounced when $\zeta = 2\%$ compared to when $\zeta = 0$. This trend is demonstrated by comparing Figures 9a and 8a.

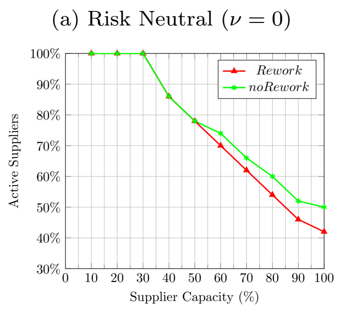

Figure 9: Active Supplier Base ($\zeta = 2\%$)

Table 4 tabulates the average unit cost, the effective yield, and the selection frequency for each supplier $k \in \mathcal{K}_m$. When rework is absent, the effective yield is equal to $\mu_{G_{mk}} = \mathbb{E}[G_{mk}]$, which represents the proportion of good quality items. With rework, the effective yield becomes $\mu_{GR_{mk}} = \mathbb{E}[G_{mk} + (1 - G_{mk})R_{mk}]$. In all cases, $\mu_{GR_{mk}} > \mu_{G_{mk}}$ is satisfied. The analysis reveals that, in the absence of rework, the average supplier selection frequencies remain consistent, 38.6 when $\zeta = 0\%$ compared to 38.3 when $\zeta = 2\%$ despite the effective yield gap of 5% (i.e. 71% - 66%). When rework is enabled, this yield differential shrinks to approximately 1%, accompanied by a noticeable reduction in selection frequency (37.6 vs 36.9) suggesting supplier consolidation. Therefore, we are able to show that enabling rework reduces yield variation, favors cheaper suppliers with low yields, and increases their order shares compared to when rework is not allowed. To analyze order allocation patterns, we compute each supplier's allocation share as the percentage ratio of their assigned quantity to the total order quantity, expressed mathematically as:

$$\frac{\sum_{m \in \mathcal{M}} q_{mk}}{\sum_{m \in \mathcal{M}} \sum_{k \in \mathcal{K}} q_{mk}} \times 100\% \tag{20}$$

We evaluated order allocation patterns across supplier capacity levels. For discussion, we highlight the order allocation when the supplier capacity is 100%, i.e. $\frac{\mathbb{E}[U_k]}{\mathbb{E}[D]} = 1$ in Table 5. The analysis yields three principal findings:

1. Supplier consolidation is more pronounced when supplier reliability is heterogeneous and when rework is enabled.

2. When supplier reliability varies, enabling rework increases order allocations to cost-efficient suppliers. In our case, the most economical supplier receives 39% of total orders under a rework regime versus 32% when rework is not allowed.

3. An increase in risk-averse behavior does not influence supplier consolidation and order allocation decisions compared to a risk neutral position.

In conclusion, our analysis demonstrates that supplier reliability becomes less critical when buyers can utilize rework to mitigate yield uncertainties. This strategic flexibility enables a stronger focus on cost optimization through more allocation to economical suppliers.

Table 4: Supplier Selection

Yield Variations (ζ)	Supplier (k)	Average Cost $\left(\frac{1}{M}\sum_{m\in\mathcal{M}} c^o_{mk}\right)$	Rework = 0		Rework = 1	
			Effective Yield ($\mu_{G_{mk}}$)	Selection Frequency	Effective Yield ($\mu_{GR_{mk}}$)	Selection Frequency
0%	1	18.3	66%	50	92%	50
	2	19.9		50		50
	3	20.8		50		50
	4	21.5		50		50
	5	21.9		49		46
	6	22.3		38		36
	7	22.6		32		30
	8	22.8		26		25
	9	23.0		21		21
	10	23.2		20		18
	Average		66%	38.60	92%	37.60
2%	1	18.3	62%	50	91%	50
	2	19.9	64%	50	91%	50
	3	20.8	66%	50	92%	50
	4	21.5	68%	50	92%	50
	5	21.9	70%	49	93%	44
	6	22.3	72%	41	93%	35
	7	22.6	74%	32	94%	30
	8	22.8	76%	25	94%	25
	9	23.0	78%	21	95%	20
	10	23.2	80%	15	95%	15
	Average		71.0%	38.30	93%	36.90

Table 5: Order Allocation

Yield Variations (ζ)	Rework	Suppliers (k)									
		1	2	3	4	5	6	7	8	9	10
0%	1	35%	29%	21%	14%	1%	0%	0%	0%	0%	0%
	0	33%	28%	20%	16%	3%	0%	0%	0%	0%	0%
2%	1	39%	29%	19%	12%	0%	0%	0%	0%	0%	0%
	0	32%	27%	22%	15%	6%	0%	0%	0%	0%	0%

4.2 Effect of Penalty (λ)

We now investigate whether the aforementioned benefits from rework improve when a waste penalty (λ) is introduced. The penalty (λ) represents a class of restrictive policies enacted by governments or municipalities to discourage the disposal of unrecovered items. Our study concentrates on the fashion industry, where discarding unsold clothing in landfills is prevalent, leading to significant environmental problems.

4.2.1 Risk Adjusted Mean Profit

In this section, we examine the profit trends of the rework and non-rework regime under different penalty (λ) values and varying degrees of risk aversion (ν). We first study the risk-neutral scenario and then compare it with cases where ν increases.

In Figure 10(a), where the penalty is set at $\lambda = 2.5\%$, rework remains financially advantageous when supplier capacity is restricted. However, this benefit gradually diminishes as supplier capacity increases. This trend aligns with Figure 2, but exhibits two key distinctions: (1) the Δ profit is reduced compared to the case without penalty ($\lambda = 0$), and (2) rework yields higher profit even at full (100%) supply capacity compared to the scenario without rework. Note that when $\lambda = 0$, the profit gap disappears, as shown in Figure 12(a)

The above trends further intensifies when λ increases (see Figure 11a) and therefore rework becomes a favorable strategy. When penalties are introduced, buyers adopt more conservative ordering strategies, resulting in smaller order sizes $\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m} q_{mk}$ (see Table 7) and increased dependence on rework and internal production, which requires a greater labor capacity (τ). As shown in Table 6, labor capacity investment (τ) grows with increasing penalty rates (λ). For a given λ, rework demands less τ than the alternative without rework due to higher labor utilization, thus minimizing excess capacity requirements (see Figure 13). At higher penalty levels ($\lambda = 10\%$), labor utilization rates converge in both regimes, making the cost efficiency of the rework operations rather than labor utilization the main source of financial advantage (Figure 14).

The observed growth in Δ profit with increasing penalty is due to two key cost-saving mechanisms:

1. Optimal labor management through reduced hiring (τ) and enhanced utilization, and

2. The synergistic effect of smaller order quantities and cost-effective rework operations.

These benefits amplify with the buyer's risk aversion (ν), particularly under stringent penalties, which produces better Δ profit (Figures 12b–c). As ν increases, buyers increasingly replace external orders with internal capacity, leveraging both rework and internal production to hedge against supply uncertainties while maximizing labor productivity.

4.2.2 Waste

This section examines how penalties influence the waste proportion and assesses the potential advantages of rework adoption. Our analysis demonstrates that rework presents an attractive sustainable solution for environmentally conscious buyers.

Figure 15 presents the waste proportion under a penalty of $\lambda = 2.5\%$. The waste proportion under no-rework regime remains 34%, as explained in Section 4.1.2. Although increased penalties reduce order quantities (affecting Y_{mk}) and consequently lower absolute waste volumes, the pro-

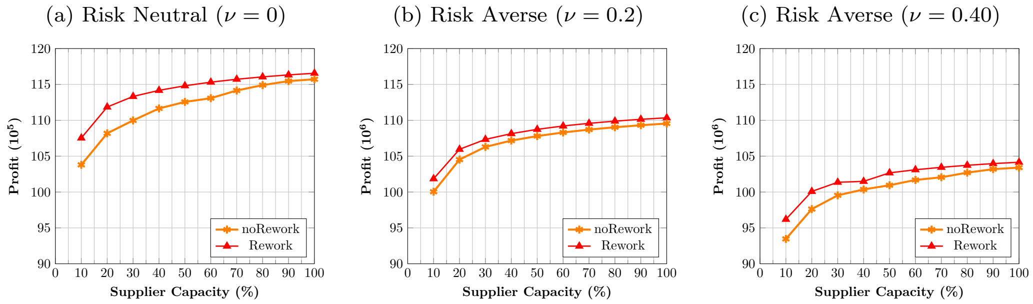

Figure 10: Profit under Penalty ($\lambda = 2.5\%$)

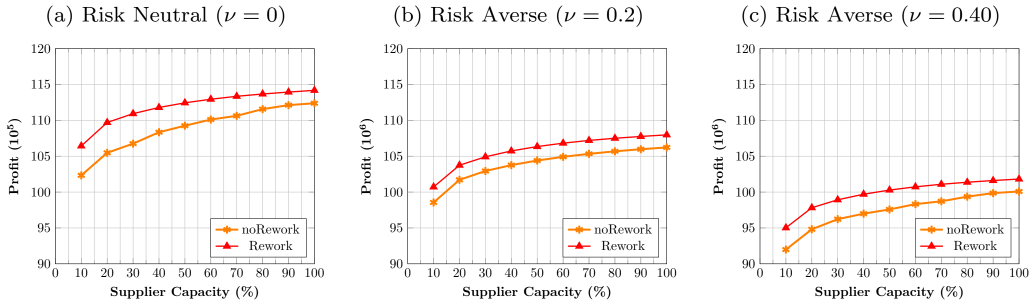

Figure 11: Profit under Penalty ($\lambda = 10\%$)

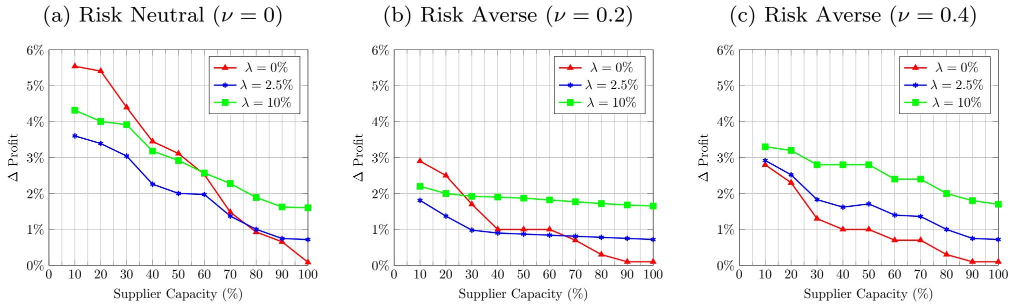

Figure 12: Effect of Penalty on Δ Profit

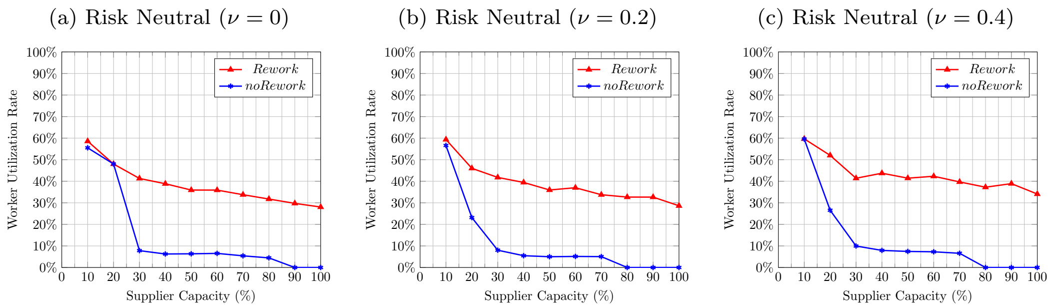

Figure 13: Worker Utilization ($\lambda = 2.5\%$)

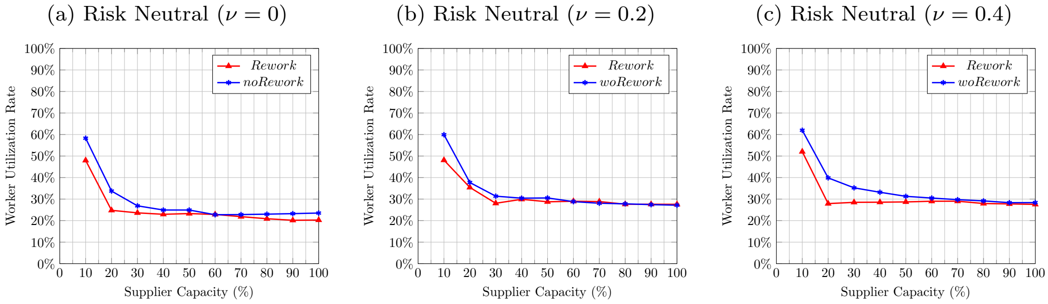

Figure 14: Worker Utilization ($\lambda = 10\%$)

Table 6: Labour Capacity (τ) under λ

Penalty	Risk Aversion	Supplier Capacity									
		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0	0	201, [301]	29, [91]	6, [18]	4, [0]	4, [0]	4, [0]	4, [0]	4, [0]	4, [0]	4, [0]
	0.2	193, [290]	25, [85]	5, [9]	3, [0]	3, [0]	3, [0]	3, [0]	3, [0]	3, [0]	3, [0]
	0.4	179, [276]	17, [74]	5, [3]	3, [0]	3, [0]	3, [0]	3, [0]	3, [0]	3, [0]	3, [0]
2.50%	0	206, [305]	44, [104]	12, [40]	12, [25]	12, [24]	11, [24]	11, [18]	11, [13]	11, [0]	11, [0]
	0.2	199, [295]	40, [95]	12, [34]	12, [20]	11, [16]	11, [14]	10, [10]	10, [6]	11, [0]	11, [0]
	0.4	198, [284]	32, [87]	13, [31]	11, [13]	11, [12]	11, [10]	10, [10]	10, [0]	10, [0]	10, [0]
10%	0	228, [325]	94, [151]	86, [125]	81, [116]	78, [106]	73, [105]	72, [96]	69, [91]	71, [90]	70, [89]
	0.2	218, [315]	86, [141]	81, [116]	76, [110]	74, [110]	71, [98]	70, [92]	69, [91]	69, [90]	70, [88]
	0.4	212, [308]	90, [140]	77, [119]	72, [110]	72, [103]	69, [102]	67, [96]	68, [93]	66, [91]	65, [91]

Note: Labor capacities are shown as τ, [τ] where the first value is for rework and the bracketed value is for no-rework.

portion of waste remains fixed at 34% in this regime. This occurs because both usable output and waste scale proportionally with the order size.

A comparison of Figure 15a and Figure 5a reveals that rework adoption leads to decreasing waste proportions as λ increases (0 to 2.5%). Although the difference in waste proportions between regimes narrows with improved supplier capacity, it persists even at full capacity utilization (i.e., when $\mathbb{E}[D_m] = \mathbb{E}[U_{mk}]$ for all $k \in \mathcal{K}_m$). This gap exhibits a positive correlation with risk aversion (ν), demonstrating that risk-averse buyers achieve a more substantial reduction in waste through rework. At $\lambda = 10\%$, we observe a significantly greater reduction in the waste proportion compared to the previous case where $\lambda = 2.5\%$, conforming to the pattern that we observed earlier. In addition, we see that when ν increases, the proportion of waste further decreases (Figure 15 b-c, Figure 16 b-c).

Therefore, as λ increases, the rework delivers better financial returns and reduces waste by increasing reliance on rework operations. This condition is true even when supply capacity is abundant. The aforementioned benefits intensify further as the buyer becomes risk-averse.

4.2.3 Net Yield

Recall that without penalty, the rework regime improved yield up to a 50% capacity threshold. However, above this threshold, the yield difference between the two regimes became statistically insignificant. Figure 17 shows that under penalty, the rework strategy consistently generates higher yields than the no-rework alternative, with statistically significant differences persisting throughout the full capacity range up to 100%. The enhancement in yield provided by the rework persists consistently at increasing levels of risk aversion (ν). Under penalty conditions, the buyer

Table 7: Δ Gap in order quantity

Penalty	Risk Aversion	Supplier Capacity									
		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0	0	0.1%	1%	3%	4.70%	6.60%	6.90%	7%	7.60%	7.70%	8.20%
	0.2	0.11%	1.04%	2.89%	4.85%	5.29%	5.90%	6.30%	7.05%	7.74%	8.40%
	0.4	0.11%	1.06%	2.95%	4.85%	5.40%	5.90%	6.80%	7.10%	7.74%	8.90%
2.50%	0	3.90%	11.36%	14.39%	16.26%	19.53%	19.72%	21.63%	22.62%	23.88%	23.30%
	0.2	4.25%	12.43%	15.30%	20.23%	20.82%	21.05%	22.10%	23.88%	25.14%	25.47%
	0.4	4.34%	12.69%	17.60%	21.27%	21.72%	22.59%	24.80%	25.48%	25.14%	25.87%
10%	0	4.40%	6.20%	15.60%	18.50%	19.80%	20.20%	23.30%	26.50%	33.20%	33.30%
	0.2	5.70%	6.70%	16.00%	23.10%	24.10%	25.00%	25.80%	27.80%	33.20%	33.90%
	0.4	5.80%	7.50%	18.20%	29.50%	25.80%	25.40%	26.10%	28.70%	33.40%	34.50%

Note: Δ Gap represents the percentage increase in the total quantity achieved in the no-rework regime relative to the quantity obtained when rework is permitted

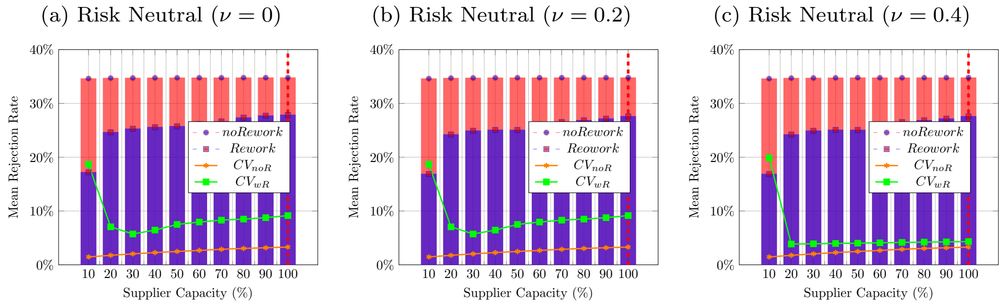

Figure 15: Wastage fraction with penalty ($\lambda = 2.5\%$)

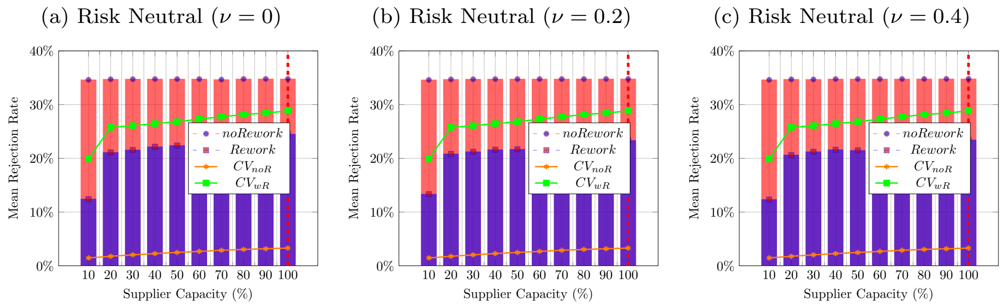

Figure 16: Wastage fraction with penalty ($\lambda = 10\%$)

adopts conservative sourcing from external suppliers, leading to reduced total order quantities $\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}_m} q_{mk}$. Consequently, the resulting yield $Y_{mk}G_{mk}$ maintains proportionality. This effect proves to be beneficial in both regimes, with and without rework. The differential in yields arises from the utilization of the rework operation, which increases when the capacity is constrained and higher values of τ are available. As supplier capacity expands, labor availability diminishes (see Table 6) and utilization gradually declines (see Figure 13 and Figure 14). This reduction in rework items ($r_{mk} \downarrow$) subsequently decreases and the yield stabilizes.

4.2.4 Order Allocation under different penalties (λ)

In Section 4.1.4, we demonstrate that with $\lambda = 0$, rework does not produce significant benefits in terms of supplier consolidation when supplier reliability is homogeneous. We will now investigate

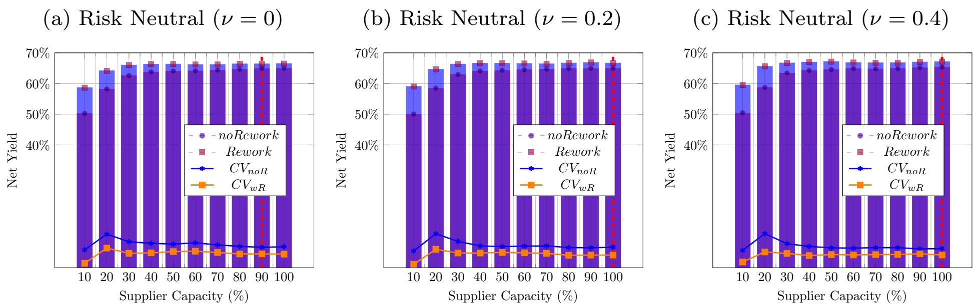

Figure 17: Net yield ($\lambda = 2.5\%$)

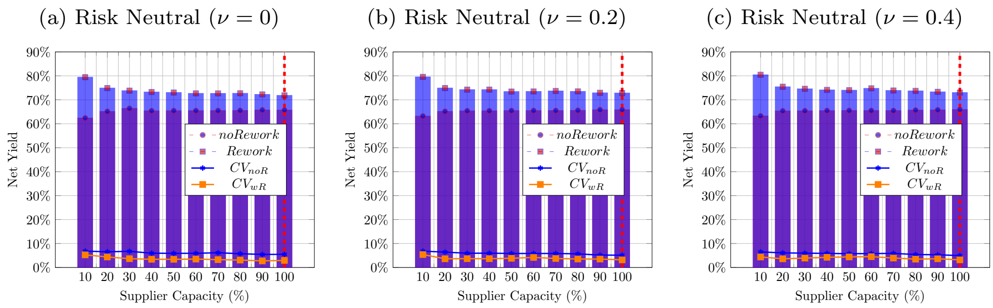

Figure 18: Net yield ($\lambda = 10\%$)

whether this trend persists when $\lambda > 0$.

When the penalty increases, buyers approach orders with external suppliers with more caution (see Table 7), while also focusing on improving internal capacity. This strategic change is clearly depicted in Table 6, which shows increased investments in τ that correlate with increasing penalty levels. Furthermore, we see that when rework is allowed, the investment in τ is reduced because the allocation of more capacity to cost-effective rework reduces the need for labor. As a result, fewer suppliers are required to meet demand, leading to supplier consolidation.

In addition, reworkable inventory is valuable to the firm because it only needs to pay for it if it chooses to re-work those items, and it can delay that decision until after observing demand. Thus, rework can also be used as a mechanism to delay decision making until after the uncertainty is resolved. In particular, suppliers with low cost and low yield (but high rework potential) become very attractive, and the firm will allocate a larger share of their business to such suppliers when rework is an option than they would allocate when rework is not an option. As suppliers with low cost and yield receive larger orders, there is an opportunity for the firm to negotiate quantity discounts, although we leave the full exploration of this effect to future research.

Figure 19 displays the trends in the active supplier base for a risk-neutral buyer with a penalty λ of 2.5% and 10%, respectively. We observe that the increase in the penalty λ from 0 to 2.5% has a significant effect on the supplier consolidation. When rework is enabled, supplier consolidation starts when supplier capacity is 30% and continues to evolve as supplier capacity improves. When supplier capacity is abundant, active suppliers under the rework regime are 36% compared to 48% when rework is not allowed. This trend is different from what we see in Figure 8a. Furthermore, when λ increases to 10%, supplier consolidation under rework regime begins earlier when the supplier capacity is 20% and becomes more pronounced as supplier capacity increases. However, when the supplier capacity is abundant, the supplier consolidation in the rework and non-rework regimes eventually converges to 30%, which means that 3 out of 10 suppliers received an order. This outcome differs from earlier observations, in which the rework maximized supplier consolidation when supplier capacity was abundant. This behavior can be attributed to the fact that with an increase in penalty, buyers place more conservative orders, causing the need for fewer suppliers compared to situations with lower λ. Consequently, when rework is enabled, the incremental effect on supplier consolidation is minimal, leading to a narrowing gap in supplier consolidation between the two regimes as supplier capacity increases.

Table 8 illustrates the order allocation when supplier capacity is at 100%. We used the same methods described in Section 4.1.4 to calculate the allocation shares. When $\lambda = 2.5\%$, four suppliers received orders under the rework regime, while six suppliers were assigned orders under the non-rework regime. In particular, the lowest-cost supplier ($k = 1$) received the largest share at 43%, compared to 33% in the alternative regime. This indicates that under penalty conditions, rework makes low-cost, low-yield suppliers more appealing and favors them in the order allocation process. As λ increases to 10%, the advantages of consolidation under rework start to diminish. Only three suppliers remain active under rework compared to four in the no-rework scenario. However, the lowest-cost supplier remains prioritized, receiving a significant share of orders at 52.7%, compared to 44% when rework is not permitted.

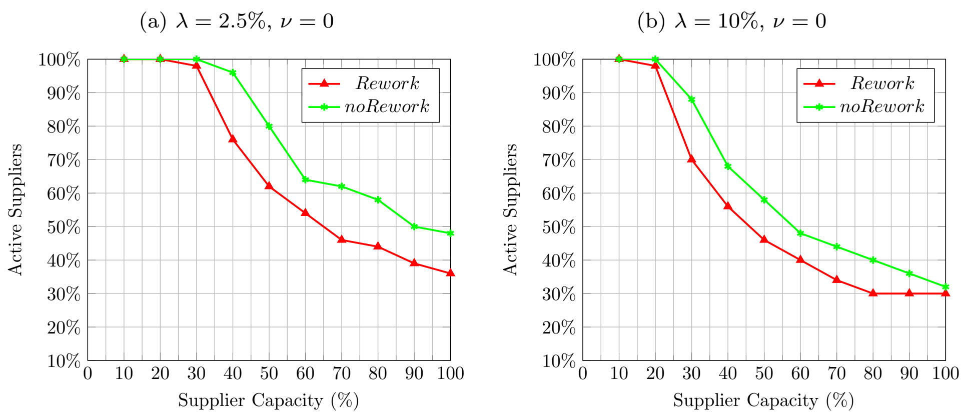

Figure 19: Active supplier base st penalty

Table 8: Order Allocation under penalty

Penalty (λ)	Rework	Suppliers (k)									
		1	2	3	4	5	6	7	8	9	10
2.5%	Yes	42.8%	29.7%	24%	3.5%	0%	0%	0%	0%	0%	0%
	No	33%	23.5%	20%	11.4%	8.2%	4%	0%	0%	0%	0%
10%	Yes	52.7%	38%	9.3%	0%	0%	0%	0%	0%	0%	0%
	No	44%	33.1%	22.7%	0.3%	0%	0%	0%	0%	0%	0%

In conclusion, when waste penalties are enforced, rework proves to be an effective strategy that boosts profits, reduces waste, and enhances yield. In addition, these benefits are amplified as risk aversion increases. Rework also facilitates supplier consolidation, which may seem counterintuitive to diversifying suppliers to address uncertainties. However, it is noted that the advantages of supplier consolidation diminish when penalties become excessively high, leading to more conservative purchasing behaviors and greater reliance on internal production. Ultimately, rework is a crucial approach to balancing profitability with sustainability, effectively managing supply uncertainties that stem from random fluctuations in capacity and varying quality.

4.3 Effect of risk averse behavior

This section summarizes how risk-averse behavior influences key performance indicators such as profit and waste, under scenarios with and without waste penalties.

As illustrated in Figure 2, expected profit declines with increasing levels of risk aversion (ν). This decline is primarily driven by the tendency of risk-averse buyers to over-order in an effort to mitigate the risk of lost sales, thereby hedging against both supply uncertainty and peak demand. Consequently, buyers accumulate two categories of inventory: (i) good-quality items that are paid for, and (ii) defective items that must be discarded. When supply yield is high, this over-ordering results in surplus inventory that exceeds demand, generating no revenue while still incurring payment to supplier. This dynamic plays a significant role in the observed profit shortfall compared to a risk neutral buyer (see Figure 3). Although the waste proportion is similar for both risk-neutral and risk-averse buyers (see Figure 5), risk-averse buyers generate significantly more waste due to their tendency to overorder. Table 6 further shows that as risk aversion increases, buyers reduce investment in internal production capacity (τ) and rely more on external suppliers. This shift supports the observed increase in waste, driven by overordering and limited internal processing.

When a waste disposal penalty (λ) is introduced, risk-averse buyers begin to shift away from over-ordering and adopt a more cautious approach by investing in internal capacity (τ) (see Table 6). When rework is not allowed, risk-averse buyers continue to face reduced profit due to elevated costs arising from three key factors: (1) higher cost of internal produced items (p) 2) investment in labor capacity (τ) and (3) penalties incurred from waste disposal (λ) - costs that outweigh the benefits of reduced order quantities (see Figure 10, 11)). Under the waste penalty regime, the total volume of waste disposal is lower compared to when no penalty is applied. This is because a comparatively larger share of production is handled internally, while the dependence on external suppliers decreases, leading to less waste overall. On the other hand, when rework is enabled, a risk-averse buyer benefits from increased profits and reduced waste, since the labor resource (τ) can partially meet demand using reworked items, which are less expensive than producing new ones and help avoid penalties. As a result, the investment in τ decreases, leading to lower initial capital costs (see Table 6). Consequently, the profit gain (Δ profit) for the risk-averse buyer under penalty gradually catches up with - and eventually surpasses - that of the risk-neutral buyer (see Figure 12).

Therefore, we conclude that a risk-averse buyer tends to experience lower profits and higher waste compared to a risk-neutral buyer. However, when rework is allowed, the profit for a risk-averse buyer increases, especially under higher penalty levels and higher degrees of risk aversion. These benefits are especially pronounced when supplier capacity is constrained, but gradually diminish as supplier capacity becomes abundant.

4.4 Effect of parameter uncertainty

Previously, we have observed the benefits of rework both when penalties are not applicable and when they are positive in situations with supply certainties. In this section, we will explore how incremental profit from rework is affected by i) variations in demand (CV_{D_m}), ii) disruptions, and iii) quality variance ($CV_{G_{mk}}$).

We assume that the buyer is risk neutral ($\nu = 0$) and there are no penalties ($\lambda = 0$). This setup isolates the effect of risk aversion and penalties on profit, allowing a focused examination of the effects introduced by the respective parameters.

4.4.1 Demand Variation

We set CV_{D_m} at 0.4, 0.6 and 0.8 to analyze the impact of rework under demand variance, comparing these results with our base case of $CV_{D_m} = 0.3$. Figure 20 shows the absolute profit for each CV_{D_m} and highlights the financial benefits of rework compared to scenarios without it. Figure 21 illustrates the change in profit due to the rework.

When CV_{D_m} increases from 0.3 to 0.4, absolute profit decreases slightly compared to the base case (see Figures 2a and 20a), but the change in profit remains stable (see Figure 21a). As we raise demand variance to 0.6 and 0.8, there is a significant drop in absolute profit. However, Δ profit remains healthy and even exceeds when the supplier capacity is abundant. Thus, when facing additional demand uncertainty alongside supply uncertainty, re-work provides a valuable risk management strategy to mitigate additional shocks in the supply chain.

Table 9 presents investments in labor capacity (τ) across different levels of supplier capacity. The trend shows that labor requirements (τ) increase with increasing demand variability (CV_{D_m}), especially in capacity-constrained situations. Additionally, for a given variance value, the investment in rework for τ is lower than when rework is not allowed. This trend underscores two key insights: (1) labor (τ) serves as an adaptive buffer against realized demand volatility, and (2) rework reduces investment in τ under the restricted capacity of the supplier. The latter effect arises because the rework operations are cost-effective, ensuring that Δ profit remains positive and healthy, which could have been significantly worse otherwise.

Our analysis demonstrates that adopting rework yields persistent financial benefits for buyers even under elevated demand volatility. Although absolute profit decreases marginally compared to stable demand scenarios, mainly due to increased labor capacity investments (τ) —the profit differential (Δ profit) remains healthy. This resilience confirms that rework serves as an effective risk mitigation strategy, where the marginal gains from recovered production outweigh the additional operational costs, particularly in volatile market conditions. The maintained profit advantage underscores rework's strategic value as both a profit-preserving mechanism and a buffer against demand uncertainty.

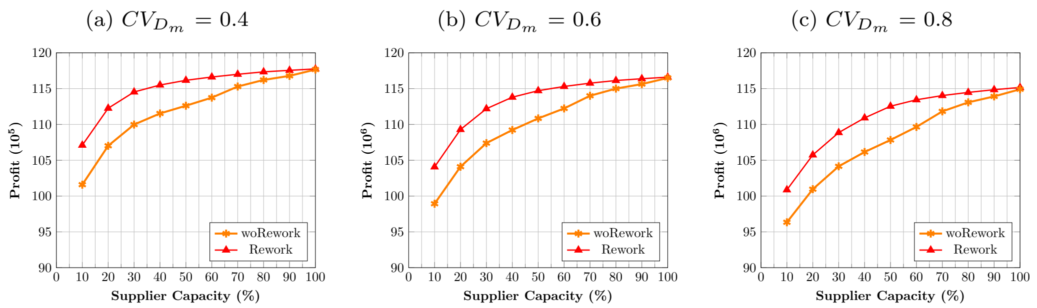

Figure 20: Profit under CV_{D_m}

4.4.2 Supply Disruption

Disruption represents a distinct form of supply uncertainty in which a supplier either fulfills the entire order or delivers nothing. In the supply chain literature, such scenarios are called "all-or-nothing" suppliers. Our model can be used to examine the impact of supply disruptions on profit. In this context, we model supplier capacity U_{mk} as a random variable with a point mass at the origin, representing the probability of supplier k experiencing a disruption. Consequently, U_{mk}

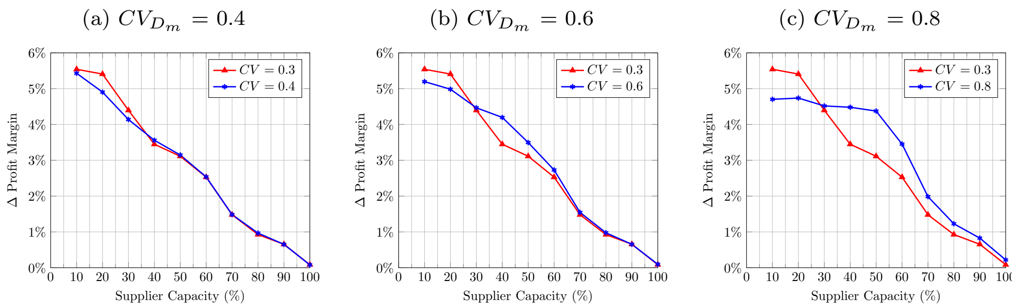

Figure 21: Δ Profit under CV_{D_m}

Table 9: Labour Capacity (τ) under CV_{D_m}

CV_{D_m}	Supplier Capacity									
	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0.3	201, [302]	29, [91]	6, [18]	4,[0]	4,[0]	4,[0]	4,[0]	4,[0]	4,[0]	4,[0]
0.4	251, [344]	66, [137]	9, [48]	5,[0]	4,[0]	4,[0]	4,[0]	4,[0]	4,[0]	4,[0]
0.6	331, [427]	137,[239]	46,[115]	11,[51]	11,[0]	11,[0]	5,[0]	5,[0]	4,[0]	4,[0]
0.8	474, [559]	277,[371]	161,[256]	66,[164]	20,[98]	19,[33]	17,[0]	16,[0]	15,[0]	14,[0]

Note: Labor capacities are shown as τ, [τ] where the first value is for rework and the bracketed value is for no-rework.

follows a mixture distribution where $U_{mk} = 0$ with a disruption probability of θ, and $U_{mk} = X$ with a non-disruption probability of $(1 - \theta)$. Here, X is a random variable that represents the available capacity in a non-disruption scenario.

The mean and variance of U_{mk} under disruption can be computed as follows:

$$\mathbb{E}[U] = (1 - \theta) \cdot \mathbb{E}[X] + \theta \cdot 0 \tag{21}$$

$$\mathrm{Var}[U] = \mathbb{E}[U^2] - (\mathbb{E}[U])^2 = (1 - \theta)\mathbb{E}[X^2] - (1 - \theta)^2(\mathbb{E}[X])^2 \tag{22}$$

The supplier capacity distribution parameters under disruption are defined in Appendix B.

In this section, we evaluate the financial impact on the buyer in different θ values and examine how rework helps mitigate this loss. Disruptions consistently lower expected profits compared to normal operations. In our case, the buyer can invest in internal capacity to offset supply shortages but must account for additional labor (τ) costs. Excessive investment in labor (τ) raises costs, while insufficient investment leaves buyers vulnerable to supply shortages and lost sales. In Table 10, we evaluated the profit levels in supplier capacity scenarios from 10% to 100% for each value θ and reported their averages. We used a similar approach to calculate and present the average value of τ. Lastly, for each θ, we show the average profit and average τ under both rework and non-rework conditions.

As θ increases, the average profit declines compared to the lower θ values. This is expected because, when capacity is limited, the buyer manages disruption risk by investing in τ, while with abundant capacity, the buyer tends to place more orders. In both scenarios, the first stage costs increase, affecting average profit. Although this trend is common, permitting rework brings additional benefits that help reduce costs. These benefits include i) lower investment in τ and improved labour utilization, and ii) more cost-effective rework operations. When rework is allowed, the change in profit (Δ profit) remains stable compared to the base case and even increases with higher θ. This trend is reinforced by the fact that the increase in τ under the rework regime is less than when rework is not allowed. Thus, allowing rework leads to higher Δ profit as θ increases, with a reduced investment in τ.

Table 10: Profit Under Disruption

θ	**Rework**	**Average Profit**	**Δ Profit**	**Average τ**
5%	Yes	11,475,732	2.53%	31
	No	11,192,060		47
10%	Yes	11,451,927	2.55%	37
	No	11,166,936		69
15%	Yes	11,391,594	2.61%	46
	No	11,101,439		70

Note: Δ profit is the percentage increase in average profit from the rework regime compared to the no-rework regime

4.4.3 Quality Uncertainty

In our study, we examine two quality categories: Good (G_{mk}) and Reworkable (R_{mk}). If the supply base has a higher expected value of G_{mk}, the advantages of rework are limited due to the small remaining reworkable portion $(1 - G_{mk})$. Therefore, we focus on the financial benefits of rework when G_{mk} has high variance.

We conduct our experiment using $CV_{G_{mk}}$ values of 0.1, 0.2, and 0.3, calculating the risk-adjusted mean profit by varying $\mathbb{E}(U_{mk})$ from 10% to 100% of $\mathbb{E}(D_m)$, both with and without rework. The results are averaged and reported as "Average Profit" for each $CV_{G_{mk}}$ along with the average labor capacity (τ). We quantify the economic benefit of rework through Δ profit, defined as the percentage increase in profit when rework is enabled relative to the baseline without rework (see Table 11). Our findings reveal two important patterns: (1) absolute profits increase as the quality variance $CV_{G_{mk}}$ increases in both rework and non-rework situations, and (2) the profit gained from rework (Δ profit) increases with higher quality variance. This suggests that rework is particularly beneficial in environments with significant quality variability.

Quality variability creates discrepancies between the quality of anticipated and realized product quality, simultaneously reducing usable output $Y_{mk}G_{mk}$ while improving the recoverable value of defective units $Y_{mk}(1 - G_{mk})R_{mk}$. Although buyers traditionally invest in labor capacity τ to mitigate yield uncertainty, rework substantially reduces τ requirements through its inherent cost and efficiency advantages—achieving lower operational costs, higher resource utilization, and reduced marginal labor needs. The gains in labor efficiency from rework increase with the variance in quality $CV_{G_{mk}}$. This is shown by the slower growth of τ in the rework regime compared to that of no-rework as $CV_{G_{mk}}$ rises. This difference is a key factor driving the higher Δ profit seen in rework-enabled operations.

Therefore, when faced with unreliable suppliers with high-quality variance, rework emerges as a financially rewarding strategy.

Table 11: Profit Under Quality Variance

$CV_{G_{mk}}$	**Rework**	**Average Profit**	**Δ Profit**	**Average τ**
0.1	Yes	11,449,385	2.53%	25
	No	11,167,164		37
0.2	Yes	11,585,853	2.83%	27
	No	11,267,345		51
0.3	Yes	11,682,668	3.60%	28
	No	11,277,173		63

Note: Δ profit is the percentage increase in average profit from the rework regime compared to the no-rework regime

5 Conclusion

This study examines a single-period inventory problem that involves multiple products and suppliers, where both demand and supply are uncertain. The buyer invests in internal production capacity and places orders with external suppliers before demand is known. These suppliers face capacity constraints and quality variability. Once demand is realized and the quality of goods received is assessed, the buyer uses internal capacity to rework defective items or produce additional units, addressing shortages and maximizing profit. The buyer faces two financial risks: lost sales from unmet demand and a landfill tax imposed for excess inventory disposal. We investigate whether rework serves as a viable strategy to increase profits, reduce waste, and improve supply yield under uncertainty, while also assessing its potential to facilitate supplier consolidation.

Given the stochastic nature of the problem, we formulate an optimization model using a weighted objective function that accounts for both risk-neutral and risk-averse (CVaR) buyer behaviors. Although the problem resembles the classic newsvendor model, its complexity precludes a closed-form solution. Instead, we transform it into a two-stage stochastic linear program using auxiliary variables and perform a numerical analysis via the sample average approximation (SAA) method to derive insights. Our findings reveal that rework provides financial benefits when no penalties are present, although these benefits diminish as the capacity of the supplier increases. In addition, rework consistently reduces waste and enhances supply yield. When penalties for landfill waste are introduced, the benefits of rework become more evident. Specifically, when internal production capacity is available, cost becomes the dominant factor in supplier selection—enabling buyers to prioritize lower-cost suppliers while addressing reliability concerns through rework and in-house production. The parametric study further demonstrates that rework remains a profitable strategy under conditions of high demand volatility, supply disruptions, and quality variability, reinforcing its economic and environmental value.

Although our study is inspired by the fashion industry, the methodology is broadly applicable to sectors characterized by short product life cycles and long supplier lead times that hinder midseason replenishment. Although the model is calibrated for labor-intensive production, its parameters can be adapted to reflect mechanized or automated processes. Future research could explore comparative analyses between investments in internal capacity and buyer-led improvements in supplier operations. Another promising direction involves examining supplier learning curves, capacity interdependencies, and quantity discount structures within the same modeling framework. Pursuing these avenues would offer valuable insights into how rework strategies can be integrated into sourcing decisions under uncertainty.

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A Solution Methodology

A.1 Sample Average Approximation

We model uncertainty using the random vector $\xi = (\mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D})$. We generate n independent and identically distributed (i.i.d.) samples of ξ, denoted by $\{\xi^1, \xi^2, \ldots, \xi^n\}$, or equivalently $\{\xi^\omega\}_{\omega=1}^n$, based on the known probability distribution specified in Table 1. Given a set of samples $\{\xi^1, \xi^2, \ldots, \xi^n\}$, the sample average approximation (SAA) problem is formulated as a two-stage stochastic linear program, where each scenario ξ^ω for $\omega = 1, \ldots, n$ occurs with equal probability $\frac{1}{n}$. When the sample set sufficiently represents the underlying distribution, the stochastic model can be reformulated as a mixed-integer deterministic program (MIP) (Birge and Louveaux 1997). Due to the typically large scenario space, we employ Monte Carlo simulation to generate a computationally tractable subset of representative scenarios.

Given a sample, we can approximate the second stage profit $E[\Pi(\mathbf{q}, \tau \mid \mathbf{G}, \mathbf{R}, \mathbf{U}, \mathbf{D})]$ by the sample average:

$$\hat{\Pi}(\mathbf{q}, \tau) = \frac{1}{n} \sum_{\omega=1}^{n} \Pi(q, \tau \mid \xi^\omega).$$

The Sample Average Approximation (SAA) model corresponding to the risk-averse problem formulation in Equation 19 is reformulated in Section A.2, while maintaining its linear and deterministic structure. The resulting model is a mixed integer linear program (MILP), which can be efficiently solved using commercial optimization solvers. In this reformulation, each second-stage decision variable is replicated for every sample scenario, denoted by the superscript ω. Consequently, we define the matrix $\mathbf{S}$ to contain elements S_m^ω for all $m \in \mathcal{M}$ and $\omega \in \{1, \ldots, n\}$. Similarly, we introduce matrices $\mathbf{L}$, $\mathbf{p}$, $\mathbf{r}$, $\mathbf{o}$, and $\mathbf{Y}$ to represent their respective scenario-dependent variables. For notational convenience, let ψ^ω denote the realized profit in scenario ω, and let $\boldsymbol{\psi}$ represent the vector of all realized profits. Finally, we define the variable VaR_α to represent the Value-at-Risk at confidence level α, and introduce auxiliary variables η^ω for computing the Conditional Value-at-Risk (CVaR), with $\boldsymbol{\eta}$ denoting the corresponding vector.

The deterministic equivalent formulation of our two-stage stochastic model, presented in Section A.2, is implemented using Python 3.8 and solved with the open-source HiGHS solver (Huangfu and Hall 2018). For each problem instance, we create M samples of size n and compute estimates of the mean and variance of the profits based on the objective values of the samples M. Then we take the first-stage decisions of the sample with the lowest objective value and create an out-of-sample estimate of the mean and variance of the realized cost for this first-stage decision. Then we can construct a confidence interval based on the t-distribution for the optimality gap. We chose our sample size $n = 500$ such that the halfwidth of such a confidence interval was less than 1% relative to the lowest objective value. Thus, all results reported in the paper are accurate to within 1%.

A.2 Deterministic equivalent of our SAA problem

$$\max_{\mathbf{q}, \tau, VaR_\alpha, \mathbf{Y}, \mathbf{p}, \mathbf{r}, \mathbf{o}, \mathbf{S}, \psi, \eta} \quad (1-\nu)\left[\frac{1}{n}\sum_{\omega=1}^{n}\psi^\omega\right] - \nu\left[VaR_\alpha + \frac{1}{(1-\alpha)n}\sum_{\omega=1}^{n}\eta^\omega\right] \tag{23}$$

Subject to

$$\psi^\omega = \sum_{m\in\mathcal{M}} \Bigg[y_m S_m^\omega - l_m L_m^\omega - c_m p_m^\omega - c_m^r \sum_{k\in\mathcal{K}_m} r_{mk}^\omega$$

$$- c_m^e o_m^\omega - \sum_{k\in\mathcal{K}_m} \left(c_{mk}^o \left(Y_{mk}^\omega G_{mk}^\omega + r_{mk}^\omega\right)\right)$$

$$- \sum_{k\in\mathcal{K}_m} c_{mk}^o \lambda \left(Y_{mk}^\omega (1 - G_{mk}^\omega) - r_{mk}^\omega\right) \Bigg] - c^{lab}\tau \qquad \forall \omega \in \{1,\ldots,n\} \tag{24}$$

$$\eta^\omega \geq -\psi^\omega - VaR_\alpha \qquad \forall \omega \in \{1,\ldots,n\} \tag{25}$$

$$\sum_{m\in\mathcal{M}} a_m o_m^\omega \leq \beta\tau \qquad \forall \omega \in \{1,\ldots,n\} \tag{26}$$

$$\sum_{m\in\mathcal{M}} a_m p_m^\omega + \sum_{m\in\mathcal{M}} \sum_{k\in\mathcal{K}_m} a_m^r r_{mk}^\omega \leq \tau \qquad \forall \omega \in \{1,\ldots,n\} \tag{27}$$

$$Y_{mk}^\omega \leq q_{mk} \qquad \forall m \in \mathcal{M}, k \in \mathcal{K}_m, \omega \in \{1,\ldots,n\} \tag{28}$$

$$Y_{mk}^\omega \leq U_{mk}^\omega \qquad \forall m \in \mathcal{M}, k \in \mathcal{K}_m, \omega \in \{1,\ldots,n\} \tag{29}$$

$$r_{mk}^\omega \leq R_{mk}^\omega Y_{mk}^\omega \left[1 - G_{mk}^\omega\right] \qquad \forall m \in \mathcal{M}, k \in \mathcal{K}_m, \omega \in \{1,\ldots,n\} \tag{30}$$

$$S_m^\omega \leq p_m^\omega + o_m^\omega + \sum_{k\in\mathcal{K}_m} r_{mk}^\omega + \sum_{k\in\mathcal{K}_m} Y_{mk}^\omega G_{mk}^\omega \qquad \forall m \in \mathcal{M}, \omega \in \{1,\ldots,n\} \tag{31}$$

$$S_m^\omega \leq D_m^\omega \qquad \forall m \in \mathcal{M}, \omega \in \{1,\ldots,n\} \tag{32}$$

$$L_m^\omega \geq D_m^\omega - S_m^\omega \qquad \forall m \in \mathcal{M}, \omega \in \{1,\ldots,n\} \tag{33}$$

$$q_{mk}, \tau \in \mathbb{Z}^+ \qquad \forall m \in \mathcal{M}, k \in \mathcal{K}_m \tag{34}$$

$$\tau, q_{mk}, p_m^\omega, o_m^\omega, r_{mk}^\omega \geq 0 \qquad \forall m \in \mathcal{M}, k \in \mathcal{K}_m, \omega \in \{1,\ldots,n\} \tag{35}$$

B Capacity distribution parameter under disruption

In our model, the capacity of the supplier U is modeled as a random variable $X \sim \Gamma(\alpha, \beta)$. The distribution parameters of U under disruption with probability θ can be computed as follows:

$$E[U] = (1-\theta)\cdot E[X] + \theta \cdot 0 = (1-\theta)\cdot(\alpha\cdot\beta) \tag{36}$$

$$\mathrm{Var}[U] = E[U^2] - (E[U])^2 = (1-\theta)(\alpha+\alpha^2)\beta^2 - (1-\theta)^2\alpha^2\beta^2 \tag{37}$$

C Summary of the literature Review

Table 12: Literature Review Summary

Reference	Supply Risk			Demand		Suppliers / Machines			Hedging Mechanism								Risk Attitude	
	Yield	Capacity	Disruption	Deterministic	Stochastic	Single	Dual	Multiple	Supplier Development	Supplier Mix	Responsive Pricing	Option Contract	Forward Contract	Spot Buy	Revenue/ Risk Share	Rework	Neutral	Risk Averse
Anupindi & Akella (1993)	✓				✓			✓									✓	
Agrawal & Nahmias (1997)	✓			✓				✓									✓	
Chen et al. (2001)	✓				✓			✓							✓		✓	
Federgruen & Yang (2008)	✓				✓			✓									✓	
Federgruen & Yang (2009)	✓				✓			✓									✓	
Burke et al. (2009)	✓				✓			✓									✓	
Merzifonluoglu & Feng (2014)	✓				✓			✓									✓	
Tang & Kouvelis (2011)	✓			✓			✓				✓						✓	
Merzifonluoglu (2017)					✓			✓				✓		✓				✓
Dada et al. (2007)		✓			✓		✓	✓		✓							✓	
Li et al. (2013)		✓		✓			✓	✓			✓						✓	
Ciarallo et al. (1994)		✓			✓	✓											✓	
Golmohammadi (2021)		✓			✓	✓			✓								✓	
Hu & Kostamis (2015)			✓		✓			✓		✓							✓	
Zhao & Freeman (2019)			✓	✓				✓		✓	✓						✓	
Giri (2011)	✓			✓			✓			✓								✓
Xie et al. (2021)	✓				✓	✓									✓		✓	

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Table 12 Continued from previous page

Reference	Yield	Cap.	Dis.	Det.	Stoch.	Sgl	Dual	Mult	SupDev	SupMix	RespPr	Opt	Fwd	Spot	RevSh	Rework	Neut	RiskA
Yuan et al. (2021)	✓			✓			✓		✓	✓							✓	
Feng et al. (2021)		✓			✓	✓											✓	
Tang & Kouvelis (2014)		✓		✓		✓									✓		✓	
Kouvelis et al. (2018)	✓			✓		✓					✓						✓	
Tan et al. (2016)		✓			✓		✓			✓							✓	
Feng et al. (2019)		✓			✓			✓									✓	
Yang & Birge (2013)					✓	✓									✓		✓	
Chao et al. (2009)	✓			✓		✓									✓		✓	
Wang et al. (2010)	✓	✓			✓		✓		✓								✓	
Golmohammadi & Hassini (2021)		✓			✓	✓			✓								✓	
Kouvelis et al. (2021)	✓			✓		✓					✓							✓
Federgruen & Yang (2011)	✓				✓			✓			✓						✓	
Sawik (2013)			✓	✓				✓		✓							✓	
Sawik (2017)			✓		✓			✓		✓							✓	
Sawik & Sawik (2024)			✓		✓		✓			✓								✓
Mohammadivojdan (2022)	✓		✓		✓			✓				✓	✓	✓				✓
Merzifonluoglu (2024)			✓		✓			✓				✓	✓	✓				✓
Merzifonluoglu (2015)	✓				✓			✓				✓						✓
Merzifonluoglu (2017)					✓			✓				✓		✓			✓	
Seifert et al. (2004)					✓			✓					✓	✓				✓
Luo & Chen (2017)	✓			✓		✓						✓		✓			✓	
Xue et al. (2020)			✓		✓	✓						✓				✓	✓	

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Table 12 Continued from previous page

Reference	Yield	Cap.	Dis.	Det.	Stoch.	Sgl	Dual	Mult	SupDev	SupMix	RespPr	Opt	Fwd	Spot	RevSh	Rework	Neut	RiskA
Fan et al. (2020)					✓	✓						✓						✓
Arbabian & Berenji (2023)		✓		✓			✓										✓	
Heydari et al. (2024)		✓		✓			✓					✓					✓	
Jadidi et al. (2024)	✓				✓			✓							✓		✓	
Jiang et al. (2025)	✓				✓		✓			✓	✓						✓	
Our Study (2025)	✓	✓	✓		✓			✓								✓	✓	✓